Journal of Forensic and Investigative Accounting
Volume 17: Issue 3, Special Issue 2025

JFIA Journal of Forensic and Investigative Accounting
LEARN MORE

Corporate Tax Avoidance and Fraud Risk

Zhonghua Cao, DBA, CPA
*Chen Wu, PhD**

Introduction

This research investigates the relationship between tax avoidance and fraud risk. Fraud risk assessment, as an effective fraud detection and prevention tool, can be evaluated for all firms in contrast to only one-third of the costly frauds (fraudulent firms) being detected (observed) (Dyck et al., 2023). In addition, as shown in the 2022 Association of Certified Fraud Examiners (ACFE) report, 85 percent of fraudsters displayed behavioral red flags of fraud, which means if appropriate and proactive fraud detection and fraud risk assessment actions were taken, the efficiency and productivity of fraud detection could be raised, and many future frauds could be deterred and prevented. Along the same vein, in October 2002, the Statement of Auditing Standards (SAS) No. 99 was announced by the American Institute of Certified Public Accountants (AICPA) as measures to improve the fraud detection processes, and three fraud risk factors, namely incentive, opportunity, and rationalization, were proposed for auditors to evaluate the possibility of fraud, to assess the effectiveness of internal controls, and to help with the fraud detection efficiency. Therefore, fraud risk evaluation has broad policy implications and warrants more attention from researchers, regulators, auditors, and investors.

Brazel et al. (2009) also find that companies that are committing fraud exhibit higher levels of fraud risk, so when abnormalities that might signal a possible material misstatement are identified, special attention should be paid to those suspicious cases and further investigation should be made about whether the risk involves fraudulent financial reporting or misappropriation of assets, whether the risk could result in a possible material misstatement of financial statements, the likelihood that it will result in misstatement, and lastly, whether the potential risk is pervasive in the financial statements or related to specific accounts. More recently, Thompson (2023) finds that, in recent years, the reported revisions (immaterial errors) of prior financial statements outnumber reported restatements (material errors) with a significant percentage (29 percent) of those revisions being suspects of restatements in at least one materiality criterion. This study provides strong empirical evidence that many managers use materiality discretion opportunistically to cover possible restatements and, to some extent, echoes the findings in 2024 ACFE report and Brazel et al. (2009) that fraudsters displayed some behavioral red flags. Therefore, the assessment of fraud risk could serve as an effective fraud detection tool for regulators, auditors, and even investors. On the other hand, for organizations, internal fraud risk assessment can help them self-identify those risks and develop an action plan for mitigating or controlling those risks to avoid the time and expense required for fraud detection and litigation and to reduce the opportunities for fraud. Organizations also can warn potential fraudsters that they are aggressively monitoring the business, which in turn deters fraud. As the observed frauds are only the visible tip of a big iceberg, the best approach to fighting fraud is to prevent it from happening in the first place.

Corporate taxes are compulsory contributions collected from firms by the government and represent a significant cost to companies and shareholders. Before the Tax Cuts and Jobs Act of 2017 (TCJA), companies could contribute more than one-third of pre-tax income to the government (Chen et al., 2010). Therefore, Tax Avoidance (TA) is used by firms to increase cash flow and provide additional value to shareholders (Cook et al., 2008; Dhaliwal et al., 2004) and is desired for shareholders based on traditional wealth transfer theory. However, the agency theory view of aggressive TA suggests that managers may use complex TA strategies for their own benefit at the expense of shareholders, including aggressive financial reporting and related party transactions (Chen et al., 2010; Desai and Dharmapala, 2009), so abnormal TA behaviors could signal the possibility of fraud.

In the accounting research literature, there are no universal definitions of tax avoidance or tax aggressiveness (Hanlon and Heitzman, 2010; Frank et al., 2009). Rego (2003) describes tax avoidance as the application of legal methods to minimize

*Southeast Missouri State University, Harrison College of Business and Computing, Department of Accounting, Economics, and Finance, Cape Girardeau, MO, USA.; Southeast Missouri State University, Harrison College of Business and Computing, Department of Accounting, Economics, and Finance, Cape Girardeau, MO, USA; respectively.

the amount of tax owed to the government. Frank et al. (2009) characterize tax aggressiveness as the manipulation of taxable income through tax avoidance strategies that may or may not be considered tax evasion. Similar to Hanlon and Heitzman (2010), we define TA as a continuum of tax planning strategies, from perfectly legal activities (e.g., municipal bond investments) to more aggressive activities (e.g., abusive tax shelter) that may fall into gray areas.

The relationship between tax avoidance and aggressive financial reporting has been well explored (Desai and Dharmapala, 2009; Erickson et al., 2004; Frank et al., 2009; Lennox et al., 2012, Cheng et al., 2022). However, to the best of our knowledge, there are no studies yet in the literature comprehensively exploring the relationship between tax avoidance and fraud risk. Therefore, TA, as a strong predictor for financial reporting quality, should be brought to the attention of various parties of interest for the assessment of fraud risk. In addition, prior studies find that tax avoidance is associated with accounting fraud (Erickson et al., 2004; Lennox et al., 2012) using the sample of accounting fraud firms[1] that were caught and formally charged by the Securities and Exchange Commission (SEC). But as discussed before, only one-third of corporate fraud is detected, which means that many firms may have committed fraud but were not caught, so it is not possible to evaluate the relationship for those fraud firms that luckily got away from the charge. Alternatively, fraud risk can provide some important information on all firms about how likely they committed or will commit fraud. Incorporating TA into the fraud risk assessment process can provide an additional measure that can be used as a first-pass screen to identify firms that warrant further investigation. Therefore, the development of the relationship between TA and fraud risk is of great importance for fraud detection and prevention.

