AUDITING: A JOURNAL OF PRACTICE & THEORY
Vol. 27, No. 1
May 2008
pp. 1–33

Is Earnings Fraud Associated with High Deferred Tax and/or Book Minus Tax Levels?

Michael L. Ettredge, Lili Sun, Picheng Lee, and Asokan A. Anandarajan

SUMMARY: The objective of this paper is to provide preliminary evidence whether SFAS No. 109 tax data might be useful in distinguishing between firms that do versus do not engage in earnings overstatement fraud (hereafter fraud). We examine the associations of various versions of deferred tax expense (DTE) variables and book income minus taxable income (BMT) variables with fraud, in the year of fraud onset and the year prior to fraud. The analysis is based upon a sample of 65 firms with positive pretax income, sanctioned by the Securities and Exchange Commission (SEC), in Accounting and Auditing Enforcement Releases (AAERs). A set of control firms are matched by asset size, two-digit SIC code, year, and nature of income (positive versus negative pretax income). We also perform analyses using a larger, nonmatched control sample. Our results indicate that, for firms with positive pretax income, DTE-based variables have strong incremental associations with fraud occurrence, beyond discretionary accruals and selected other explanatory variables, in the year of fraud onset. DTE-based variables have modest incremental power to explain future (next-year) fraud occurrence (but only when using matched samples). BMT-based variables generally lack explanatory power. In summary, this study provides new information about managers' tax reporting behavior in the presence of fraud, and suggests that DTE-based variables are likely to be useful in detecting fraud.

Keywords: earnings overstatement; fraud; book income; taxable income; deferred tax expenses; SFAS No. 109.

INTRODUCTION

The revelation of financial statement fraud can impose significant legal costs and risks on auditors (Feroz et al. 1991; Carcello and Palmrose 1994; Palmrose and Scholz 2004). For example, when Xerox was sanctioned for overstating earnings by $3

Michael L. Ettredge is a Professor at The University of Kansas, Lili Sun is an Assistant Professor at Rutgers, The State University of New Jersey, Newark, Picheng Lee is an Associate Professor at Pace University and a Visiting Professor at Soochow University, Taiwan, and Asokan A. Anandarajan is a Professor at the New Jersey Institute of Technology.

Earlier versions of this paper were entitled, "Using SFAS No. 109 Tax Data to Predict Fraud," "Do Deferred Tax Data Signal Earnings Fraud?," and "Are High Deferred Tax Levels Associated with Earnings Fraud?" The paper was presented at the 2006 American Accounting Association national meeting and benefited from participant comments.

Submitted: August 2006
Accepted: November 2007

billion, its auditor KPMG was liable for $22 million in penalties (SEC 2005). Enron's fraud resulted in the demise of its external auditor, Arthur Andersen. When revealed, financial statement fraud also has serious impacts on investors, via drastically reduced stock prices. Browning and Dugan (2002) estimate that financial statement fraud and its consequences have cost investors close to $7 trillion in recent years, particularly in the technology sector. Given the adverse legal consequences to the auditor and potential costs to investors if such fraud goes undetected for a significant period of time, research that can help auditors understand managers' methods of committing fraud is desirable.

Corporate managers face conflicting incentives when manipulating earnings. On one hand, managers frequently desire to increase income reported to shareholders and other external users (Sweeney 1994; DeFond and Jiambalvo 1994; DeAngelo et al. 1994; Burgstahler and Dichev 1997; Barth et al. 1999; Beatty et al. 2000; Bartov et al. 2002). However, managers also desire to minimize taxable income reported to the IRS and other taxing authorities (Dhaliwal et al. 1994; Mills and Newberry 2001; Schnee 2004; Schnee 2006). Managers can pursue both goals simultaneously by manipulating income upward for financial reporting, but not for tax reporting.[1] Managers biasing earnings upward for financial reporting arguably will prefer not to pay income taxes on the overstated components. This should increase the gap between pre-tax "book" and taxable incomes, generating detectable changes in firms' deferred tax liabilities, deferred tax expenses, and effective tax rates. Deferred tax data therefore are likely to reflect some of the effects of fraudulently overstated financial income. On the other hand, prior research (Erickson et al. 2004) indicates that some managers do pay taxes on fraudulent income, presumably to help conceal the fraud. Thus the tax-related behavior of managers, when committing fraud, is an empirical phenomenon deserving further research.

Prior studies of deferred taxes provide empirical evidence that higher deferred tax expenses (or book-tax income differences) are associated with poor earnings quality (proxied by barely meeting/beating various earnings benchmarks; Phillips et al. 2003), low predictability for future earnings growth (Lev and Nissim 2004), lower earnings persistence (Hanlon 2005), and manipulations of core expenses (Penman 2001). Although financial statement fraud is an extreme case of earnings management, prior literature has not investigated whether its presence is associated with higher levels of deferred tax variables. Two recent studies do investigate the extent to which managers appear to "conform" income for tax reporting to overstated or fraudulent book income (Erickson et al. 2004; Badertscher et al. 2006). Conforming behavior reduces the likelihood overstatements will be detected, whereas nonconforming behavior reduces tax payments. Prior and concurrent studies have not investigated whether the nonconforming earnings reported by fraud firms are large enough to generate significant associations between tax-related variables and the existence of fraud.[2] This paper provides preliminary evidence whether financial reporting tax data (under SFAS No. 109) can be used to distinguish between firms committing earnings overstatement fraud (hereafter fraud) and control samples of nonfraud firms.

---

[1] For example, Sapsford and Beckett (2002) state that Citigroup Inc. cooperated with Enron to disguise Enron's borrowing as energy sales. Enron reported to its shareholders revenues that were, in effect, the proceeds of borrowing, but Enron treated the transactions as loans for tax purposes.

[2] Neither Erickson et al. (2004) nor Badertscher et al. (2006) attempt to determine whether deferred tax related variables are useful in distinguishing between fraud or misstatement firms and "clean" firms. Erickson et al. (2004) investigate a sample of fraud-only firms to determine the extent of income taxes they paid on fraudulent income. To control for selection bias, Badertscher et al. (2006) use "clean" control firms in the first step of a Heckman two-step estimation, but their main multivariate analyses and hypotheses testing are restricted to restatement firms only.

The main objective is accomplished via estimation of models in which fraud versus nonfraud status is explained using tax-related variables. If managers report enough fraudulent income as taxable, and pay associated taxes, then tax-related variables will not distinguish between fraud and control samples.[3] On the other hand, if managers attempt to increase "book" income while avoiding taxes on fraudulent components, then tax-related variables will differ between fraud and control samples. Some managers might employ one strategy, while others use the opposite, so the ability of tax-related variables to detect fraud onset will provide (only) an indication of managerial behavior in the aggregate.

As previously discussed, from the perspective of managers who commit fraud, conforming earnings management behavior has both costs and benefits. The benefit is that it reduces the gap between book and tax income and helps conceal the fraud. The cost is the increased tax burden and cash outflow. However, when firms have negative or zero book incomes, they often have negative or zero taxable incomes. In these cases, the benefit of conforming earnings management still exists but the cost is eliminated. Such firms should adopt the conforming earnings management strategy, with resulting minimization of book-tax income differences and deferred tax liabilities. Therefore, we focus our hypotheses and tests primarily on firms having positive pre-tax book income.

Our tax-related test variables include some based on deferred tax expense (*DTE*), and others based on pretax book income minus estimated taxable income (*BMT*). *DTE* and *BMT* are represented as dummy variables, continuous variables, and ranked-data variables. Different proxies for *BMT* and *DTE* allow us to examine the robustness of their associations with fraud. We control for discretionary accruals (measured in four different ways) and also control for several other factors known to have significant association with earnings overstatement fraud. The control variables represent audit firm type, auditor change, revenue change, leverage, demand for external financing, exchange membership, change in operating cash flow, and growth prospects measured by a market-to-book-equity ratio.

We employ two control samples. First, we maximize the variance of the fraud status dependent variable by employing a matched control sample.[4] This provides the explanatory variables with an opportunity to reveal any associations they might have with fraud occurrence. We match the fraud firms with control firms based on industry (two-digit SIC code), firm size (total assets), year, and book income status (positive versus negative). Given our matching procedure, we use conditional logistic regression models to differentiate between the fraud companies and the control group.[5] The dependent variable is a dichotomous variable coded "one" for the fraud sample companies, and "zero" for the control firms. We examine the association between different measures of *DTE* and *BMT* and the likelihood of fraud, controlling for discretionary accruals and other control variables, both in the year of fraud onset and in the year prior to fraud. When calculating variables for the fraud firms, information for the fraudulent year is measured using as-originally-reported fraudulent data.

Although we view this study as preliminary from a fraud prediction standpoint, we perform additional analyses utilizing a nonmatching design. In these tests the control samples consist of all nonfraud Compustat firms meeting certain selection criteria. The proportion of fraud firms relative to these larger samples is about 0.01 or less. Our purpose is to provide preliminary evidence whether tax-related variables have explanatory power when

---

3 An alternative explanation for no difference could be that managers manipulate book earnings by fraudulently manipulating the SFAS No. 109 data itself (Dhaliwal et al. 2004; Schrand and Wong 2003).

4 The variance of a dichotomous variable reaches its maximum when 50 percent of the observations are coded "zero" and 50 percent are coded "one."

5 See Hosmer and Lemeshow (2000); Agrawal and Chadha (2005).

employing a sample that is more representative (than the matched sample) of the actual prevalence of fraud.

We provide additional analyses that include use of pre-SFAS No. 109 fraud observations and data, that exclude firms having net operating loss carry forwards, and that simultaneously incorporate *DTE* and *BMT* variables in the same models. Finally, we examine behavior of fraud firms' *DTE* and *BMT* levels for the five years preceding and following fraud onset.

Our main results and contributions are summarized as follows. First, and most importantly, we find that tax-related variables (in particular those based on *DTE*) are associated with earnings overstatement fraud. This finding is restricted to firms having positive pretax book income. The association of deferred tax variables with fraud status suggests that managers committing fraud do not fully "cover their tracks" on this dimension. Although managers who overstate earnings engage in some conforming tax reporting behavior (Erickson et al. 2004; Badertscher et al. 2006), the nonconforming portion of fraudulent earnings is large enough on average to be detectable in our sample. This study also observes higher deferred tax expenses for fraud firms in the year prior to fraud onset, indicating the existence of nonconforming earnings management behavior preceding fraud.[6] Pre-fraud tax reporting behavior has not been studied in prior literature. In conclusion, our study enriches the stream of research that examines the usefulness of tax-related variables as proxies for earnings quality, by exploring an extreme case of earnings management, i.e., earnings fraud.

The remainder of this paper is organized as follows. The first additional section provides background on auditors' responsibility, and on book-tax differences. The succeeding section reviews relevant literature. That is followed by sections covering the hypothesis development, research methodology, and empirical results. A final section concludes.

BACKGROUND

Beasley (2003) calls for studies that can either influence future standard setting initiatives or provide further guidance to auditors in their enhanced responsibilities regarding fraud detection.[7] This study presents initial evidence regarding a novel set of metrics for potential use in detecting fraud. While SAS No. 99, like SAS No. 82, recommends a list of red flags to guide auditors, those red flags do not include any based on the difference between reported earnings for financial reporting purposes (referred to as book income) and earnings reported to the Internal Revenue Service (IRS), (referred to as taxable income).

Managers calculate two versions of corporate income each year. One version is for financial reporting purposes and is computed under generally accepted accounting principles (GAAP). The second version is computed in accordance with IRS rules to determine the corporation's federal tax liabilities. Observers note that the differences between book income and taxable income can be large (Mills 1998; Plesko 2002). For financial reporting purposes, GAAP provides managers with considerable discretion in the choice of accounting estimates and methods. The IRS allows substantially less discretion for tax reporting purposes. Hence, the difference between book income and taxable income potentially reflects the *level of discretion* used by management to overstate earnings (Mills 1998). Managers biasing earnings upwards for financial reporting arguably prefer not to pay taxes on

[6] Given that *ex post* investigation by the SEC determined that fraud began in the subsequent year, the large DTEs observed in the year prior to fraud onset likely represent upward management of book income that does not rise to the level of fraud.

[7] Auditor responsibility for detecting material misstatements due to fraud has been expanded under Statement of Auditing Standard (SAS) No. 99, entitled *Consideration of Fraud in a Financial Statement Audit* (AICPA 2003). This standard superseded SAS No. 82 (AICPA 1997).

the manipulated profits. Minimization of taxable income, in conjunction with upward manipulation of book income, should increase the gap between the two. The book-tax gap could simply reflect aggressive earnings management and is not necessarily indicative of fraud. In fact, fraud companies likely are a subset of those companies having large discretionary accruals (Beneish 1997). Hence, differences between book and tax data suggest tax-related variables might be useful to auditors and investors in assessing the quality of earnings and the likelihood of current or near-term fraud.

We turn now to a discussion of relevant prior literature.

PRIOR LITERATURE

This section discusses how our paper fits into the literatures on deferred tax reporting and earnings management.