To more comprehensively assess the fraud risk a firm is exposed to, we follow the literature to use various proxies for fraud risk, including financial measures such as accrual quality, performance variables, and non-financial measures (NFMs). Dechow et al. (2011) find that fraud companies show unusually high accruals in fraud years and that fraud companies attempt to increase performance variables through manipulation. On the other hand, Brazel et al. (2009) find that fraud companies show a larger difference between financial and NFMs than non-fraud companies, suggesting that NFMs can be used to assess fraud risk. The PCAOB (2004) also notes that analytical procedures with financial information are not sufficient in detecting fraud due to managers' manipulation of financial statements and suggests financial and NFMs be combined in detecting accounting fraud.

This study investigates the relationship between TA and fraud risk using a sample over the years from 2000 to 2017. Similar to Armstrong et al. (2015), Cheng et al. (2022), Dyreng et al. (2008), and Robinson et al. (2010), we use the GAAP effective tax rate (GAAPETR), the cash effective tax rate (CASHETR), and the permanent book-tax difference (PBTD) to measure TA, with lower ETRs and higher PBTD indicating more aggressive TA. Following Brazel et al. (2009) and Dechow et al. (2011), we adopt those financial and non-financial measures as proxies for fraud risk, including accrual quality, performance variables, and an NFM: the abnormality in the number of employees. The accrual quality is measured as the percentage change in receivables (PCHGREC) and the percentage change in inventory (PCHGINV) because these two accruals are related to revenue recognition and the cost of goods sold that affect a firm's gross profit. The accrual quality is also measured as the discretionary accrual (DISCACC) because managers can manipulate this accrual to influence reported earnings. The performance variables are measured as the percentage change of cash sales (PCHGCASHSALES) and the change of return on assets (CHGROA) because fraud companies may increase sales and earnings in fraud years. The revenue-related NFMs, such as the number of employees and the number of order backlogs, are calculated as the difference between the average change in NFMs and the change in sales or total assets. Then, further following Brazel et al. (2009), we use 20 percent or higher changes in NFMs as the benchmark to categorize firms into high-fraud-risk groups or not, as they find that 20 percent is the average difference in NFMs between fraud and non-fraud firms. We agree with Brazel et al. (2009) that only abnormal differences in the NFMs and the financial counterparts indicate a possible risk for fraud that is worth the auditor's further investigation. Due to the unavailability of order backlogs for most firms in our sample, we only use the number of employees to calculate NFM. The fraud data used in our study is the Accounting and Auditing Enforcement Releases (AAER)'s fraud (fraudulent financial reporting), which is defined as the deliberate manipulation of financial statements by a company's managers to build a distorted picture of financial condition, results of operation, and cash flow to deceive creditors and shareholders (Nicholas, 2021). A fraud risk assessment is a process to evaluate the entity's fraud exposure, the associated risks, and the strength of existing controls.

[1] Similar to Dechow et al. (2011) and Lennox et al. (2012), we define fraud companies as those committing accounting fraud on the AAERs list.

Our results show that TA is positively related to fraud risk, which is consistent with the predictions of Fraud Triangle Theory and Agency Theory, such that complex tax planning strategies provide more opportunities for managers to conduct fraud. In addition, our results indicate that fraud risk proxies that we use can significantly predict accounting fraud with our matched sample experiment.

This study contributes to the TA and fraud risk literature in several ways. First, while prior studies provide competing arguments regarding whether TA is positively or negatively associated with financial reporting aggressiveness, we conduct an empirical analysis to explore the relationship between TA and fraud risk and find that TA is positively related to fraud risk because managers may use complex TA activities to mask fraudulent financial reporting activities. Various parties of interest, including internal auditors, managers, regulators, and investors, need to pay more attention to firms' aggressive TA for better-informed decisions since it may indicate higher risk of fraud. It provides real-world tools for the assessment of fraud risk and fraud detection. Second, we use accrual quality, performance variables, and NFM to measure fraud risk for a more comprehensive picture of the impact of TA on fraud risk and provide managers, auditors, regulators, and other parties of interest with multiple ways to evaluate the effect of TA on fraud risk from different perspectives. Third, this research bridges the gap between TA and accounting fraud through fraud risk. A limited number of fraud companies are disclosed by the SEC; however, fraud risk can be measured for all companies, so all firms could be investigated using the relationship between TA and fraud risk measures.

The remainder of the article is organized as follows: the next section presents literature review and hypothesis development; the following section explains the research method and data collection process; followed by research results; and the final section, the implications, limitations, and future research opportunities are discussed.

Literature Review and Hypothesis Development

Literature

Regarding the connection between TA and fraud risk, there are two major theories in the literature: Agency Theory and Fraud Risk Triangle Framework**.** The economic theory of agency was first developed by Ross (1973) to interpret and solve problems in the relationship between principals (shareholders) and agents (managers). Principals have employed agents to operate businesses on their behalf; however, there are many different opinions, priorities, and interests between principals and agents because agents are delegated to make decisions that may financially affect principals. Principal-agent problems exist when the interests of owners are not aligned with those of managers, as principals provide resources but do not have daily input in business operations. Agents use resources to make business decisions and take little or at least less risk because all losses are shared by principals. Regarding tax avoidance, risk-neutral shareholders hire managers to maximize profits through efficient tax planning tools. But opportunistic managers may conduct aggressive tax avoidance actions for their own benefit (Desai and Dharmapala, 2009) and can utilize opaque TA activities to mask aggressive financial reporting and unfavorable information (Chen et al., 2010). Some TA activities, such as seeking offshore tax havens and creating related-party transactions, are complex and easy for managers to conceal fraudulent activities (Desai and Dharmapala, 2006). For example, managers in Dynegy Company overstated operating cash flows by three hundred million dollars by misclassifying cash flows produced from TA activities as operating cash flows. Tyco International Company utilized the complex TA activities to hide its rent extraction behaviors, resulting in the company's stock price crash after rent extraction was disclosed in 2002. In conclusion, TA strategies offer more opportunities for managers to commit fraud (fraud risk) by purposely inflating companies' cash flows and firm performance.

On the other hand, from the perspective of auditors, **t**he fraud risk triangle framework (Cressey, 1953) defines the characteristics that must be present for fraud to take place, and the three elements that contribute to increasing fraud risk are opportunity, incentive, and rationalization. TA strategies present those three elements to managers and can potentially indicate the risk level at which firms are committing fraud. Opportunity is described as conditions under which people are more able to commit fraud. TA, as discussed before, offers managers more opportunities to perpetrate fraud by utilizing complex TA activities. The incentive is defined as employees' motivation towards committing fraud, and TA strategies often can bring benefit to managers. For example, Enron Company's management inflated its earnings until 2001 by using twelve large tax shelters to hide its poor performance from operations to boost the stock price of Enron in hopes of earning bigger compensation for them. Rationalization is represented as employees' justification for perpetrating fraud. Most of tax planning strategies are legal and commonly used, so managers can justify their use of more aggressive TA activities such as contested liability acceleration strategies, cross-border dividend capture, and intellectual property havens (Graham and

Tucker, 2006) to conceal their rent extraction behavior. In conclusion, complex TA creates more opportunities, incentives, and rationalization for managers to commit fraud; therefore, it could indicate the fraud risk that firms are exposed to.

Empirically, there are no studies investigating the impact of TA on fraud risk, with some on whether TA is positively or negatively related to aggressive financial reporting, which is one of the financial indicators for fraud risk, so we briefly summarize the mixed evidence below. Shackelford and Shevlin (2001) document the trade-off that companies confront when they make decisions about financial and tax reporting. Specifically, companies attempting to raise book income in financial statements may experience higher tax costs, while companies attempting to lower taxable income in the tax return may report lower income in financial statements. Therefore, there is a negative relationship between aggressive financial reporting and aggressive tax reporting. In contrast, other studies find that companies do not always trade off financial and taxable income (Hanlon et al., 2012; Phillips et al., 2003). Management may report different amounts of income to investors and creditors (higher) and the IRS (lower). Frank et al. (2009) suggest that areas of nonconformity between financial and tax reporting provide more opportunities for companies to maximize book income in the financial statements and minimize the taxable income simultaneously. Thus, there is a strong and positive association between aggressive financial reporting and aggressive tax reporting. Cheng et al., (2022) examine the association between firms' tax planning behavior measured by their effective tax rates (ETRs), and financial restatements. They find a nonlinear relation between ETRs and tax-related financial reporting quality with both low and high ETRs being positively related to subsequent tax-related restatements. For the low ETR firms, the evidence is especially strong with an increased likelihood of both tax and non-tax restatement. Thompson (2023) finds that, in recent years, more firms report revisions (immaterial errors) of prior financial statements than those reporting restatements (material errors) with 29 percent of those revisions being suspects of restatements in at least one materiality criterion. Those suspect revisions are 15 percent to 29 percent more likely to be reported when managers have a strong incentive to avoid restatements—when they face the threat of a compensation clawback for reporting a restatement. This result is especially salient when the clawback policy does not require misconduct for recoupment and when the error correction significantly reduces prior period net income. This study provides strong empirical evidence that some managers use materiality discretion opportunistically to cover possible restatements.

On the other hand, Erickson et al. (2004) argue that companies may intentionally overpay their taxes to validate fraudulent financial income. Using a sample of accounting fraud companies, they analyze the taxes paid on the overstated earnings and create a proxy for accounting fraud from the issuance of AAER by the Securities and Exchange Commission (SEC), which describes the SEC's actions to enforce fairness in financial statement reporting through civil litigation and administrative proceedings. The evidence suggests that some companies overstate their tax obligations to cover the aggressive financial reporting. Furthermore, Lennox et al. (2012) examine the relationship between tax reporting aggressiveness and the incidence of accounting fraud and find managers cannot manipulate book income and taxable income simultaneously. Aligned with Erickson et al. (2004), Lennox et al. (2012) find that aggressive tax reporting is negatively related to aggressive financial reporting. To cover- up fraudulent financial reporting, companies may purposely overpay taxes.

Dhaliwal et al. (2004) examine the effect of tax expenses on earnings management and find that firms may manipulate tax planning to reduce ETR in the last two quarters if pre-tax accruals earnings management does not meet the target. The results indicate that TA can be used as a tool to increase earnings. Cook et al. (2008) investigate how the amount of tax fees paid to auditors is related to the change in ETR in the last two quarters of the year, with a similar finding to Dhaliwal et al. (2004) that firms can change tax expenses to manage earnings and that the amount of tax fees paid to auditors is positively associated with the change in ETR from the third to the fourth quarter. Building on the agency theory, Desai and Dharmapala (2009) argue that TA may not be positively related to firm value but can be used by managers for their own benefit. Balakrishnan et al. (2012) find that tax aggressiveness is associated with lower transparency and information asymmetry. With all the findings above, one can see that complex TA strategies with resulting lower transparency provide managers with more opportunities to commit accounting fraud and can serve as a good indicator of fraud risk.