Association between Earnings Management and Fraud

Management has various incentives to materially overstate earnings (Healy and Wahlen 1999; McNichols 2000). In particular, pressures can arise due to the desire to camouflage financial distress (Argenti 1976; Summers and Sweeney 1998; Rosner 2003); desire to avoid violating debt covenants (Chen and Wei 1993; DeFond and Jiambalvo 1994; Beatty and Weber 2003); desire to attract external financing at low cost (Dechow et al. 1996), desire to meet earnings expectations (Burgstahler and Dichev 1997; Bartov et al. 2002; Graham et al. 2005); desire to signal competence and enhance career reputation (Bartov et al. 2002; Farrell and Whidbee 2003; Feng 2004; Francis et al. 2004; Desai et al. 2006); and desire to maintain high stock prices for compensation benefits and insider trading benefits (Healy 1985; Matsunaga and Park 2001; Beneish 1999; Crocker and Slemrod 2005).

There is a thin line between acceptable earnings management and fraud. In the financial/capital markets literature, Beneish (1997) investigates differences between fraud firms and a group of nonfraud firms having large discretionary accruals. He finds that firms that violate GAAP, and commit earnings overstatement fraud, tend to have longer days sales in receivables, are more likely to have consecutive positive accruals preceding fraud, and have lower stock market returns. Dechow et al. (1996) and Richardson et al. (2006) document a significantly higher level of abnormal accruals made by fraud firms compared to nonfraud firms. Rosner (2003) predicts and finds that as bankrupt firms that did not (*ex ante*) appear to be distressed approach bankruptcy, their incomes exhibit greater magnitudes of positive accruals, in non-going-concern years, than do control firms. The accruals behavior of these firms resembles that of bankrupt firms that the SEC has sanctioned for fraud. These studies suggest use of accruals in fraud prediction models.

Association between Earnings Management and Book-Tax Differences

A number of recent studies focus on the association between SFAS No. 109 tax data and earnings management. Early research (Revsine et al. 1999) suggests that the ratio of pretax book income to taxable income can be used as a measure of accounting conservatism or aggressiveness. Penman (2001) concludes that differences in the ratio help to detect material manipulation of core expenses, although he does not go so far as to suggest that the differences could also indicate fraud. Joos et al. (2000) argue that firms with large book-tax differences opportunistically manage earnings, and investors recognize this fact. Mills and Newberry (2001) report evidence consistent with the magnitude of book-tax differences being positively associated with financial reporting incentives such as prior earnings patterns, financial distress, and bonus thresholds. Phillips et al. (2003) show that deferred tax data can be used to detect nonfraudulent overstatements of earnings. The Phillips et al.

results provide a model that distinguishes between firms likely to have overstated earnings, and other firms, in three particular circumstances. The three circumstances are (1) reported earnings are equal to or slightly greater than the prior year's earnings; (2) reported earnings are equal to or slightly greater than zero; and (3) reported earnings are equal to or slightly greater than analysts' consensus forecasts. Phillips et al. (2003) conclude that deferred tax data are informative about firms' earnings management activities. Lev and Nissim (2004) examine whether the difference between book income and tax income can be used to predict future earnings growth. Hanlon (2005) finds large positive book-tax differences are associated with lower earnings persistence.

Erickson et al. (2004) investigate a sample of 27 firms accused by the SEC of fraudulently overstating their earnings. They find that many of the firms partially "conformed" their taxable incomes to their book incomes, and paid tax on a portion of the overstated earnings. The fraud firms recorded deferred tax liabilities for the remaining portions of the overstatements (i.e., "nonconforming" book-tax behavior). Erickson et al. (2004) estimate that the average fraud firm paid $11.84 million to the IRS on overstated earnings, which was the equivalent of $0.11 in additional income taxes per $1 of inflated pretax earnings. They conclude that, based on their sample, managers appear to believe that $1 of overstated accounting earnings is more valuable than $0.11 of cash.

Using a sample of firms that restated financial statements downward due to accounting irregularities, Badertscher et al. (2006) focus on exploring firms' characteristics that impact the choice between conforming and nonconforming earnings management strategies. They find that nonconforming earnings management is more prevalent than conforming earnings management among restatement firms (i.e., managers do not report all of the earnings overstatements as taxable income). In particular, firms with net operating loss carryforwards, high free cash flow, higher quality auditors, and fraud were more inclined to adopt a conforming earnings management strategy.

Prior studies have examined the association of a number of factors with the existence of fraudulent financial reporting, including auditor change (Sorenson et al. 1983), poor financial performance (Loebbecke et al. 1989), rapid growth (Loebbecke et al. 1989), lower proportion of outside members on the board of directors (Beasley 1996), extensive insider trading (Summers and Sweeney 1998), a weak control environment and aggressive management attitude (Loebbecke and Willingham 1988; Bell and Carcello 2000), a greater disparity between earnings and cash flow from operations (Lee et al. 1999), abnormal accruals (e.g., Dechow et al. 1996; Beneish 1997; Rosner 2003; Richardson et al. 2006), and greater increases in receivables, inventory, and accruals (Feroz et al. 1991; Dechow et al. 1996; Summers and Sweeney 1998; Rosner 2003). However, no published research to date has examined whether variables capturing book-tax income differences and deferred tax expenses are useful in distinguishing between fraud firms and nonfraud firms.

HYPOTHESES

Evidence found in prior and concurrent studies leads to divergent predictions regarding the association between deferred tax data and existence of fraud. On the one hand, large book-tax income differences, or deferred tax liabilities, are associated with more earnings management (e.g., Joos et al. 2000; Phillips et al. 2003). Since fraud is an extreme case of earnings management (Beneish 1997), it is reasonable to expect that fraud firms have larger book-tax income differences or deferred tax liabilities than nonfraud firms. This line of reasoning posits that managers manipulating earnings upward, or committing overstatement fraud, practice nonconforming earnings management. That is, they desire to increase book income but without increasing taxable income (Hanlon and Krishnan 2006; Frank et al.

2005). Erickson et al. (2004) provide some support for the nonconformist scenario by showing that fraud firms do not pay taxes on the full amount of fraudulent earnings.

On the other hand, managers who overstate earnings also have incentives to practice conforming earnings management. Managers can mask or camouflage earnings overstatements or fraud by paying applicable taxes on the overstated income amounts. Under this scenario, taxable incomes (and taxes payable) are positively associated with the amounts of earnings overstatements. If managers are willing to pay taxes on earnings that do not exist, in the hope of masking the fraud, then fraud existence might not be associated with differences between book and taxable income or deferred tax expenses.

Our hypotheses are developed for firms with positive pretax income only. Since firms with negative pretax book incomes are more likely to have negative or zero taxable incomes, adopting the conforming strategy is less costly for them relative to firms with positive pretax book income. Thus, we do not expect to observe large book-tax income differences or deferred tax expenses for fraud firms having negative pretax book income.[8] We state our hypotheses in alternative form.

> **H1A:** For firms with positive pretax book income, there is a significant positive association between deferred tax metrics and earnings overstatement fraud in the year of fraud occurrence.

Two sets of deferred tax metrics are examined: those based on deferred tax expense, and those based on book-minus-tax income.

Our next hypothesis examines the relation between potential fraud and deferred tax data in the year preceding fraud. Literature suggests that firms tend to exhibit persistent earnings management in consecutive periods. For instance, Richardson et al. (2006) show that accruals are unusually high not only for the year of fraud onset but also for two preceding years. Ettredge et al. (2008) find that restatement firms (including fraud firms) exhibit increases in working capital components of net operating assets relative to sales for several years prior to fraud occurrence, reaching the highest point in the year of fraud onset. Since the balance sheet accumulates the effects of previous accounting choices (Barton and Simko 2002), the increase in net assets found in Ettredge et al. (2008) reflects the existence of earnings management preceding the misstatement or fraud period.

If fraud firms manage earnings upward in the pre-fraud period, it might be possible to employ deferred tax data to distinguish between fraud and nonfraud firms in the year prior to fraud. Whether deferred tax data possess such ability depends upon the managers' choice between conforming and nonconforming tax reporting strategies. Again, we state the hypothesis in alternative form:

> **H2A:** For firms with positive pretax book income, there is a significant positive association between deferred tax metrics and earnings overstatement fraud, in the year prior to fraud occurrence.

Rejection of the alternative hypothesis, due to a lack of association, would be consistent with strong book-tax conformity in a pre-fraud setting. Acceptance of the alternative would provide support for book-tax nonconformity.

As discussed above, discretionary accruals are associated with earnings overstatements. Phillips et al. (2003) argue that accruals metrics are subject to measurement error, which

[8] We wish to thank an anonymous reviewer for this insight.

can be compensated for by deferred tax variables. On the other hand, accruals metrics arguably should capture some differences between tax expense and cash paid for taxes, thus robbing tax-related metrics of explanatory power. These considerations suggest that we examine whether tax-based variables have incremental explanatory power, beyond discretionary accruals, in detecting existence of fraud. Therefore, we employ various accruals metrics as control variables in our models, in addition to a variety of other variables that prior literature suggests distinguish between fraud and nonfraud situations. Based on prior literature, we expect accruals to be positively associated with fraud occurrence.

METHODOLOGY

Sample Selection

Consistent with several prior studies (Beasley 1996; Dechow et al. 1996; Summers and Sweeney 1998; Erickson et al. 2004), we identify fraud firms using the SEC's Accounting and Auditing Enforcement Releases (AAERs). We use key word searches including terms such as "overstatement," "earnings management," and "earnings manipulation" to identify frauds involving overstated earnings. Panel A of Table 1 summarizes the sample selection process. We initially obtain a sample of 405 fraud companies. We delete 83 firms that initiated fraud prior to 1988, because SFAS No. 95 became effective in 1988, and substantially altered the reporting of operating cash flow, and therefore the calculation of accruals measures. Similar to Phillips et al. (2003), we delete 42 firms in the following industries: utilities (SIC codes 4900–4999), and financial institutions (SIC codes 6000–6999), because their accruals behaviors are very different from firms in other industries. We also delete 12 foreign firms. The above procedures leave us with a sample of 268 firms that were sanctioned by the SEC for fraudulent over-statement of earnings, with first fiscal year of fraud ranging from 1988–2002. We require financial information for the fraud year and the year prior to the onset of fraud. With respect to the fraud year, from the sample of 268 firms we delete 99 firms because of missing information on variables of interest, leaving a sample of 169 firms. We further delete 34 firms that are accused by SEC for misstating only quarterly income data. We delete 25 firms with tax fraud onset prior to December 1992, since SFAS No. 109 is effective after December 1992.[9] These procedures leave 110 firms. In this subset, 65 firms had positive pretax income and 45 firms had negative pretax income.[10] With respect to the year prior to fraud onset, we delete 105 firms from our sample of 268 fraud firms due to missing information for relevant variables. We further delete 32 firms whose fraud affected (only) quarterly income, and 36 firms whose frauds occurred in the pre-SFAS No. 109 era. This leaves a subset of 95 fraud firms available for observation in the pre-fraud year. In this subset, 65 firms had positive pretax income and 30 firms had negative pretax income.

For our initial analyses, employing a matched control sample, each fraud year and pre-fraud year observation for a test firm is matched with a control firm observation. We match

[9] SFAS No. 109 supersedes Accounting Principles Board (APB) Opinion No. 11 and SFAS No. 96, both of which had been considered acceptable methods of accounting for income taxes since 1987. SFAS No. 109 shifts the focus of income tax accounting from the income statement to balance sheet. Specifically, deferred income taxes are viewed as assets and liabilities of the firm, and deferred tax expense is determined based upon the current-year change in the firm's deferred tax liabilities and assets. Empirical evidence suggests that SFAS No. 109 tax data has incremental value-relevance relative to APB Opinion No. 11 (Ayers 1998).

[10] Although all firms in the fraud sample overstated book income, not all had positive pre-tax book income. We investigated the subsequent bankruptcy status of fraud firms having negative pre-tax book income. Among the 45 (30) firms having negative pre-tax book income in the year of fraud onset (prior year), 8 (9) firms subsequently went bankrupt. The average time between fraud onset and bankruptcy filing varies from one year to seven years, with a median of three years.