Most of the studies explore the consequences of TA using financial measures, with little research using non-financial measures. In this study, we extend the literature on the impact of TA on fraud risk with different proxies to measure fraud risk, including financial and non-financial measures. Prior studies find that financial and nonfinancial measures of firm performance are highly correlated (Brazel et al., 2009; Dechow et al., 2011). Companies that report an increase in NFMs will likely exhibit a similar increase in revenues and net income. Some airline companies use NFMs (such as the number of passengers) to predict financial numbers such as total revenues and profits (Behn et al., 1999). Along with serving as leading indicators for future financial performance, NFMs may be useful in detecting fraudulent financial reporting as managers can create false financial information to reach their objectives, while it is much harder for them to create false NFMs. Brazel et al. (2009) report that the revenue growth rate is 20 percent greater than the average NFMs growth rate in those companies that have committed fraud, while for non-fraud companies this difference is below 20 percent; therefore, they use 20 percent as the benchmark of the abnormality that indicates high fraud risk.

For the financial indicator of fraud risk, material misstatement is the most commonly used measure, and prior studies provide different methods to identify material misstatements. First, Dechow et al. (2011) propose accrual quality-related variables, such as working capital accruals and discretionary accruals. For working capital accruals, they investigate two specific accruals that impact firm performance (percentage change in receivables and percentage change in inventory) since these two accounts are related to revenue recognition and cost of goods sold and find that all fraud companies have unusually high levels of abnormal accruals and have greater ability to manipulate short-term earnings. For discretionary accruals, they examine various models of discretionary accruals developed in prior studies (Dechow et al., 1995; DeFond and Jiambalvo, 1994; Kothari et al., 2005) and propose to use residuals estimated from the modified Jones model developed by Dechow et al. (1995). Second, they explore firm performance variables for fraud companies, including change in return on assets and percentage change in cash sales, and find that return on assets (ROA) is generally increasing in fraud companies, suggesting that fraud companies attempt to increase earnings through manipulation. In addition, they find that cash sales are increasing during misstatement periods, as misstating firms tend to increase capital investments and expand the scale of business operations to boost both credit and cash sales. Many firms also misstate sales by boosting sales at the end of the period through transaction management, such as encouraging sales with return provisions and selling goods to related parties.

Hypothesis Development

As discussed above, although prior studies document mixed evidence on how tax aggressiveness[2] is related to aggressive financial reporting, we believe that there is a strong and positive relationship between TA and aggressive financial reporting as proposed by Desai (2005), Desai and Dharmapala (2006), Frank et al. (2009), and Hanlon et al. (2012). Managers can report different amounts of income to the public (higher) and the IRS (lower), and this nonconformity between financial and tax reporting provides more opportunities for companies to maximize book income in the financial statements and minimize the taxable income simultaneously. Further, the agency theory and fraud risk triangle framework also imply that aggressive TA is associated with higher fraud risk as various complex TA strategies provide managers with ways to hide rent extraction behaviors and offer them more opportunities, incentives, and justification to manipulate financial statements for their benefit. Therefore, we predict that TA is positively related to fraud risk with the following hypothesis:

H1: *TA is positively related to fraud risk*

Research Method

Multivariate Model 1

To test our hypotheses on whether TA is positively related to fraud risk, we use the following cross-sectional OLS regression model:[3]

$$FRAUDRISK=\beta_0 + \beta_1 TA + \beta_2 AuditFees + \beta_3 AuditTenure + \beta_4 ChairTenure + \beta_5 ChairGender + \beta_6 LnTA + \beta_7 MB + \beta_8 PCHGSales + \beta_9 Loss + \beta_{10} Restate + \beta_{11} PA + \beta_{12} Big4 + \beta_{13} Lev + \beta_{14} ICME + Year\ Dummies + Industry\ Dummies + \varepsilon$$

Dependent Variables

The dependent variable for the model is fraud risk (FRAUDRISK), measured by the following three categories of proxies: accrual quality, NFM, and performance variables. Accrual quality is measured by the percentage change in receivables (PCHGREC), the percentage change in inventory (PCHGINV), or discretionary accrual (DISCACC). PCHGREC is the difference in accounts receivable between the current year and the prior year divided by the prior year's accounts receivable. PCHGINV is the difference in inventory between the current year and the prior year divided by the prior year's inventory. In the literature, PCHGREC and PCHGINV are used to capture fraud risk, as these two metrics can be easily misstated by managers to increase revenues and gross margins and are closely evaluated by investors (Dechow et al., 2011). For the

[2] Frank et al. (2009) define tax aggressiveness as aggressive tax avoidance, which may be legal or illegal.
[3] There are 3,587 firms with 1,494 firms providing only one-year observation. In addition, most firm-year observations are nonconsecutive with different starting and ending years, so no dynamic relationship over time could be captured and panel data model is not adopted.

discretionary accrual variable, we follow Dechow et al. (2011) to estimate discretionary accrual using the modified Jones model developed by Dechow et al. (1995). NFM is measured by the indicator variable of DIFFBSE, which is equal to 1 if the difference between the percentage change of revenues and the percentage change of employees is greater than 20 percent and 0 otherwise. Prior studies find that the larger inconsistency between financial and NFM performance indicates higher fraud risk (Brazel et al., 2009; Dechow et al., 2011) with 20 percent as the benchmark. To some extent, the difference between the percentage change of revenues and the percentage change of employees could measure the improvement in the productivity, but a larger than normal range of improvement such as 20 percent could be seen as an indicator of possible fraud behavior.