TABLE 1
Sample Selection and Industry Distribution

Panel A: Sample Selection—Fraud Firms and Matched Nonfraud Firms

Initial fraud sample, identified from AAERs issued by the SEC	405
Delete: firms with 1st year fraud prior to 1988	(83)
Delete: foreign firms	(12)
Delete: firms with SIC 4900-4999, 6000s	(42)
Subtotal for fraud sample	268

	Fraud Onset Year	One Year Prior to Fraud
Delete: firms with missing data for variables	(99)	(105)
Delete: firms with (only) quarterly financial statement fraud	(34)	(32)
Delete: firms with tax variables calculated using pre-SFAS No. 109 data (prior to December 1992)	(25)	(36)
Final fraud sample with earnings overstatements	110	95
Sub-sample of fraud firms with positive pretax income (used for hypotheses tests)	65	65
Sub-sample of fraud firms with nonpositive pretax income	45	30
Control firms matched with fraud firms by 2-Digit SIC code, year, and assets with complete financial data	110	95
Total of fraud plus control firms	220	190

Details on Number of Firms with Missing Data for Variables	Fraud Onset	Year Prior to Fraud
Deferred tax expenses missing	50	60
Discretionary accruals calculation data missing	39	32
Other financial variables missing	10	13
Subtotal	99	105

Panel B: Sample Distribution by Industry of Firms with Positive Pretax Income[a]

	Industry	Primary SIC Code	Number of Fraud Firms	% of Fraud Sample	% of Total Sample[b]
0	Agricultural, forestry, and fisheries	0100–0999	0	0%	0%
1	Mining and Construction	1000–1999, except for 1300–1399	2	3%	12%
2	Food	2000–2111	3	5%	1%
3	Textiles, printing and publishing	2200–2799	4	6%	3%
4	Chemicals	2800–2824, 2840–2899	0	0%	0%
5	Pharmaceuticals	2830–2836	2	3%	2%
6	Extractive Industries	2900–2999 and 1300–1399	1	2%	1%
7	Durable manufacturers	3000–3999, except for 3570–3579, 3670–3679	21	32%	1%

(*continued on next page*)

TABLE 1 (continued)

	Industry	Primary SIC Code	Number of Fraud Firms	% of Fraud Sample	% of Total Sample[b]
8	Computers	7370–7379, 3570–3579, and 3670–3679	14	22%	1%
9	Transportation	4000–4899	2	3%	2%
10	Utilities	4900–4999	0	0%	0%
11	Retail	5000–5999	11	17%	2%
12	Financial institutions	6000–6411	0	0%	0%
13	Insurance and real estate	6500–6999	0	0%	0%
14	Services	7000–8999, except for 7370–7379	5	8%	1%
15	Other	>9000	0	0%	0%
Total (in first two columns), Average (in third column)			65	100%	1%

Panel C: Sample Selection—the Nonmatching Control Sample

	Control Sample with Positive Pretax Income	Control Sample with Nonpositive Pretax Income	Full Control Sample[c]
Initial control sample including all firm-year observations covered by Compustat during the study period of 1992–2002 (21,352 * 11 years)	234,872	234,872	234,872
Delete: Non-U.S. incorporated firms	(20,460)	(20,460)	(20,460)
Delete: Financial and utilities firms	(55,143)	(55,143)	(55,143)
Delete: Fraud firm-year data from 1992 to 2002	(3,400)	(3,400)	(3,400)
Delete: Firms with missing/unqualified data for discretionary accruals computation as well as tax-related data	(93,011)	(93,011)	(93,011)
Delete: Firms with nonpositive pretax income	(31,835)	—	—
Delete: Firm with positive pretax income	—	(31,023)	—
Delete: Firms which do not operate in any one of the industries to which our fraud firms belong.	(24,186)	(24,741)	(43,164)
Delete: Firms with other missing control variables data	(895)	(2,893)	(5,095)
Final control sample	5,942	4,201	14,599

[a] The table in this panel is prepared using the final fraud sample for the year of fraud onset. Utilities (SIC codes 4900–4999) and financial institutions (SIC codes 6000–6999) are not included in this study's sample because their accruals behaviors are different from firms in other industries (Phillips et al. 2003).

[b] Percentage of fraud firms in the total sample = number of fraud firms/(number of fraud firms + number of nonfraud firms), where nonfraud firms are the nonmatching control sample with positive pretax income presented in Panel C of Table 1.

[c] Note that the number of control firms in the full sample (14,599) is larger than the sum of control firms in the positive (5,942) and negative (4,201) pretax income samples. To understand this, assume that potential control firm "A" operates in industry *i*, and has positive pretax income in year *t*. Suppose that there is no fraud firm having positive pretax income in industry *i* for year *t*. Then the year *t* observation of firm *A* will not be included as a control observation for analysis with positive pretax incomes. Neither will it be included in the control sample with negative pretax incomes. However, if our sample of fraud firms having negative pretax incomes contains any fraud firm in industry *i* for year *t*, the year *t* observation of firm *A* will be included in the full sample analysis.

by year, by two-digit SIC industry code, by firm size (total assets),[11] and by the sign of pretax book income (positive versus nonpositive).[12]

Panel B of Table 1 provides the industry distribution of fraud firms with positive pretax income. Consistent with prior literature (Bonner et al. 1998; Beasley et al. 1999; Bell and Carcello 2000), we observe that fraud is more likely to occur in durable goods manufacturing industries (32 percent of the fraud sample) and in high-technology industries (22 percent of the fraud sample). The panel also presents the number of fraud firms as a percentage of the total sample of fraud firms plus nonmatching control firms introduced subsequently.

Model

To test the association between deferred tax variables and fraud occurrence in the year prior to fraud onset, and in the fraud year, we perform the following conditional logistic regression:

$$\begin{aligned} FRAUD = {} & \beta_0 + \beta_1(\text{Accruals Proxy}) + \beta_2(DTE \text{ or } BMT \text{ proxy}) + \beta_3 AUD\_CHG \\ & + \beta_4 CHG\_REV + \beta_5 BIG4 + \beta_6 LEVERAGE + \beta_7 EX\_FIN \\ & + \beta_8 MBRATIO + \beta_9 OTEXCHG + \beta_{10} CHG\_OCF. \end{aligned} \tag{1}$$

Year subscripts are omitted. If fraud onset occurs in year t, we measure all explanatory variables as of year t to test H1A for the year of fraud onset, and as of year $t - 1$ to test H2A for the year prior to fraud onset. Explanatory variables are discussed below and are defined at more length in Table 2. Control variables include several accruals metrics and other variables drawn from prior literature (Krishnan and Krishnan 1997; Bonner et al. 1998; Summers and Sweeney 1998; Albrecht and Albrecht 2004). For the purpose of testing hypotheses, Model (1) is estimated using firms whose pretax book income is positive. For completeness, we also report results for the full sample including firms with positive and negative pretax income, and for the sample with negative pretax income only. When using the full sample (including positive and negative pre-tax incomes), we add two more variables, discussed below.

Test Variables

Deferred Tax Expenses

We compute several proxies for deferred tax expenses. These include a continuous variable (*DTE*), equal to deferred tax expense divided by average total assets. We employ a dichotomous variable (*DTE_DUM*) coded "one" if a firm reports deferred tax expense,

---

[11] Fraud firms are matched with control firms based upon total assets measured at the end of the year of fraud onset (year t). Auditors do not know when fraud commences. When it does, an auditor desiring to select comparables is likely to use the client's fraudulent total assets value to select similar-size companies in the same industry. From this perspective, our matching process resembles the auditors' actual use of client data in analytical review. However, to assess whether the fraud component of total assets is likely to have had an important effect on our choice of control companies, we perform the following additional analyses. First, we compare differences in means of total assets between the fraud sample and the matching sample for year $t - 1$ and year $t - 2$. T-test results show that there are no significant differences in year $t - 1$ ($p = 0.86$) or year $t - 2$ ($p = 0.90$). Second, we compare differences in means of total assets for fraud companies between year t and year $t - 1$, and between year $t - 1$ and year $t - 2$. Results indicate that fraud firms' total asset levels do not experience significant changes over time ($p = 0.64$ for the comparison of year t with year $t - 1$; $p = 0.36$ for the comparison of year $t - 1$ with $t - 2$).

[12] In additional analyses, we employ a nonmatched sample consisting of all Compustat nonfraud companies meeting certain criteria.

TABLE 2
Definitions of Variables[a]

Dependent Variable	Expected Sign	Measurement
FRAUD		= 1 for firms committing earnings-overstatement fraud in year *t*, and 0 otherwise.
Test (Tax) Variables		
DTE	+	= deferred tax expense (annual Compustat data item #50) in year *t*, scaled by Avg. *TA*. Avg. *TA* = [firm *i*'s total assets (Compustat data item #6)) for $t - 1$ (TA_{it-1}) + firm *i*'s total assets for *t* (TA_{it})] divided by 2.
DTE_DUM	+	= 1 if *DTE* is positive in year *t*, 0 otherwise. *DTE* is defined as above.
DTE_TOP20	+	= 1 if a firm's *DTE* is ranked in the top 20th percentile among all Compustat firms in the same two-digit SIC industry and in the same year, 0 otherwise.
DTE_LOW20	–	= 1 if a firm's *DTE* is ranked in the bottom 20th percentile among all Compustat firms in the same two-digit SIC industry and in the same year, 0 otherwise.
DTE_RANK	+	All *DTE* observations are ranked by year within two-digit SIC industries. In a given year, the observation with the highest value of *DTE* in an industry having "n" firms is assigned a value of "n." The next largest observation is ranked as "n − 1," and so on until the observation having the lowest value of *DTE* is assigned a value of 1. Then, all assigned values are scaled by n, the number of firms in the industry. Thus, *DTE_RANK* ranges in value from (1/n) to 1 within each industry and year.
BMT	+	= $(BK_{it} - TX_{it})$/Avg. *TA*; where: BK_{it} = firm *i*'s book income before taxes, accounting changes, and extraordinary items, in year *t* (annual Compustat data item # 170). TX_{it} = firm *i*'s estimated taxable income in year *t*. If net operating loss (NOL) carry-forwards (annual Compustat data item # 52) equal zero for year $t - 1$, and if the firm reports positive pretax book income (annual Compustat data item #170 exceeds zero for year *t*), TX_{it} equals firm *i*'s total current tax expense (annual Compustat data item #16 − annual Compustat data item #50) divided by the statutory rate, 0.35. If NOL carry-forwards are nonzero for year $t - 1$, or if pretax book income is negative in year *t*, TX_{it} equals zero. Avg. *TA* = [firm *i*'s total assets (Compustat data item data #6) for year $t - 1$ (TA_{it-1}) + firm *i*'s total assets for year *t* (TA_{it})] divided by 2.
BMT_DUM	+	= 1 if *BMT* is positive in year *t*, 0 otherwise. *BMT* is defined as above.
BMT_TOP20	+	= 1 if a firm's *BMT* is ranked in the top 20th percentile among all Compustat firms in the same two-digit SIC industry and in the same year, 0 otherwise.

(*continued on next page*)

TABLE 2 (continued)

Dependent Variable	Expected Sign	Measurement
BMT_LOW20	−	= 1 if a firm's *BMT* is ranked in the bottom 20th percentile among all Compustat firms in the same two-digit SIC industry and in the same year, 0 otherwise.
Control Variables		
AUDIT_CHNG	+	= 1 if auditor was changed in year t; 0 otherwise.
CHG_REV	+	= firm i's change in revenue as a percentage of beginning of year assets, computed as $(REV_{it} - REV_{it-1})/TA_{it-1}$ where REV_{it} = net sales (Compustat data item #12) in year t, REV_{it-1} = net sales in year $t - 1$, TA_{it-1} = total assets (Compustat data item #6) in year $t - 1$.
BIG4	−	= 1 if a firm employs a big eight/five/four auditor, 0 otherwise.
LEVERAGE	+	= Total liabilities (Compustat data item #181) scaled by total assets (Compustat data item #6) for year t.
EX_FIN	+	= 1 if firm i's *FreeC* is less than −0.5, 0 otherwise. $FreeC_{it}$ is defined as $(OCF_{it} - CPTEXP_{it-1})/CA_{it-1}$, where OCF_{it} = operating cash flow in year t (Compustat data item # 308), $CPTEXP_{it-1}$ = capital expenditure in year $t - 1$ (Compustat data item #128), CA_{it-1} = current assets in year $t - 1$ (Compustat data item #4).
MBRATIO	+	Market value of equity/book value of equity for year t. Market value of equity = Compustat data item #24*#25; Book value of equity = Compustat data item #60.
OTCEXCHG	+	= 1 if a firm's stock is traded over-the-counter for year t, 0 otherwise.
CHG_OCF	−	= change in a firm's operating cash flows (Compustat item #308) from year $t - 1$ to year t, scaled by beginning year total assets (Compustat data item #6).
Abnormal Accruals Proxies		
REDCA Discretionary current accruals controlling for firm performance by including ROA as a regressor	+	We estimate the parameters for the following equation by two-digit SIC and by year: $$CA_{it} = \alpha_0 + \beta_1[1/TA_{it-1}] + \beta_2[\Delta REV_{it}] + \beta_3[\mathrm{ROA}_{it-1}] + \epsilon_{it}.$$ Then, the discretionary current accruals (*REDCA*) are calculated by using the estimated parameters as follows: $$REDCA_{it} = CA_{it} - \{a_0 + b_1[1/TA_{it-1}] + b_2[\Delta REV_{it} - \Delta \mathrm{AR}_{it}] + b_3[\mathrm{ROA}_{it-1}]\}$$ where current accruals CA_{it} is net income before extraordinary items (Compustat data item # 123) plus depreciation and amortization (Compustat data item # 125) minus operating cash flows (Compustat data item

(*continued on next page*)

TABLE 2 (continued)

Dependent Variable	Expected Sign	Measurement
		# 308) scaled by beginning of year total assets; ΔREV_{it} = net sales (Compustat data item #12) in year t less net sales in year $t-1$ scaled by the beginning of the year total assets; ΔAR_{it} = accounts receivable (Compustat item #2) in year t less accounts receivable in year $t-1$, scaled by beginning of year total assets; ROA_{it-1} is income before extraordinary items (Compustat data item # 18) scaled by total assets for firm i in year $t-1$.
PADCA performance adjusted current discretionary accruals using portfolio technique	+	We estimate the parameters for the following equation by two-digit SIC and by year: $$CA_{it} = \alpha_0 + \beta_1[1/TA_{it-1}] + \beta_2[\Delta REV_{it}] + \epsilon_{it}.$$ The current discretionary accruals are calculated as: $$DCA_{it} = CA_{it} - \{a_0 + b_1[1/TA_{it-1}] + b_2[\Delta REV_{it} - \Delta AR_{it}]\}.$$ All variables are defined same as for *REDCA* calculation. In order to obtain *PADCA*, we partition firms within each two-digit SIC code into deciles based on their year $t-1$'s return on assets (ROA), and obtain median value of *DCA* for each ROA portfolio: $PADCA_{it} = DCA_{it}$ − median DCA_t of matching portfolio.
DA Discretionary total accruals	+	We estimate the parameters for the following equation by two-digit SIC and by year: $$TAcc_{it} = \alpha_0 + \beta_1[1/TA_{it-1}] + \beta_2[\Delta REV_{it}] + \beta_3[PPE_{it}] + \epsilon_{it}$$ where total accruals ($TAcc_{it}$) are defined as income before extraordinary items and discontinued operations (Compustat data item # 18) minus net cash flow from operating activities (Compustat data item # 308) adjusted for the extraordinary items and discontinued operations (Compustat data item # 124) reported on the statement of cash flows, scaled by the beginning of the year total assets; ΔREV_{it} = net sales (Compustat data item #12) in year t less net sales in year $t-1$ scaled by the beginning of the year total assets; PPE_{it} is Gross Property and Plant Equipment (Compustat data item # 7), scaled by the beginning of the year total assets. The discretionary accruals (*DA*) are defined as: $$DA_{it} = TAcc_{it} - \{a_0 + b_1[1/TA_{it-1}] + b_2[\Delta REV_{it}] + b_3[PPE_{it}]\}.$$

(*continued on next page*)

TABLE 2 (continued)

Dependent Variable	Expected Sign	Measurement
DA_ROA Discretionary total accruals controlling for firm performance	+	We estimate the parameters for the following equation by two-digit SIC and by year: $$TAcc_{it} = \alpha_1 + \beta_1[1/TA_{it-1}] + \beta_2[\Delta REV_{it}] + \beta_3[PPE_{it}] + \beta_4[\mathrm{ROA}_{it-1}] + \epsilon_{it}$$ Where ROA is income before extraordinary items (Compustat data item # 18) scaled by total assets for firm i in year $t - 1$. All other variables are defined the same as for *DA* calculation. The discretionary accruals controlling for firm performance (*DA_ROA*) are defined as: $$DA\_ROA_{it} = TAcc_{it} - \{a_0 + b_1[1/TA_{it-1}] + b_2[\Delta REV_{it}] + b_3[PPE_{it}] + b_4\,[\mathrm{ROA}_{it-1}]\}.$$

[a] Year t denotes the fiscal year of fraud onset. Variable definitions in Table 2 are used in analyses of the year of fraud onset, presented in Panel A of Table 3, and in Tables 4 and 6. All variables except *FRAUD* are measured in the year prior to fraud onset for the analyses of one year prior to fraud onset, presented in Panel B of Table 3, and in Table 5.

and coded "zero" if a firm reports deferred tax credits. We use a dummy variable to capture firms whose scaled deferred tax expenses (that is, *DTE* as defined above) are in the top 20th percentile among all Compustat firms in the same two-digit SIC industry, and in the same year (*DTE_TOP 20*). A second dummy variable captures firms whose scaled deferred tax expenses are in the bottom 20th percentile (*DTE_LOW20*). For the nonmatching design analysis, we also employ a *DTE* variable based on ranked *DTE* data (*DTE_RANK*). To investigate whether association of *DTE* with fraud status differs for firms having positive versus negative pretax book income, we add to Model (1) a dichotomous variable (*POS*) coded "one" for positive pretax income, and "zero" otherwise. Variable *POS* also is interacted with *DTE* (i.e., *POS* * *DTE*) when employing the whole sample (firms having positive and negative pretax book incomes).

Book Income-Tax Income Difference

To test H1A and H2A for book-minus-tax income differences, we employ a continuous variable (*BMT*), equal to pretax book income, minus estimated taxable income, divided by average total assets. We also employ a dichotomous variable (*BMT_DUM*) coded "one" if *BMT* is positive (see above), and coded "zero" otherwise. We use a dummy variable to capture firms whose scaled book-minus-tax incomes (that is, *BMT* above) are in the top 20th percentile among all Compustat firms in the same two-digit SIC industry, and in the same year (*BMT_TOP20*). A second dummy variable captures firms whose scaled book-minus-tax incomes are in the bottom 20th percentile (*BMT_LOW20*). To investigate whether association of *BMT* with fraud status differs for firms having positive versus negative pretax book income, we create a dichotomous variable (*POS*) coded "one" for positive pretax income, and "zero" otherwise. Variable *POS* is interacted with *BMT* (i.e., *POS* * *BMT*) when employing the whole sample (firms having positive and negative pretax book incomes).

Control Variables

Discretionary Accruals

Earnings overstatement often is accomplished using discretionary accruals. In order to ascertain whether the variables in our study have incremental association with fraud, we control for discretionary accruals. To ensure robustness of results, this study employs four measures of discretionary accruals based upon prior literature (Ashbaugh et al. 2003; Kothari et al. 2005). The four versions are: total discretionary accruals (*DA*), performance adjusted total discretionary accruals (*DA_ROA*), performance adjusted current discretionary accruals using ROA as a regressor (*REDCA*), and performance adjusted current discretionary accruals using a portfolio technique (*PADCA*).[13] The calculations of accruals are discussed in detail in Table 2. We expect positive coefficients for the accruals variables. Estimation results are similar for all four proxies, so we tabulate results for only one version, *REDCA*.

Other Control Variables

Prior literature shows that fraud is more likely to occur if a company experiences auditor change (Sorenson et al. 1983; Loebbecke et al. 1989; Krishnan and Krishnan 1997), has an unusual increase in revenue (Bonner et al. 1998), moves closer to violating debt covenants (DeFond and Jiambalvo 1994; Dechow et al. 1996), has the desire to attract external financing at low cost (Dechow et al. 1996), or experiences high market expectations of future profitability growth (Loebbecke et al. 1989; Beasley 1996; Summers and Sweeney 1998). Firms traded over-the-counter tend to be smaller and more risky, and hence are more likely to commit fraud (Jiambalvo 1996; Beasley 1996). Since Big 8/6/4 (abbreviated as Big 4) auditors are of higher quality than non-Big 4 auditors (Simunic 1980; Palmrose 1988; DeFond 1992; Becker et al. 1998; Geiger and Rama 2006), commission of fraud arguably is less prevalent among clients of the Big 4. Increases in operating cash flows reflect improvement in current performance and reduce the need to manipulate earnings (Philips et al. 2003). We control for these factors in our models. Their detailed definitions are presented in Table 2.

RESULTS

Main Results

Table 3 provides descriptive statistics for our fraud and matching control firms. We present descriptive statistics for fraud firms having positive pretax book income, and their matching control firms, because these are the subjects of our hypotheses tests. We conduct both parametric t-tests and nonparametric Wilcoxon rank tests to investigate differences in continuous variables between the two sub-samples. We use z-tests of differences in proportions for dichotomous variables. In the year of fraud onset (Panel A), deferred tax expenses (*DTE*) for fraud firms are significantly higher than for nonfraud firms, based upon both parametric and nonparametric tests (mean 0.003 versus −0.002; median 0.002 versus 0.000). The percentage of fraud firms having deferred tax expenses rather than credits

[13] Hribar and Collins (2002) argue there is an advantage to measuring accruals using data from the statement of cash flows (SCF) as opposed to using data from the balance sheet, especially in the presence of mergers and acquisitions or discontinued operations. They further propose two alternative definitions of accruals obtained from the SCF (see Hribar and Collins 2002, 109, Equations 2 and 3). Our accrual measures *DA* and *DA_ROA* are defined as in Equation (2) of Hribar and Collins. Hribar and Collins use Compustat annual data item #123, earnings before extraordinary items taken from the SCF. We use Compustat annual data item #18, earnings before extraordinary items taken from the income statement. For 99 percent of the Compustat population, these two items are the same.

TABLE 3
Descriptive Statistics for Firms with Positive Pretax Income

Panel A: Year of Fraud Onset

Continuous Variables	Fraud Firms (n = 65) Mean	Fraud Firms (n = 65) Median	Nonfraud Firms (n = 65) Mean	Nonfraud Firms (n = 65) Median	t-statistic for Parametric Test in Means Differences t-stat	p-value[a]	z-statistic for Nonparametric Wilcoxon Rank Test z-stat	p-value
Assets	4185.930	145.914	3750.970	146.272	0.16	0.88	0.01	0.99
DTE	0.003	0.002	−0.002	0.000	1.49	0.07	1.84	0.03
BMT	0.032	0.023	0.020	0.003	0.91	0.18	1.67	0.05
CHG_REV	0.521	0.371	0.239	0.143	3.44	0.00	3.70	0.00
LEVERAGE	0.530	0.495	0.501	0.505	0.60	0.27	0.33	0.37
MBRATIO	4.550	2.424	2.802	2.359	1.67	0.05	1.22	0.06
CHG_OCF	−0.019	−0.020	−0.025	0.010	0.12	0.45	−1.59	0.06
REDCA	0.098	0.074	0.021	0.003	3.93	0.00	3.99	0.00
DA	0.093	0.069	0.029	0.013	3.38	0.00	3.36	0.00
DA_ROA	0.085	0.073	0.022	0.008	3.37	0.00	3.43	0.00
PADCA	0.170	0.078	0.059	−0.017	1.52	0.07	3.64	0.00

Discrete Variables	Proportion Coded "one" Fraud Firms	Proportion Coded "one" Nonfraud Firms	z-statistic for Difference in Proportions z-stat	p-value
DTE_DUM	55.4%	41.5%	1.58	0.06
DTE_TOP20	30.8%	10.8%	2.80	0.00
DTE_LOW20	16.9%	21.5%	−0.66	0.25
BMT_DUM	66.2%	55.4%	1.25	0.11
BMT_TOP20	23.1%	16.9%	0.87	0.19
BMT_LOW20	18.5%	24.6%	−0.85	0.20
AUDIT_CHNG	15.4%	3.08%	2.46	0.01
BIG4	84.6%	90.8%	−1.06	0.14
EX_FIN	6.15%	1.54%	1.37	0.09
OTCEXCHG	36.9%	18.5%	2.39	0.01

Panel B: One Year Prior to Fraud[b]

Continuous Variables	Fraud Firms (n = 65) Mean	Fraud Firms (n = 65) Median	Nonfraud Firms (n = 65) Mean	Nonfraud Firms (n = 65) Median	t-statistic for Parametric Test in Means Differences t-stat	p-value[a]	z-statistic for Nonparametric Wilcoxon Rank Test z-stat	p-value
Assets	2226.740	148.461	1801.350	150.249	0.46	0.65	0.07	0.95
DTE	0.003	0.000	−0.002	−0.001	1.67	0.05	1.34	0.05
BMT	0.037	0.012	0.016	0.010	1.40	0.08	1.16	0.12
CHG_REV	0.670	0.334	0.325	0.188	2.52	0.01	3.19	0.00

(*continued on next page*)

TABLE 3 (continued)

Continuous Variables	Fraud Firms (n = 65)		Nonfraud Firms (n = 65)		t-statistic for Parametric Test in Means Differences		z-statistic for Nonparametric Wilcoxon Rank Test	
	Mean	Median	Mean	Median	t-stat	p-value[a]	z-stat	p-value
LEVERAGE	0.502	0.483	0.468	0.394	0.69	0.25	1.02	0.16
MBRATIO	5.169	3.064	2.597	2.090	2.96	0.00	2.93	0.00
CHG_OCF	0.050	0.041	0.043	0.026	0.22	0.42	0.74	0.23
REDCA	0.077	0.053	0.026	0.015	2.20	0.02	1.96	0.03
DA	0.050	0.043	0.035	0.027	0.64	0.27	0.73	0.23
DA_ROA	0.045	0.040	0.030	0.013	0.62	0.27	0.59	0.28
PADCA	0.144	0.051	0.102	0.009	0.40	0.35	1.99	0.02

Discrete Variables	Proportion Coded "one"		z-statistic for Difference in Proportions	
	Fraud Firms	Nonfraud Firms	z-stat	p-value
DTE_DUM	49.2	41.5	0.88	0.19
DTE_TOP20	24.6	18.5	0.85	0.20
DTE_LOW20	13.8	23.1	−1.36	0.09
BMT_DUM	62.5	56.3	0.72	0.24
BMT_TOP20	28.1	14.1	1.96	0.03
BMT_LOW20	18.8	21.9	−0.44	0.33
AUDIT_CHNG	7.69	1.54	1.68	0.05
BIG4	86.2	90.8	−0.82	0.21
EX_FIN	4.62	0.00	1.76	0.04
OTCEXCHG	35.4	12.3	3.18	0.00

[a] p-value for "Assets" is two-tailed; p-values for all other variables are one-tailed.
[b] The difference between mean assets in Panel A versus Panel B is mostly due to size outliers in Panel A. When Panel A asset outliers are winsorized, the mean level of assets in Panel A is 2507.33 millions for fraud firms and 1931.68 for nonfraud firms. Remaining size (assets) difference between the two panels is due to differences in sample composition for the two panels. Panel A is based upon 65 fraud firms with positive pretax income in year t (fraud onset). Panel B is based upon 65 fraud firms with positive pretax income in year $t-1$ (one year prior to fraud). There are 49 fraud firms common to both Panels A and B.
See Table 2 for variable definitions.