Performance variables are measured by the percentage change of cash sales (PCHGCASHSALES) and the change of return on assets (CHGROA). PCHGCASHSALES is the difference in cash sales between the current year and the prior year divided by the prior year's cash sales. According to some empirical inspections of AAER, many firms misstate sales through transaction management- for example, encouraging sales to customers with return provisions that violate the definition of a sale, selling goods to related parties, or forcing goods onto customers at the end of the quarter. CHGROA is net income divided by total assets minus prior period net income divided by prior period total assets. PCHGCASHSALES and CHGROA are used as proxies for fraud risk, as is well documented in the literature that fraud companies may increase sales and earnings in fraud years, resulting in an increase in PCHGCASHSALES and an increase in CHGROA (Dechow et al., 2011). Therefore, we predict that higher PCHGCASHSALES and CHGROA during fraud periods indicate higher fraud risk.

Independent Variables

In this study, we focus on the relationship between TA and fraud risk, so the independent variable of interest is TA. Similar to Armstrong et al. (2015), Dyreng et al. (2008), and Robinson et al. (2010), we use GAAPETR, CASHETR, and PBTD as proxies for TA. These TA proxies are used to measure the effects of nonconforming transactions, which have different impacts on financial and tax reporting (Lennox et al., 2012). According to the conceptual foundation in Hanlon and Heitzman (2010), TA is defined as a continuum of tax planning activities, so various ETR and BTD measures should be used to capture tax avoidance from different perspectives. GAAPETR is the ratio of the total tax expenses to the total pre-tax income minus special items for the same periods, which impacts on the firm's accounting earnings. This ratio is used to capture tax avoidance strategies that reduce total tax expense through a reduction in its components of current and deferred tax expense. CASHETR is computed as cash taxes paid divided by pre-tax accounting income minus special items, and this ratio is used to capture tax avoidance through deferral strategies that reduce cash tax payments. Unlike GAAPETR, CASHETR is not affected by the strategies that change the tax accounting accruals. PBTD is defined as the total book-tax difference minus temporary book-tax difference, divided by total assets, where the temporary book-tax difference is equal to total deferred tax expense divided by the statutory tax rate. PBTD is used to capture tax avoidance strategies that raise accounting earnings by reducing the firm's GAAPETR and measures the income effect rather than the tax effect of differences between book income and taxable income. Conceptually, GAAPETR, CASHETR, and PBTD are connected to the continuum because TA strategies that produce PBTD decrease GAAPETR and CASHETR and increase book income.[4] Since lower ETR indicates high lever TA, we predict the coefficients for GAAPETR and CASHETR to be negative while the coefficient for PBTD to be positive, as large PBTD indicates a higher level of TA.

Next, following the literature, we control for the characteristics of auditors and audit committee members for a better isolation of the impact of TA on fraud risk, as the literature has documented the evidence of the effect of auditors and audit committees on fraud detection and fraud risk identification. First, we include the tenure of auditors (Audit Tenure) and the tenure of the audit committee (Chair Tenure) and expect the coefficient for both to be negative since auditors with longer tenure are more familiar with clients' operations and are more effective in reducing fraud risk. Second, we control for auditors' effort with Audit Fees as the natural logarithm of the total audit fees (Auditees) billed in year t (DeMond and Francis, 2005) and predict a negative relationship with fraud risk since auditors with more efforts can apply more audit procedures to alleviate fraud risk. Last, we include the gender of the audit committee chair (Chair Gender) as an indicator variable of 1 if the gender of the chair is male and 0 otherwise to control for the gender difference, and we expect a positive

[4] BTDs and ETRs are relevant since BTDs refer to the difference between financial income and tax income and ETRs reflect the ratio of taxes to income. In other words, BTDs represent the income effects of TA activities, whereas ETRs represent the tax effects.

coefficient for the gender variable since a female chair may be considered more conservative and better at monitoring the audit engagement.

We also control for several variables associated with financial reporting quality by following Reichelt and Wang (2010). First, we control for company size with the log of the book value of total assets (Lanta) as a proxy because size is an important predictor of fraud risk as shown in Lawrence et al. (2011). We expect a negative coefficient for company size, as large companies are more conservative with financial reporting because they are subject to more strict scrutiny. Second, we control for operating growth (MB) measured by the market value of equity divided by the book value of equity with an expected negative coefficient. Abbott et al. (2004) find a negative relationship between the growth rate of a company and financial reporting quality, with the conclusion that a growing company is likely to have a less effective internal control system. Third, we include the sales growth rate (PCHGSALES), defined as the difference between the current year's sales and the previous year's sales divided by the previous year's sales. Since companies with rapid sales growth are more aggressive in earnings management, we predict a positive coefficient for sales growth rate. Fourth, the operating loss (Loss) is included as a dummy variable equal to 1 if there is an operating loss and 0 otherwise, as companies with operating losses are more aggressive with financial reporting, therefore higher fraud risk. Fifth, we use the indicator variable of financial restatement (Restate) to indicate if a financial restatement has been reported during the last three years and predict a positive coefficient for it. Next, the plant assets (PA) ratio is calculated as the net value of plant assets divided by total assets. As shown in Barton and Simko (2002), firms with greater net operating assets have more accounting flexibility to report positive earnings surprises, so on the other hand, when firms have more plant assets on their balance sheet, there is less discretion for management to manipulate revenues and expenses to meet short-term earnings goals. We predict a negative relationship between plant assets and fraud risk. Next, we use the indicator variable of the big four CPA firms (Big4) to indicate if a company is audited by a big four CPA firm. We predict a negative coefficient for Big4 since Big4 firms have more experiences to reduce fraud risk. Next, we include financial leverage (Lev) following Dechow et al. (2011), which is measured by total long-term debt divided by total assets, as we believe that higher leverage value means greater financial distress and, therefore, higher fraud risk.[5] Next, we control for internal control material effectiveness (ICME), which is an indicator variable from CompStat with one indicating an effective internal control and zero for an ineffective internal control. We expect a negative relationship between ICME and fraud risk. For all our estimations, we also include the year and industry dummies to control for the time trends and industry differences.