(*DTE_DUM*) is significantly higher (p-value = 0.06) than the percentage for nonfraud firms (55 percent versus 42 percent). The proportion of fraud firms whose deferred tax expense amounts are among the top 20 percentile in their industries (*DTE_TOP20*) is 31 percent, significantly greater (p value = 0.00) than for nonfraud firms, at 11 percent. The proportion of fraud firms whose deferred tax expense amounts are among the lowest 20 percentile of firms in their industries (*DTE_LOW20*) is 17 percent, less than that for nonfraud firms, at 22 percent; however the difference is insignificant. Overall, univariate analysis reveals that means and/or medians of some *DTE*-related variables differ significantly between the fraud and nonfraud samples, providing some support to H1A.

In regards to *BMT*-related variables, fraud firms have higher book-tax income differences (*BMT*) compared to nonfraud firms (mean 0.032 versus 0.020; median 0.023 versus

0.003); however only the nonparametric test result is significant (p value = 0.05). The inconsistent significance between the two tests is probably due to the high skewness of *BMT*. *BMT*-related dichotomous variables exhibit expected directional differences, although the differences are not significant. Fraud firms are more likely to have positive *BMT* (*BMT_DUM*), more likely to have *BMT* in the top 20 percentile (*BMT_TOP20*), and less likely to have *BMT* in the lowest 20 percentile (*BMT_LOW20*). Therefore, only weak univariate evidence supports the association of *BMT*-related variables with fraud onset.

Panel B reports univariate results for the year prior to fraud onset. For the comparison of deferred tax expenses, fraud firms are observed to have significantly larger *DTE*, based upon both parametric and nonparametric tests (mean of 0.003 versus −0.002; median of 0.000 versus −0.001). *DTE_DUM* and *DTE_TOP20* are higher in the fraud group, although the difference is insignificant. *DTE_LOW20* is significantly lower for fraud firms compared to nonfraud firms (14 percent versus 23 percent), indicating that a firm within the bottom 20 percentile for deferred tax expenses has a lower likelihood of committing fraud. These results provide some evidence to support H2A for the positive association between deferred tax expenses and next-year fraud occurrence.

In the year prior to onset, fraud firms have higher *BMT* compared to control firms (mean of 0.037 versus 0.016; median of 0.012 versus 0.010), although only the parametric test is significant. Among dichotomous *BMT*-related variables, *BMT_TOP20* is highly significant (p = 0.03), indicating that firms within the top 20 percentile of *BMT* are more likely to commit future fraud. Thus, univariate analysis provides limited support of the usefulness of *BMT* in providing early warning of fraud.

To summarize, Table 3 offers at least some support for all of our four hypotheses. These results are univariate and might differ using the multivariate models.[14] We turn now to a discussion of descriptive statistics for control variables presented in Table 3. Means for total assets do not differ between fraud firms and nonfraud firms in either Panel due to size matching.[15] In the year of fraud onset, Panel A, the means of all four accruals metrics differ between the fraud and control samples, with highly significant p-values. Other significant differences are found for growth in scaled revenue (*CHG_REV*), and market expectations for growth (*MBRATIO*). Both are higher for fraud firms. A nonparametric test shows that fraud firms have significantly lower increase in operating cash flow (*CHG_OCF*) than nonfraud firms. Among the discrete variables, as expected, the fraud group is more likely to have a new auditor (*AUDIT_CHNG*), to need external financing (*EX_FIN*), and to be traded over-the-counter (*OTCEXCHG*). Interestingly, most control variables in the year prior to fraud onset (Panel B) exhibit similar patterns. Unlike in Panel A, only current discretionary accruals (*REDCA* and *PADCA*) still differ between the fraud and control firms, but total discretionary accruals (*DA*, *DA_ROA*) show no difference. Further, no significant difference is observed for *CHG_OCF*.

Correlations (not shown in the paper) among variables in the fraud year are similar to those measured in the prior-to-fraud year. For both years, only a few correlations are higher

---

[14] In general, the univariate support for the *BMT*-related variables is weaker than for the *DTE*-related variables. Only *BMT* differs between fraud and matched control companies in Panel A (z-statistic) and in Panel B (t-statistic), and only *BMT_Top20* differs in Panel B (z-statistic). None of the *BMT*-related variables are significant in subsequent multivariate models. Accordingly, we do not report those results in tables.

[15] The difference between mean assets in Panel A versus Panel B is mostly due to size outliers in Panel A. When Panel A asset outliers are winsorized, the mean level of assets in Panel A for fraud firms is reduced to 2507.33 millions. The remaining difference in mean assets between the two panels is due to differences in sample composition. Panel A is based upon 65 fraud firms with positive pretax income in year t (fraud onset). Panel B is based upon 65 fraud firms with positive pretax income in year $t - 1$ (one year prior to fraud). There are 49 fraud firms common to both Panels A and B.

than 0.35, and these tend to be correlations between different measures of discretionary accruals, or between different versions of the tax variables. We do not enter these variables together in our multivariate models, and estimation diagnostics provide no evidence of multicollinearity.

Table 4 reports results of conditional logistic regressions for Model (1) using *DTE*-based variables in the year of fraud onset. The first three results columns, from left to right, contain results based upon sub-samples of firms with positive pretax income. Results in these three columns are the basis for our tests of H1A. For completeness, we also report results for the full sample (firms with both positive and negative pretax income) in the fourth column, and results for the sub-sample of firms having negative pretax income in the fifth column.

In the first column of Table 4, the coefficient of deferred tax expense (*DTE*) is significantly positive (p-value = 0.06), indicating fraud firms have higher deferred tax expenses in the fraud onset year. In the second column, the coefficient of the variable *DTE_DUM* is positive and significant (p-value = 0.08), suggesting firms with deferred tax expenses are more likely to commit fraud compared to firms with deferred tax credits. In the third column, the coefficient of *DTE_TOP20* is positive and significant (p value = 0.1). *DTE_LOW20* has a significantly negative coefficient (p-value = 0.08). These results indicate that if a firm's deferred tax expenses fall into the highest (lowest) 20 percentile among all Compustat firms in the same industry, its likelihood of fraud onset is much higher (lower).

In summary, for firms with *positive* pretax income, deferred tax expenses have incremental association with fraud onset status beyond our control variables. Specifically, higher levels of deferred tax expense, compared to similar-size firms in the same industry, are associated with a higher likelihood of earnings overstatement fraud. Therefore, our hypothesis H1A is supported for several *DTE*-based test variables.

The fourth results column presents estimation results for Model (1) using the full sample of firms having either positive or negative pre-tax income. The sign of the *DTE* coefficient is negative (−28.811, p-value = 0.03) for firms having negative pretax book income. The coefficient of *DTE* for firms having positive pretax book income is positive (= 53.438 − 28.811). The interaction term between the positive income dummy and *DTE* is highly significant and positive (p-value 0.01), confirming our expectation that the positive association between deferred tax expenses and fraud likelihood is reduced for loss firms. The final column of results attempts to distinguish between fraud and nonfraud firms having negative pretax book income. The coefficient of *DTE* is significantly negative (p-value = 0.08). This may indicate that the low cost (in tax payable) of conforming taxable income to negative book income, together with managers' incentives to conceal fraud, result in lower deferred tax expenses compared to nonfraud firms. Overall, our results provide support to hypothesis H1A for *DTE*-based test variables. We find that, for firms with positive pretax income, deferred tax expenses have incremental usefulness in detecting fraud onset.

Table 4 also reports the incremental goodness-of-fit for models with *DTE*-related variables beyond the same models without such variables. Chi-square tests indicate that all models with *DTE*-related variables have significantly better model fit with the positive pretax sample. This provides further support to our H1A. Interestingly, incremental improvement in model fit also is observed in the full sample and in the negative pretax sample.

Moving to the control variables, we employ *REDCA* as the proxy for accruals in all estimations. The other three accruals metrics provide similar results but have less significant coefficients. For Columns 1 to 4, we use signed *REDCA*, while for Column 5, we use the

TABLE 4

Conditional Logit Regressions: Association between Deferred Tax Expenses and Fraud in the Year of Fraud Onset

(Dependent Variable: Fraud = 1 for firms committing earnings-overstatement fraud, 0 otherwise)

		Column 1: Sample with Positive Pretax Income			Column 2: Sample with Positive Pretax Income			Column 3: Sample with Positive Pretax Income			Column 4: Full Sample			Column 5: Sample with Negative Pretax Income		
Variable	Expected Sign	Coefficient	Chi-square[b]	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value
REDCA[a]	+	5.929	4.431	0.04	5.528	4.353	0.04	4.483	1.671	0.20	3.370	5.746	0.02	17.351	4.473	0.03
DTE	+	37.019	3.640	0.06							−28.811	4.546	0.03	−64.345	3.132	0.08
DTE_DUM	+				1.089	2.998	0.08									
DTE_TOP20	+							1.832	2.734	0.10						
DTE_LOW20	−							−1.460	3.020	0.08						
POS	?										0.000	0.000	1.00			
*POS * DTE*	+										53.438	6.460	0.01			
AUDIT_CHNG	+	1.866	1.964	0.16	1.714	1.859	0.17	2.258	2.483	0.12	0.634	1.161	0.28	0.179	0.011	0.92
CHG_REV	+	1.485	3.737	0.05	1.425	3.831	0.05	1.483	3.868	0.05	0.603	3.318	0.07	0.145	0.059	0.81
BIG4	−	0.170	0.017	0.90	0.570	0.202	0.65	0.091	0.005	0.95	−0.906	2.083	0.15	−3.140	3.864	0.05
LEVERAGE	+	−0.542	0.308	0.58	−0.300	0.114	0.74	−0.489	0.233	0.63	−0.070	0.010	0.92	0.510	0.089	0.77
EX_FIN	+	0.694	0.234	0.63	0.778	0.334	0.56	0.152	0.010	0.92	0.159	0.065	0.80	−1.168	1.363	0.24
MBRATIO	+	0.301	4.709	0.03	0.274	4.183	0.04	0.295	3.787	0.05	0.087	4.850	0.03	0.007	0.007	0.93
OTCEXCHG	+	2.324	7.486	0.01	2.260	7.531	0.01	2.573	7.966	0.00	1.138	6.847	0.01	−0.346	0.158	0.69
CHG_OCF	−	0.820	0.363	0.55	0.885	0.449	0.50	0.862	0.397	0.53	−0.788	1.725	0.19	−5.147	3.790	0.05
n			130			130			130			220			90	
Likelihood Ratio Test																
Chi-square			38.193			37.057			42.305			42.976			33.779	
(p-value)			0.00			0.00			0.00			0.00			0.00	
Incremental Chi-square			4.476			3.340			8.588			8.592			5.498	
(p-value)			0.03			0.07			0.01			0.04			0.02	
Pesudo-R^2			41.92%			41.12%			46.95%			28.18%			54.15%	

[a] Signed *REDCA* is used in Columns 1–4, and absolute value of *REDCA* is used in Column 5.

[b] Incremental Chi-square tests indicate the model fit difference between models with deferred tax variables and models without deferred tax variables.

See Table 2 for variable definitions.

absolute value of *REDCA* for firms with nonpositive pretax income.[16] The coefficient of discretionary accruals (*REDCA*) is significantly positive as expected in all Table 4 models except in Column 3. Among the other control variables, *CHG_REV*, *MBRATIO,* and *OTCEXCHG* typically have significant coefficients in Columns 1 to 4. This is consistent with prior literature (Beasley 1996). In the final results column *CHG_REV*, *MBRATIO*, and *OTCEXCHG* are no longer significant. Instead, *BIG4* and *CHG_OCF* have significant negative coefficients, implying that among firms with negative pretax income, those with Big 4 auditors and having greater increases in operating cash flows are less likely to commit fraud. These findings indicate that fraud factors' explanatory power is contingent on loss status. Our results suggest that researchers and practitioners should consider developing separate models for predicting fraud among firms having positive versus negative pretax earnings.[17]

The *BMT*-based variables generally lack significance in the year of fraud onset, so those results are not shown in the paper.[18] Therefore, unlike the univariate analysis, multivariate analysis fails to support H1A for *BMT*-related variables.

Table 5 is similar to Table 4, except it examines the incremental explanatory power of *DTE* in the year *prior* to fraud occurrence, rather than in the year of fraud onset. In Column 1, *DTE* possesses a significant positive coefficient (p-value = 0.08), implying that firms with higher amounts of deferred tax expenses are more likely to commit fraud next year. In the second column, *DTE_DUM* has a significant positive coefficient (p-value = 0.07), indicating that firms with deferred tax expenses are more likely to commit future fraud than firms with deferred tax credits. Chi-square tests also indicate that models with either *DTE* or *DTE_DUM* have significantly better model fit (p-value = 0.05) than models without these variables. However, no significant results are observed in the remaining columns of the table, in which models are estimated to test variables *DTE_TOP20*, *DTE_LOW20*, and the interaction between the positive income dummy and *DTE*. Table 5 provides modest support to H2A for *DTE*-related variables. However, the positive associations observed are not as strong as those observed for the fraud year, as reported previously in Table 4.

Regression results (not shown in the paper) indicate that none of the *BMT*-related variables have significant relations with fraud in the year prior to fraud occurrence, after

[16] The absolute value of discretionary accruals has a significant positive association with fraud occurrence within the sample having negative pretax income. In other words, both large positive discretionary accruals and large negative discretionary accruals are signals of fraud for firms with negative pretax income. Large positive discretionary accruals indicate aggressive upward earnings management, while large negative discretionary accruals could reflect financial distress (Butler et al. 2004). Financial distress could both motivate fraud and trigger asset write-downs. We experiment with signed *REDCA* and find no association between discretionary accruals and fraud among firms with nonpositive pretax income.

[17] Rather than using loss status as an explanatory variable to predict fraud, separate fraud prediction models might be needed for companies reporting income versus losses. Such an approach has a precedent. Beneish (1997) presents a model to distinguish between fraud firms and nonfraud firms given that all sample companies have large discretionary accruals and poor cash flow performance. In contrast to Beneish, we propose the use of two separate models to distinguish between fraud and nonfraud companies: one model when both groups have positive pre-tax incomes, and another model when both groups have negative pre-tax income. Also unlike Beneish, we propose the use of explanatory variables based on tax-related data.

[18] In the year of fraud onset, for the sample with positive pretax income, the estimated coefficients (p-values) for *BMT*, *BMT_DUM*, *BMT_TOP20*, *BMT_LOW20* are respectively as follows: 2.051 (p = 0.48), 0.432 (p = 0.39), −0.104 (p = 0.88), −0.577 (p = 0.33). For the full sample including both positive and nonpositive pretax income, *BMT* has a coefficient of −3.665, (p = 0.04); the interaction term *POS* ∗ *BMT* has a coefficient of 4.128, (p = 0.18). For the sample with negative pretax income, *BMT* has a coefficient of −2.265, (p = 0.38).

TABLE 5

Conditional Logit Regressions: Association between Deferred Tax Expenses and Fraud in the Year Prior to Fraud Onset

(Dependent Variable: Fraud = 1 for firms committing earnings-overstatement fraud, 0 otherwise.)

		Column 1: Sample with Positive Pretax Income			Column 2: Sample with Positive Pretax Income			Column 3: Sample with Positive Pretax Income			Column 4: Full Sample			Column 5: Sample with Negative Pretax Income		
Variable	Expected Sign	Coefficient	Chi-square[b]	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value
REDCA[a]	+	2.770	1.147	0.28	1.937	0.626	0.43	1.937	0.639	0.42	0.369	0.102	0.75	−1.274	0.139	0.71
DTE	+	46.371	2.999	0.08							0.005	0.000	1.00	−18.265	1.471	0.23
DTE_DUM	+				1.176	3.246	0.07									
DTE_TOP20	+							0.494	0.712	0.40						
DTE_LOW20	−							−0.522	0.764	0.38						
POS	?										13.353	0.000	0.99			
*POS * DTE*	+										13.100	0.604	0.44			
AUDIT_CHNG	+	2.051	2.298	0.13	2.085	2.212	0.14	2.090	2.327	0.13	0.784	0.896	0.34	−2.551	1.371	0.24
CHG_REV	+	0.536	2.357	0.12	0.510	2.192	0.14	0.567	2.347	0.13	0.808	5.869	0.02	1.281	1.613	0.20
BIG4	−	1.067	0.777	0.38	1.161	1.008	0.32	0.776	0.465	0.50	0.484	0.471	0.49	−1.811	0.685	0.41
LEVERAGE	+	−0.519	0.211	0.65	−0.598	0.406	0.52	−0.438	0.211	0.65	−0.515	0.653	0.42	0.814	0.321	0.57
EX_FIN	+	15.959	0.000	0.99	15.974	0.000	0.99	15.722	0.000	0.99	0.575	0.597	0.44	−0.989	0.875	0.35
MBRATIO	+	0.269	6.005	0.01	0.289	6.383	0.01	0.271	6.131	0.01	0.031	1.427	0.23	−0.035	0.606	0.44
OTCEXCHG	+	1.324	3.969	0.05	1.821	6.769	0.01	1.433	4.705	0.03	1.096	5.542	0.02	1.300	1.591	0.21
CHG_OCF	−	3.058	2.337	0.13	2.764	2.194	0.14	2.346	1.583	0.21	−0.776	1.012	0.31	−3.154	2.312	0.13
n			130			130			130			190			60	
Likelihood Ratio Test																
Chi-square			37.032			36.787			34.868			28.251			14.708	
(p-value)			0.00			0.00			0.00			0.00			0.14	
Incremental Chi-square			3.945			3.703			1.784			1.444			1.504	
(p-value)			0.05			0.05			0.18			0.70			0.22	
Pesudo-R^2			41.10%			40.83%			38.70%			21.45%			35.36%	

[a] Signed *REDCA* is used in Columns 1–4, and absolute value of *REDCA* is used in Column 5.

[b] Incremental Chi-square tests indicate the model fit difference between models with deferred tax variables and models without deferred tax variables.

See Table 2 for variable definitions.

controlling for other fraud factors.[19] Therefore, multivariate analysis for *BMT* in the year prior to fraud, again in contrast to univariate analysis, fails to support H2A. We propose two explanations for the different findings for *BMT* versus *DTE*. First, *DTE* captures only temporary differences between book and taxable income, whereas *BMT* captures both temporary and permanent differences. It is possible that permanent differences between book and taxable income cause *BMT* to lose explanatory power. Future research could investigate whether (and why) this explanation for the observed results is correct. Second, Hanlon (2003) argues that *BMT* is subject to serious measurement error, due to numerous problems arising from estimating a firm's taxable income from its income tax expense.

Among control variables, in the year prior to fraud occurrence, we do not observe a significantly higher amount of discretionary accruals for pre-fraud firms. However, for pre-fraud firms with positive pretax income, variables *OTCEXCHG* and *MBRATIO* are significant in the expected directions. (See results in Columns 1 to 3). Variables *CHG_REV* and *OTCEXCHG* are significant in the full sample.[20] (See results in Column 4). Finally, none of the variables is significant for the subset of firms with negative pretax income. (See results in Column 5). This could be due to the relatively small sample size (only 30 fraud firms), or could simply reflect the difficulty of differentiating between pre-fraud firms and nonfraud firms when they have negative pretax income.

Additional Analyses

Analysis Employing a Nonmatching Control Sample

In this section, we perform additional analyses using a larger, nonmatching control sample. The purpose is to determine whether tax-related variables have any explanatory power when the proportion of fraud observations in the sample is more representative of the actual prevalence of fraud. Panel C of Table 1 provides details of the selection process for the nonmatching control sample. All firm-years that satisfy the following criteria are included in the nonmatching control sample. First, foreign firms are deleted. Financial and utilities firms are deleted. Firms retained should have the following additional characteristics. The firm should not have been accused of fraud commission by the SEC. Firms with missing data required for discretionary accruals calculation, deferred tax expenses, or other variables used in the study are also excluded. The firm should operate in any one of the industries to which our fraud firms belong. In other words, if a firm does not belong to one of the industries in which our fraud sample firms operate, it is eliminated from the control sample. The purpose of this screening procedure is to make the control sample more comparable to the test sample. These criteria result in the following control sample. There are 5,942 firm-year observations for positive pretax income analysis, 4,201 firm-year observations for nonpositive pretax income analysis, and 14,599 firm-year observations for full

[19] In the year prior to fraud onset, for the sample with positive pretax income, the estimated coefficients (p-values) for *BMT*, *BMT_DUM*, *BMT_TOP20*, *BMT_LOW20* are respectively as follows: 2.602 ($p = 0.47$), 0.700 ($p = 0.19$), −0.482 ($p = 0.49$), −0.518 ($p = 0.48$). For the full sample with both positive and nonpositive pretax income, *BMT* has a coefficient of −0.717, ($p = 0.71$); the interaction term *POS* ∗ *BMT* has a coefficient of 5.137, ($p = 0.14$). For the sample with negative pretax income, *BMT* has a coefficient of −0.719, ($p = 0.81$).

[20] Following a reviewer's suggestion, we perform additional analyses using *LEVERAGE* and *MBRATIO* measured at the end of the previous year. That is, we use the year $t - 1$ value for the analysis in the year of fraud onset (year t), and we use the year $t - 2$ value for the analysis in the year prior to fraud onset (year $t - 1$). Our main results for test variables still hold. Our results for the two control variables *LEVERAGE* and *MBRATIO* are also unchanged.

sample analysis.[21] Given that the proportion of fraud observations is about 0.01 or less in the resulting analyses, the dependent variable has little variance that can be explained, posing a substantial challenge for the test and control variables.

We employ modified versions of Model (1) to examine the explanatory power of *DTE*-related and *BMT*-related variables for both the year of fraud onset and the prior year. One modification consists of adding industry dummy variables to control for industry effects.[22] The only significant test variable results are observed for *DTE*-related variables in the fraud onset year, which are reported in Table 6. Similar to prior tables, Columns 1–3 provide results for samples of firms with positive pretax income; Column 4 presents full sample results; and the Column 5 results are for firms with negative pretax income. In Column 1, we do not observe a significant association between continuous *DTE* and fraud occurrence. In Column 2, we find that *DTE_DUM* is significantly (p-value = 0.08) and positively associated with fraud. Adding *DTE_DUM* to the model provides a significantly higher goodness-of-fit (p-value = 0.08).

In Column 3, we implement our second large-sample modification to the model, by employing a ranked version of *DTE*, *DTE_RANK*. Use of ranked data eliminates large *DTE* outliers and facilitates pooling of thousands of diverse observations from a variety of industries. *DTE_RANK* is defined as follows. We rank all *DTE* observations by year and by industry. In a given year, the observation with the highest value of *DTE* in an industry having "n" firms is assigned a value of "n." The next largest observation is ranked as "n − 1," and so on until the observation having the lowest value of *DTE* is assigned a value of 1. Then, all assigned values are scaled by n, the number of firms in the industry. Thus, *DTE_RANK* ranges in value from (1/n) to 1 within each industry and year. The coefficient of *DTE_RANK* is highly significant and positive (p-value = 0.01) in Column 3. Adding variable *DTE_RANK* to the model increases model fit (p-value = 0.01). These results provide support to our H1A, i.e., deferred tax expenses have incremental contribution in detecting fraud in the year of fraud onset. In Columns 4 and 5, the *DTE*-related variables are not significant.

Among control variables, accruals (*REDCA*) are positively and significantly associated with fraud among firms reporting positive earnings (Columns 1–3). Similar to the *DTE*-based variables, *REDCA* loses its explanatory power when used with the full sample or with firms reporting negative earnings (Columns 4 and 5). The variable most consistently associated with fraud onset in the full sample is auditor change (*AUDIT_CHNG*). OTC exchange membership (*OTCEXCHG*) consistently exhibits positive and significant coefficients, except when used with negative earnings firms. Big-4 auditors (*BIG4*) are associated with lower incidence of fraud among firms reporting negative earnings.[23]

---

[21] Note that the number of control firms in the full sample (14,599) is larger than the sum of control firms in the positive (5,942) and negative (4,201) pretax income samples. To understand this, assume that potential control firm "*A*" operates in industry *i*, and has positive pretax income in year *t*. Suppose that there is no fraud firm having positive pretax income in industry *i* for year *t*. Then the year *t* observation of firm *A* will not be included as a control observation for analysis with positive pretax incomes. Neither will it be included in the control sample with negative pretax incomes. However, if our sample of fraud firms having negative pretax incomes contains any fraud firm in industry *i* for year *t*, the year *t* observation of firm *A* will be included in the full sample analysis.

[22] Industry dummies are defined to represent the industries in Panel B of Table 1. For brevity, the industry coefficients are not reported.

[23] The full sample results in Table 6 support the conclusion based on Table 4, that researchers and practitioners should consider developing separate fraud prediction models for firms reporting positive versus negative earnings.