Sample Selection and Descriptive Statistics

Our original sample is on all companies from CompStat for the years 2000 to 2017. Following Brazel et al. (2009) and Dechow et al. (2011), we use revenue related NFM, the number of employees, since previous research indicates this measure is highly associated with revenue and recorded by most companies as a common NFM. Both non-financial and financial data, such as revenues, accounts receivable, ETRs, and PBTD, are collected from CompStat. Auditors' tenure and audit fees are obtained from Audit Analytics. The audit committee's tenure and the chair's gender are collected from Board Ex. Accounting fraud information is collected from the SEC website and Lexis-Nexis AAER, a resource that contains the results of the SEC's investigation into accounting violations. A single fraud can cause several AAER reports as the SEC challenges and investigates different individuals implicated in the fraud. We remove non-accounting fraud firms as they are not related to the research question.

Table 1 Panel A presents the details of the sample selection procedures. In summary, we start with 240,683 firm-year observations on all firms in the CompStat database from 2000 to 2017. After deleting those firm-year observations with either negative or missing pre-tax income or missing values for computing CASHETR, GAAPETR, PBTD, and other key variables and excluding some outliers and those firm-year observations of financial, utility, and foreign companies due to their different reporting standards, our final sample contains 23,681 firm-year observations on 3,587 firms.

Table 1, Panel B reports the industry distribution of our final firm-year observations following the industry classification scheme in Dechow et al. (2011). There are 13 industries included in the sample, and the data concentrated in industries of

[5]Although the absolute value of leverage ratio may not be a necessary indicator of financial distress, especially from 2000 to 2017 when the interest rate was low due to loose monetary policy, we believe that the change in the ratio over time and relative value between firms can be used to measure the change in the financial distress of firms. Leverage has been commonly used in the literature for the study of fraud or fraud risk, including Dechow et al. (2011) and Brazel and Schmidt (2019).

transportation, computers, durable manufacturers, retail, services, and pharmaceuticals, with more than 1,500, or 5 percent, of the firm-year observations from each industry.

We report the distribution of the key variables of interest (CASHETR, GAAPETR, PBTD, and Fraud risk) by industry in Table 2. As one can see from Table 2, companies in the computers and transportation industries show the lowest CASHETR (e.g., <0.23) while the agriculture, retail, and textiles and apparel industries have the highest CASHETR (e.g., >0.30). For GAAPETR, the lowest GAAPETR (e.g., <0.28) is from companies in the computer industries, with the highest GAAPETR (e.g., >0.35) from companies in the transportation, retail, and service industries.

Table 3 reports the descriptive statistics for all our key variables, showing that the means and medians of our TA variables are similar to what is documented in the literature. Specifically, the means and median of CASHETR (0.250 and 0.248, respectively) and GAAPETR (0.319 and 0.342, respectively) are similar to those in Chen et al. (2010) and Lennox et al. (2012). For PBTD, the mean and median (0.046 and 0.032, respectively) are comparable to those in Frank et al. (2009) and Lennox et al. (2012). For the other two TA proxies, the mean and median are 0.203 and 0.085, respectively, for the percentage change of accounts receivable and 0.117 and 0.074 for the percentage change of inventory, respectively.

We also check Pearson's correlations of the key variables to provide some empirical support for our choice of variables. Table 4 shows that GAAPETR, CASHETR, and PBTD are significantly correlated at the 0.001 level, with GAAPETR and CASHETR being positively correlated (coefficient of correlation of 0.268), while both GAAPETR and CASHETR are negatively correlated to PBTD with the coefficients of correlation of -0.064 and -0.456, respectively. The negative correlations indicate that GAAPETR, CASHETR, and PBTD measure TA from different perspectives of tax avoidance strategies as explained in Section II, while there is no severe multicollinearity issue among them. In addition, the proxies of fraud risk are significantly correlated. PCHGREC is positively correlated to PCHGINV, DISCACC, PCHGCASHSALES, and CHGROA with coefficients of correlation of 0.197, 0.124, 0.156, and 0.129, respectively. However, NFM for fraud risk is not significantly correlated to other financial measures, showing some nonconformity between NFM and the financial measures.

Furthermore, Table 4 shows that PCHGREC is negatively correlated to CASHETR and positively correlated to GAAPETR and PBTD with the coefficients of correlation of -0.026, 0.007, and 0.04, respectively, indicating a higher level of TA increases fraud risk. PCHGINV is also negatively correlated to CASHETR and positively correlated to GAAPETR and PBTD, with the coefficients of correlation of -0.052, 0.004, and 0.053, respectively. These correlations suggest that the proxies of TA are positively correlated to the proxies of fraud risk.

Empirical Results

Empirical Results for Fraud Risk Model

We use six proxies to capture fraud risk from three perspectives: percentage change of accounts receivable (PCHGREC), percentage change of inventory (PCHGINV), and discretionary accrual (DISCACC) from accrual quality variables, percentage of cash sales (PCHGCASHSALES) and change of return on assets (CHGROA) from performance variables, and difference between sales growth rate and employee growth rate (DIFFBSE) from NFM. Table 5 presents the estimates of the relationship between TA and fraud risk with those six proxies as the dependent variable in panels A, B, C, D, E, and F, respectively. For each panel, NEGCASHETR, NEGGAAPETR, and PBTD are used as the TA proxies for Model 1, respectively.

To interpret the results consistently, we use the converted effective tax rate to capture TA in the regression analysis. Specifically, we multiply effective tax rates by -1 (e.g., NEGCASHETR = - CASHETR and NEGGAAPETR = - GAAPETR) so that the large values of NEGCASHETR, NEGGAAPETR, and PBTD represent a higher level of tax avoidance.

In all our models, we find that generally higher levels of tax avoidance are significantly related to higher fraud risk. In Model A1, where fraud risk is measured by the percentage change in accounts receivable (PCHGREC), the coefficient of NEGCASHETR indicates that assuming everything else remains constant, a one percent increase in NEGCASHETR implies a 0.232 percent increase in PCHGREC. This result supports hypothesis 1 that TA is positively related to fraud risk and is consistent with the agency theory indicating that more TA activities provide more opportunities for managers to conduct rent extraction, therefore increasing the fraud risk that the firms are exposed to. The coefficient (-0.104) of the natural logarithm of audit fees (Auditees) describes that a one percent increase in Auditees suggests a 0.104 percent decrease in

PCHGREC. This fact is consistent with the findings from Brazel and Schmidt (2019) that an increase in auditor efforts reduces fraud risk because auditors understand their clients' businesses better and can apply more appropriate audit procedures to alleviate fraud risk. The coefficient (-0.001) of Audit Tenure indicates that a one percent increase in auditor tenure implies a 0.001 percent decrease in PCHGREC. This result is aligned with the results from Brazel and Schmidt (2019) that state long auditor-client relationships help auditors understand the nature of a client's business and industry that may affect the risk of business operation and the risk of fraudulent financial reporting. Auditors may use their knowledge of these risks to determine the appropriate audit procedures. Therefore, long auditor tenure increases audit quality and reduces fraud risk. Similar to the coefficient of auditor tenure, the coefficient (-0.007) of Chair Tenure suggests that a longer audit committee chair's tenure decreases fraud risk because an audit committee chair with long tenure can better understand the client's business and internal control so that they can oversee the entire audit engagement. The coefficient of Chair Gender indicates that a male audit committee chair increases fraud risk. This result is consistent with the literature on gender diversity because our results support that female chairs are more conservative and better at monitoring audit engagement.

The coefficient (0.043) of Lanta suggests that a one percent increase in the log value of total assets is associated with a 0.043 percent increase in PCHGREC. This result indicates that large companies have more complex transactions, and managers may use those transactions to conduct rent extraction, thus increasing fraud risk. The coefficient of PCHGSALES shows that a one percent increase in percentage of sales growth rate is associated with a 0.747 percent increase in PCHGREC. This result is consistent with the literature that high-growth companies are more likely to commit accounting fraud. The coefficient for the percentage of plant assets and the coefficient for the big four CPA firms do not show significant results. The coefficient of leverage shows an insignificant relationship between leverage and PCHGREC.

In Model A2, the coefficient of NEGGAAPETR suggests that a one percent increase in NEGGAAPETR is associated with a 0.420 percent increase in PCHGREC. All other variables in Model A2 have the same signs as those in Model A1 and are statistically significant. In Model A3, the coefficient (0.017) of permanent book-tax difference (PBTD) indicates that TA is positively and significantly related to fraud risk. All other variables have the expected signs and are statistically significant.

In panels B, C, and E, we examine the relationship between various TA proxies and PCHGINV, DISCACC, and CHGROA, respectively. These results are consistent with those in Models A1 to A3, showing TA is positively related to fraud risk and other control variables.

In panel D, where fraud risk is measured by PCHGCASHSALES, the coefficient of NEGCASHETR suggests that a one percent increase in NEGCASHETR is associated with 0.080 PCHGCASHSALES, indicating a positive relationship between TA and fraud risk. This result is consistent with the findings in Dechow et al. (2011), even though it is opposite to the prediction of some theory or our findings in the preliminary study that PCHGCASHSALES is negatively related to fraud risk or fraud because managers may use accruals management for accrual-based sales such as credit sales. As explained in Dechow et al. (2011), when managers conduct accrual management to increase accrual-based sales, cash sales could increase as well. Another explanation for this positive relationship is that some companies front-load earnings and make unusual transitions later, thus increasing cash sales. The third reason could be that managers may overpay taxes to cover their fraudulent financial reporting behavior. Therefore, higher cash sales can indicate high fraud risk, and CASHETR can be positively related to PCHGCASHSALES.

In panels F, we use NFM DIFFBSE to proxy for fraud risk. In Model F1, the coefficient (1.507) of TA indicates that a higher level of TA is more likely to relate to large fraud risk with a 1 percent significance level. Specifically, a one percent increase in TA is associated with a 1.507 increase in log(P/1-P), which further means P/(1-P) increases by exp (1.507) = 4.51. This result is a 451 percent increase in the odds of increasing fraud risk (assuming all other variables remain constant). In models F2 and F3, the coefficients of TA show a positive and significant relationship between TA and DIFFBSE as well. Out of these three models, PBTD has the largest impact on fraud risk.

Overall, our results support hypothesis 1, indicating that TA is positively related to fraud risk. Generally, we find TA is a positive and significant factor that can help predict fraud risk when fraud risk is measured either using financial or nonfinancial variables. Similar to Brazel et al. (2009), we define large fraud risk as an indicator variable equal to 1 and 0 otherwise if the difference between financial and non-financial performance is greater than 20 percent. We find that all three TA proxies are significantly related to fraud risk. The results from above are consistent with the agency theory in TA, such that opportunistic managers may use complex TA strategies to conduct managerial rent extraction, thus increasing fraud risk.