TABLE 6

Logistic Regressions: Association between Deferred Tax Expenses and Fraud in the Year of Fraud Onset (Nonmatching Design)

(Dependent Variable: Fraud = 1 for firms committing earnings-overstatement fraud, 0 otherwise.)

		Column 1: Sample with Positive Pretax Income			Column 2: Sample with Positive Pretax Income			Column 3: Sample with Positive Pretax Income			Column 4: Full Sample			Column 5: Sample with Negative Pretax Income		
Variable	Expected Sign	Coefficient	Chi-square[c]	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value	Coefficient	Chi-square	p-value
Intercept		−4.88	35.95	0.00	−5.12	37.78	0.00	−5.519	41.042	0.00	−4.519	87.535	0.00	−3.428	29.085	0.00
REDCA[a,b]	+	0.86	3.26	0.07	0.86	3.17	0.08	0.932	3.740	0.05	0.004	0.036	0.85	−0.028	0.038	0.85
DTE	+	10.58	1.60	0.21							−4.679	0.856	0.35	−4.878	1.187	0.28
DTE_DUM	+				0.45	3.03	0.08									
DTE_RANK	+							1.171	6.837	0.01						
POS	?										0.446	3.737	0.05			
*POS * DTE*	+										13.615	2.505	0.11			
AUDIT_CHNG	+	0.92	6.58	0.01	0.92	6.64	0.01	0.937	6.841	0.01	0.877	12.233	0.00	0.817	5.095	0.02
CHG_REV	+	0.08	2.77	0.10	0.08	2.59	0.11	0.088	3.022	0.08	0.005	0.041	0.84	−0.002	0.001	0.98
BIG4	−	0.44	1.42	0.23	0.40	1.17	0.28	0.424	1.316	0.25	−0.241	1.077	0.30	−0.897	7.224	0.01
LEVERAGE	+	0.04	0.04	0.84	0.06	0.08	0.78	0.024	0.014	0.90	−0.274	1.446	0.23	−0.555	1.811	0.18
EX_FIN	+	−0.97	2.18	0.14	−0.94	2.08	0.15	−1.003	2.340	0.13	−0.102	0.143	0.71	−0.110	0.109	0.74
MBRATIO	+	0.00	0.01	0.92	0.00	0.01	0.91	0.000	0.020	0.89	0.000	0.085	0.77	0.000	0.040	0.84
OTCEXCHG	+	1.22	19.16	0.00	1.26	20.24	0.00	1.228	19.344	0.00	0.738	11.103	0.00	0.032	0.009	0.92
CHG_OCF	−	−0.85	1.85	0.17	−0.88	1.96	0.16	−0.837	1.809	0.18	0.003	0.036	0.85	−0.003	0.030	0.86
n (Fraud and Nonfraud)			65 & 5,942			65 & 5,942			65 & 5,942			110 & 14,599			45 & 4,201	
Likelihood Ratio Test																
Chi-square (p-value)			45.470 0.00			47.002 0.00			50.971 0.00			52.438 0.00			38.964 0.00	
Incremental Chi-square (p-value)			1.518 0.22			3.050 0.08			7.019 0.01			6.086 0.11			1.047 0.31	
Pesudo-R^2			6.34%			6.55%			7.10%			4.05%			7.81%	

[a] Signed *REDCA* is used in Columns 1–4, and absolute value of *REDCA* is used in Column 5.
[b] Industry dummies are included in regression analysis and coefficients are not presented in the paper.
[c] Incremental Chi-square tests indicate the model fit difference between models with deferred tax variables and models without deferred tax variables.

See Table 2 for variable definitions.

Analysis Based upon Both Pre and Post SFAS No. 109 Data

SFAS No. 109 became effective for fiscal periods beginning after December 15 1992, and altered the rules for reporting deferred taxes. Previously, Accounting Principles Board (APB) Opinion No. 11 and SFAS No. 96 had been considered acceptable methods of accounting for income taxes since 1987. We perform additional analysis by adding back pre-SFAS No. 109 fraud observations (i.e., 25 firms in the fraud onset year, and 36 firms in the year prior to fraud). Matched control firms also are added to the sample. The resulting analyses therefore employ larger test and control samples, but at the possible expense of added noise in the measurement of *DTE*. Our main results continue to hold (not shown in the paper). Some *DTE*-related variables show even higher significance in the year of fraud onset than in Table 4.

Net Operating Loss (NOL) Carry-Forwards

Badertscher et al. (2006) show that firms with net operating loss (NOL) carry-forwards (CF) are more likely to use conforming earnings management. Further, existence of NOL CF could introduce additional error in estimating *BMT* (Hanlon 2005). We conduct additional analyses to address the effects of *NOL CF*. First, we add existence of *NOL CF* as a dichotomous control variable, which is defined as "one" if a firm has *NOL CF*, "zero" otherwise. The *NOL CF* variable is insignificant and our main results for *DTE*-related and *BMT*-related variables do not change.

Given the small sample size of fraud firms, our primary analyses do not exclude *NOL CF* firms from our sample, as Hanlon (2005) does. However, we perform additional analyses that do exclude *NOL CF* firms. Our reduced sample consists of 41 (39) fraud firms with positive pretax income in the year of fraud onset (year prior to fraud onset), together with matching control firms. *DTE*-related variables retain significance in the fraud onset year, but lose significance in the prior year. *BMT*-related variables remain insignificant in the fraud onset year. However, in the prior year, the coefficient of *BMT* is positive and significant (p-value = 0.06), and the coefficient of *BMT_DUM* also is positive and significant (p-value = 0.05). Book-tax income differences have incremental explanatory power for future (next year) fraud occurrence, for firms without *NOL CF*. This suggests that, in the presence of *NOL CF*, estimation errors in *BMT* could be a partial explanation for the insignificance of *BMT*-related variables in multivariate analysis (Hanlon 2005). Using the larger, nonmatching control sample and excluding *NOL CF* firms, all results for *DTE* and *BMT*-related variables remain the same, except that *DTE* gains significance (p-value = 0.06) for firms with positive pretax income (compare to Column 1 of Table 6).

Time Series Characteristics of Tax Variables for Fraud Firms

Some fraud cases span multiple fiscal periods. Additional univariate analyses are performed to examine the time series characteristics of tax-related variables for fraud firms. Figure 1 depicts the average *DTE* and *BMT* value from five years prior to fraud onset to five years after fraud onset, using 49 firms[24] having positive pretax income in both the fraud onset year and the year prior to fraud. Panel A shows the pattern for *DTE*, and Panel B for *BMT*. In the period of five years to two years prior to fraud onset, *DTE* is observed to be relatively stable, with some slight fluctuations around the value of −0.002. However, in the year prior to fraud onset, the *DTE* of fraud firms experiences a large upward movement, reaching its highest level. It starts to drop dramatically one year after fraud onset. According to Panel B, on average, *BMT* increases for several years prior to

[24] The number of observations used in each year varies from 30 to 49, due to missing information.

fraud onset, reaching its highest point in that year. *BMT* stays high for one year after fraud onset, then drops dramatically for two years. The patterns plotted in Figure 1 for deferred tax variables are interestingly similar to the accruals patterns documented in Richardson et al. (2006). However, our other results show that tax-related variables, especially those derived from *DTE*, have incremental explanatory power for fraud, beyond that provided by discretionary accruals. For completeness, in Panel C of Figure 1, we also present the movement of discretionary accruals over time. Five years prior to fraud onset, fraud firms' discretionary accruals (*REDCA*) are close to zero. During the five-year pre-fraud period, we observe a general trend of increasing *REDCA*, albeit with some fluctuations from year to year. The level of discretionary accruals continues to increase in the year after fraud onset, reaching its highest level. This is likely due to the fact that many fraudulent misstatements last more than one accounting period. Fraud firms' discretionary accruals exhibit sharp downward reversals in the second and third year after fraud onset and become unusually low at the end of third year. Beginning in the fourth year after fraud onset, *REDCA* moves upward, and is close to zero at the end of the fifth year after fraud onset.

Simultaneous Effect of BMT and DTE

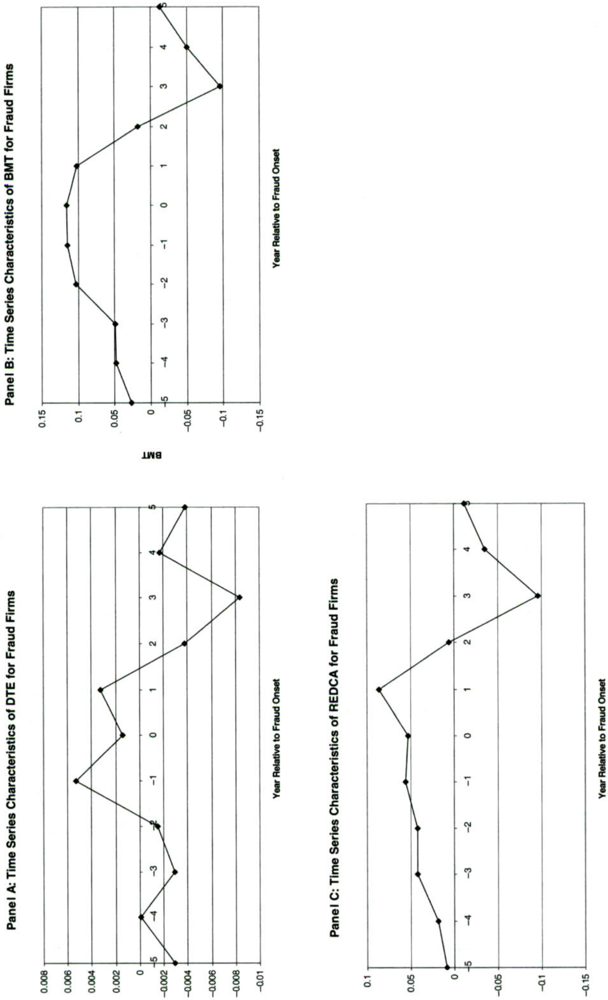
Additional analyses are performed to simultaneously incorporate *BMT*- and *DTE*-related variables into the regression models using the matched samples. For both years (fraud onset and prior year), we observe the same results for *DTE*-related and *BMT*-related variables as previously reported. Simultaneous incorporation of *BMT*- and *DTE*-related variables into our models does not improve performance of the fraud analysis models beyond that provided by the individual tax variables.

CONCLUSION

This study investigates whether several tax-related variables are associated with existence of fraud. In particular, we examine whether the scaled difference between book income and taxable income (BMT) and deferred tax expense (DTE), are associated with fraudulent overstatements of earnings, in the year prior to fraud and in the fraud onset year, for a sample of firms with positive pretax income. For the fraud year analysis (the year prior to fraud), our final sample consists of 65 (65) firms sanctioned by the SEC in AAERs for fraudulently overstating earnings, and a similar number of nonfraud firms matched by total assets, two-digit SIC codes, and earnings status (positive income).

Our empirical findings can be summarized as follows. We find strong evidence that higher levels of deferred tax expenses (DTE) are associated with higher likelihood of fraud occurrence *in the year of the fraud onset*. We provide modest evidence that higher levels of deferred tax expenses are associated with higher likelihood of fraud occurrence *in the year prior to fraud onset*. (The latter result holds when using the matching sample, but not when using a larger, nonmatched control sample.) The evidence generally indicates that book-tax income differences (BMT) are not useful in explaining fraud occurrence. Additional results suggest that our findings hold when employing fraud observations from the pre-SFAS No. 109 period. Our results also generally are robust after excluding firms with net operating loss carry-forwards. Simultaneous incorporation of DTE and BMT in the models does not improve the explanatory power of the tax related variables. Finally, a time series analysis of the tax variables for fraud firms having positive incomes indicates that fraud firms' DTE and BMT generally increase for several years as fraud approaches, reach highs about the year of fraud occurrence, and then decrease dramatically beginning one year following fraud occurrence.

FIGURE 1
Time Series Characteristics of Deferred Tax Variables and Discretionary Accruals (*REDCA*) for Fraud Firms



From an academic perspective, our findings contribute to two lines of research. First, we provide additional evidence for the usefulness of tax-related variables as proxies for earnings quality. Second, we identify variables that deserve further research as potential new signals of fraud. Our findings should be of interest to auditors, and to other parties examining and using financial statements, for the purpose of fraud risk assessment. Our findings for the year prior to fraud, although not strong, are particularly interesting, since they indicate that it might be possible to distinguish between fraud firms and similar non-fraud firms in the year prior to fraud onset.

The study has several limitations, some of which may lead to future research. Like most other fraud studies, this study draws its fraud sample from among those companies that the SEC has sanctioned in AAERs. These firms might not be representative of all firms that fraudulently overstate earnings. Similar to other studies that rely on fraud samples detected by the SEC (Beasley 1996; Summers and Sweeney 1998), a selection bias could exist. If the probability of fraud detection is higher for nonconforming earnings management, the AAER fraud sample is likely biased towards firms that employ nonconforming earnings management. Also, we caution that while our results report reliable statistical associations, the results are preliminary from the standpoint of real-world usefulness. For example, to maximize estimation sample size, we do not attempt to predict fraud using a holdout sample. We leave this effort to future research.

REFERENCES

Accounting Principles Board (APB). 1967. *Accounting for Income Taxes*. Accounting Principles Board Opinion No. 11. New York, NY: APB.

Agrawal, A., and S. Chadha. 2005. Corporate governance and accounting scandals. *The Journal of Law and Economics* 48: 371–406.

Albrecht, W. S., and C. Albrecht. 2004. *Fraud Examination and Protection*. Mason, OH: South-Western Publishers.

American Institute of Certified Public Accountants (AICPA). 1997. *Consideration of Fraud in a Financial Statement Audit.* Statement on Auditing Standards No. 82. New York, NY: AICPA.

———. 2003. *Consideration of Fraud in a Financial Statement Audit.* Statement on Auditing Standards No. 99. New York, NY: AICPA.

Argenti, J. 1976. *Corporate Collapse: Causes and Symptoms*. London, U.K.: McGraw-Hill.

Ashbaugh, H., R. LaFond, and B. W. Mayhew. 2003. Do nonaudit services compromise auditor independence? Further evidence. *The Accounting Review* 78 (3): 611–639.

Ayers, B. 1998. Deferred tax accounting under SFAS 109: An empirical investigation of its incremental value relevance relative to APB No. 11. *The Accounting Review* 73 (April): 195–212.

Badertscher, B., J. Phillips, M. Pincus, and S. Rego. 2006. Tax implications of earnings management activities: Evidence from restatements. Working paper, University of Connecticut.

Barth, M. E., J. A. Elliot, and M. W. Finn. 1999. Market rewards associated with patterns of increasing earnings. *Journal of Accounting Research* 37: 387–412.

Barton, J., and P. J. Simko. 2002. The balance sheet as an earnings management constraint. *The Accounting Review* 77 (Supplement): 1–27.

Bartov, E., D. Givoly, and C. Hayn. 2002. The rewards for meeting or beating earnings expectations. *Journal of Accounting and Economics* 33 (June): 172–204.

Beasley, M. S. 1996. An empirical analysis of the relation between the board of director composition and financial statement fraud. *The Accounting Review* 71 (October): 443–465.

———, J. Carcello, and D. Hermanson. 1999. Fraudulent financial reporting: 1987–1997—An analysis of U.S. public companies. Committee of Sponsoring Organizations of the Treadway Commission (COSO). Jersey City, NJ: AICPA.

———. 2003. SAS No. 99: A new look at auditor detection of fraud. *Journal of Forensic Accounting* 4: 1–20.

Beatty, A., B. Ke, and K. Petroni. 2000. Earnings management to avoid earnings declines across publicly and privately held banks. *The Accounting Review* 77 (3): 547–570.

———, and J. Weber. 2003. The effects of debt contracting on voluntary accounting method changes. *The Accounting Review* 78 (1): 119–142.

Becker, C. L., M. L. DeFond, J. Jiambalvo, and K. R. Subramanyam. 1998. The effect of audit quality on earnings management. *Contemporary Accounting Research* 15: 1–24.

Bell, T. B., and J. V. Carcello. 2000. A decision aid for assessing the likelihood of fraudulent financial reporting. *Auditing: A Journal of Practice & Theory* 19 (1): 169–184.

Beneish, M. D. 1997. Detecting GAAP violations: Implications for assessing earnings management among firms with extreme financial performance. *Journal of Accounting and Public Policy* 16 (Fall): 271–309.

———. 1999. Incentives and penalties related to earnings overstatements that violate GAAP. *The Accounting Review* 74 (4): 425–457.

Bonner, S. E., Z. Palmrose, and S. M. Young. 1998. Fraud type and auditor litigation: An analysis of SEC accounting and auditing enforcement releases. *The Accounting Review*: 73 (4): 503–532.

Browning, E. S., and I. Dugan. 2002. Aftermath of a market mania. *Wall Street Journal* (December 16): C1.

Burgstahler, D., and I. Dichev. 1997. Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics* 24 (December): 99–126.

Butler, M., A. J. Leone, and M. Willenborg. 2004. An empirical analysis of auditor reporting and its association with abnormal accruals. *Journal of Accounting and Economics* 37: 139–165.

Carcello, J. V., and Z. V. Palmrose. 1994. Auditor litigation and modified reporting on bankrupt clients. *Journal of Accounting Research* 32 (Supplement): 1–30.

Chen, K. C. W., and K. C. J. Wei. 1993. Creditors' decisions to waive violations of accounting-based debt covenants. *The Accounting Review* 68 (2): 218–232.

Crocker, K. J., and J. Slemrod. 2005. The economics of earnings manipulation and managerial compensation. Working Paper, Pennsylvania State University and University of Michigan.

DeAngelo, H., L. DeAngelo, and D. J. Skinner. 1994. Accounting choice in troubled companies. *Journal of Accounting and Economics* 17: 113–143.

Dechow, P., R. Sloan, and A. Sweeney. 1996. Causes and consequences of earnings manipulations: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research* 13 (1): 1–36.

DeFond, M. L. 1992. The association between changes in client firm agency costs and auditor switching. *Auditing: A Journal of Practice & Theory* (Fall): 16–31.

———, and J. Jiambalvo. 1994. Debt covenant violation and manipulation of accruals: Accounting choice in troubled companies. *Journal of Accounting and Economics* 17: 145–176.

Desai, H., C. E. Hogan, and M. S. Wilkins. 2006. The reputational penalty for aggressive accounting: Earnings restatements and management turnover. *The Accounting Review* 81 (1): 1, 83–112.

Dhaliwal, D. S., M. Frankel, and R. Trezevant. 1994. The taxable and book income motivations for a LIFO layer liquidation. *Journal of Accounting Research* 32 (2): 278–289.

———, C. A. Gleason, and L. F. Mills. 2004. Last-chance earnings management: Using the tax expense to meet analysts' forecasts. *Contemporary Accounting Research* Summer 21 (2): 431–459.

Erickson, M., M. Hanlon, and E. Maydew. 2004. How much will firms pay for earnings that do not exist? Evidence of taxes paid on allegedly fraudulent earnings. *The Accounting Review* 79 (2): 387–408.

Ettredge, M., K. Smith, S. Scholz, and L. Sun. 2008. How do misstatements begin? Evidence of earnings management from restatements. Working Paper, University of Kansas and Rutgers University.

Farrell, K., and D. Whidbee. 2003. Impact of firm performance expectations on CEO turnover and replacement decisions. *Journal of Accounting and Economics* 36 (1–3): 165–196.

Feng, M. 2004. Earning management strategies to beat multiple thresholds. Working Paper, University of Michigan.

Feroz, E. H., K. Park, and V. S. Pastena. 1991. The financial and market effects of the SEC's accounting and auditing enforcement releases. *Journal of Accounting Research* 29 (Supplement): 107–142.

Financial Accounting Standards Board (FASB). 1987. *Accounting for Income Taxes*. Statement of Financial Accounting Standards No. 96. Stamford, CT: FASB.

———. 1992. *Accounting for Income Taxes*. Statement of Financial Accounting Standards No. 109. Stamford, CT: FASB.

Francis, J., A. Huang, S. Rajgopal, and A. Zang. 2004. CEO reputation and reporting quality. Working paper, Duke University.

Frank, M., L. Lynch, and S. Rego. 2005. Does aggressive financial reporting accompany aggressive tax reporting and vice versa? Working paper, University of Virginia.

Geiger, M. A., and D. V. Rama. 2006. Audit firm size and going-concern reporting accuracy. *Accounting Horizons* 20 (1): 1–17.

Graham, J. R., C. R. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics* 40: 3–73.

Hanlon, M. 2003. What can we infer about a firm's taxable income from its financial statements? *National Tax Journal* LVI (4): 831–863.

———. 2005. The persistence and pricing of earnings, accruals and cash flows when firms have large book-tax differences. *The Accounting Review* 80 (1): 137–166.

———, and G. Krishnan. 2006. Do auditors use the information reflected in book-tax differences? Working Paper, University of Michigan and George Mason University.

Healy, P. 1985. The impact of bonus schemes on the selection of accounting principles. *Journal of Accounting and Economics* 7: 85–107.

———, and J. M. Wahlen. 1999. A review of the earnings management literature and its implications for standard setting. *Accounting Horizons* 13 (4): 365–383.

Hosmer, D, and S. Lemeshow. 2000. *Applied Logistic Regression*. New York, NY: John Wiley & Sons.

Hribar, P., and D. W. Collins. 2002. Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research* 40 (1): 105–134.

Jiambalvo, J. 1996. Discussion of "Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC." *Contemporary Accounting Research* 13 (Spring): 37–47.

Joos, P., J. Pratt, and D. Young. 2000. Book-tax differences and the value relevance of earnings. Working Paper, Massachusetts Institute of Technology, Indiana University, and INSEAD.

Kothari, S. P., A. J. Leone, and C. E. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39: 163–197.

Krishnan, J., and J. Krishnan. 1997. Litigation risk and auditor resignations. *The Accounting Review* 72 (October): 539–560.

Lee, T. A., R. W. Ingram, and T. P. Howard. 1999. The difference between earnings and operating cash flow as an indicator of financial reporting fraud. *Contemporary Accounting Research* 16 (Winter): 749–786.

Lev, B., and D. Nissim. 2004. Taxable income, future earnings, and equity values. *The Accounting Review* (October): 1039–1074.

Loebbecke, J. K., and J. J. Willingham. 1988. Review of SEC accounting and auditing enforcement releases. Working Paper, University of Utah.

———, M. M. Eining, and J. J. Willingham. 1989. Auditors' experience with material irregularities: Frequency, nature, and detectability. *Auditing: A Journal of Practice & Theory* 9 (Fall): 1–28.

Matsunaga, S., and C. Park. 2001. The effect of missing a quarterly earnings benchmark on the CEO's annual bonus. *The Accounting Review* 76: 313–332.

McNichols, M. 2000. Research design issues in earnings management studies. *Journal of Accounting and Public Policy* 19: 313–345.

Mills, L. 1998. Book-tax differences and Internal Revenue Service adjustments. *Journal of Accounting Research* (Autumn): 343–356.

———, and K. Newberry. 2001. The influence of tax and non-tax costs on book-tax reporting differences: Public and private firms. *The Journal of American Taxation Association* 23 (Spring): 1–19.

Palmrose, Z. 1988. An analysis of auditor litigation and audit service quality. *The Accounting Review* (January): 55–73.

———, and S. Scholz. 2004. The circumstances and legal consequences of non-GAAP reporting: Evidence from restatements. *Contemporary Accounting Research* 21 (1): 139–80.

Penman, S. 2001. *Financial Statement Analysis and Security Valuation*. New York, NY: McGraw-Hill Irwin.

Phillips, J., M. Pincus, and S. Rego. 2003. Earnings management: New evidence based on the deferred tax expense. *The Accounting Review* 78 (April): 491–522.

Plesko, G. 2002. Reconciling corporations' book and taxable income, 1996–1998. *SOI Bulletin* (Spring): 111–132.

Revsine, L., D. Collins, and W. B. Johnson. 1999. *Financial reporting and analysis*. Upper Saddle River, NJ: Prentice Hall.

Richardson, S., R. Sloan, M. Soliman, and I. Tuna. 2006. The implications of accounting distortions and growth for accruals and profitability. *The Accounting Review* 81 (3): 713–743.

Rosner, R. L. 2003. Earnings manipulation in failing firms. *Contemporary Accounting Research* 20 (2): 361–408.

Sapsford, J., and P. Beckett. 2002. Citigroup deals helped Enron disguise its debts as trades. *Wall Street Journal* (July 22): A1, A8.

Schnee, E. J. 2004. Corporate acquisition expenses. *Journal of Accountancy* 197 (3): 66–67.

———. 2006. Can trusts deduct adviser fees? *Journal of Accountancy* 201 (1): 75–77.

Schrand, C., and M. H. F. Wong. 2003. Earnings management using the valuation allowance for deferred tax assets under SFAS No. 109. *Contemporary Accounting Research* 20 (3): 579–611.

Securities and Exchange Commission (SEC). April 19, 2005. Litigation Release No. 19191/Accounting and Auditing Enforcement Release No. 2235. SEC v. KPMG LLP, et al., Civil Action No. 03 CV 0671 (DLC) (S.D.N.Y.)

Simunic, D. 1980. The pricing of audit services: Theory and evidence. *Journal of Accounting Research* (Spring): 161–190.

Sorenson, J. E., H. D. Grove, and F. H. Salto. 1983. Detecting management fraud: An empirical approach. *Symposium on Auditing Research* 5: 73–116.

Summers, S. L., and J. T. Sweeney. 1998. Fraudulently misstated financial statements and insider trading: An empirical analysis. *The Accounting Review* 73 (1): 131–146.

Sweeney, A. P. 1994. Debt-covenant violations and managers' accounting responses. *Journal of Accounting and Economics* 17: 281–308.