Validation Analysis: Using Fraud Risk to Predict Fraud

According to the fraud triangle theory, managers in companies with higher fraud risk have more incentives and opportunities to commit accounting fraud. Prior studies find that fraud companies are associated with higher fraud risk when different proxies are used to measure fraud risk. For example, Brazel et al. (2009) find that fraud companies have a larger difference between financial and non-financial performance. Dechow et al. (1996) note that fraud companies are more likely to have a weak corporate governance system, and a weak internal control system in turn increases the fraud risk, as shown in Bell and Carcelle (2000). Therefore, we predict that fraud risk proxies in this study can be used to predict accounting fraud. To validate the predictability of those fraud risk proxies for accounting fraud, we use the following logistic model to estimate the relationship using financial proxies for fraud risk.

Multivariate Model 2

$$Logit\ (FRAUD)=\beta_0+\beta_1 Fraudrisk+\beta_2 PCHGSales+\beta_3 LnTA+\beta_4 Auditfees+\beta_5 AuditTenure+ \beta_6 Loss+\beta_7 PA+\beta_8 Restate+\beta_9 Big4+\beta_{10} ICME$$

where the dependent variable fraud is a dummy variable with a value of 1 for fraud companies and 0 otherwise, and the independent variable is fraud risk proxied by PCHGREC for Model 2a, DISCACC for Model 2b, PCHGCASHSALES for Model 2c, and PSOFTASSET for Model 2d. The percentage of soft assets is defined as total assets minus property, plant, and equipment (PPE) minus cash, then divided by total assets.

We select the same number of non-fraud companies based on SIC and size to match those 292 fraud companies listed on AAER's website from 2000 to 2017. Appendix C presents the total asset size (Lanta) comparison and sample sizes of those fraud and non-fraud firms for each of the twelve industries. The data on those fraud companies comes from the year when the SEC disclosed the violations. The pre- or post-fraud periods are not considered in this study. As shown in the literature, fraud and fraud risk are associated with similar control variables in similar ways, therefore, for model 2, we use the same control variables as in model 1, including LnTA, Restate, PCHGSALES, ICME, etc. We expect the same signs for the coefficients of these variables as those in Model 1 because high fraud risk is associated with a higher possibility of accounting fraud.

The results in Table 6 show that all the fraud risk proxies can well predict the likelihood that a firm commits fraud. Especially in Model 2a, the coefficient of PCHGREC suggests that a one percent increase in PCHGREC is associated with a 15.90 increase in odds ratio, indicating a very strong association between PCHGREC and accounting fraud. In Model 2b, the coefficient of DISCACC indicates that a one percent increase in DISCACC is associated with an 8.82 increase in odds ratio. In Model 2c, the coefficient shows that a one percent increase in PCHGCASHSALES is associated with a 0.063 decrease in odds ratio, indicating a negative association between PCHGCASHSALES and fraud. In Model 2d, the coefficient shows that a one percent increase in PSOFTASSET is associated with a 1.53 increase in the odds ratio. The results indicate that a higher level of tax avoidance could be considered a red flag for accounting fraud, so the auditors and regulators may need to pay additional attention to those companies for fraud detection.

Discussion and Conclusion

Implications for Practice

This study is quite meaningful for practitioners. Our findings suggest that regulators and external auditors should assess fraud risks from different perspectives. Higher fraud risk can be used to predict accounting fraud. In addition, higher levels of TA should draw more attention from regulators and external auditors since a high level of TA is positively related to high fraud risk, which could serve as an effective indicator of actual accounting fraud.

Among TA proxies, PBTD is most significantly related to four of six fraud risk proxies. It suggests that tax avoidance strategies that increase accounting earnings by reducing the firm's GAAPETR are the most predictive TAs for fraud risk. For more efficient fraud detection, auditors should focus on the income effect rather than the tax effect of differences between book income and taxable income. When auditors observe an abnormally high PBTD in the firms' financial statements, they should initiate further investigation for possible fraud. In addition, GAAPETR is also significantly related to fraud risk proxies. It shows that tax avoidance strategies that reduce total tax expense through a reduction in its components of current and deferred tax expense can help predict fraud risk. Auditors should pay additional attention to TA strategies that impact accounting earnings and total tax expenses. Furthermore, CASHETR is also significantly related to fraud risk, indicating that tax avoidance strategies for reducing cash tax payments through tax deferrals are associated with fraud risk. Unlike GAAPETR, CASHETR is not affected by the strategies that change the tax accounting accruals; therefore, auditors should also keep an eye on aggressive TA through deferral strategies, although those TAs are earnings management strategies and not fraud yet. For regulators, more rules need to be set to prevent firms from deferring large cash tax payments to future periods to deter fraud. According to the estimation of Dyck et al. (2023), reducing the percentage of firms that engaged in fraud from 10 percent to 9 percent could save $25 billion in fraud costs. So, if some regulations incorporating the warning signals of aggressive TA and more effective fraud risk assessment can be introduced to deter fraud, a large amount of economic deadweight loss from fraud could be prevented, which usually is borne by equity holders. Firms should improve internal controls and balance between cash flow and tax deferrals because extremely high PBTD or low ETR may draw more attention and increase scrutiny from external auditors and regulators, thereby inducing a much heavier auditing burden and cost to firms. Firms should also improve corporate governance to prevent managers from manipulating their earnings by using tax deferral strategies for their own benefit at the expense of firms' long-term performance, such as in the case of the Enron and Tyco scandals. When fraud occurs and is detected, there will be long-term reputational damage to the organization, up to 25 percent of a firm's market value based on KLM's cost estimate. Even when fraud is not yet uncovered, the firm would have to pay a high premium to silence those knowledgeable insiders or to cover up the fraud.

Among fraud risk proxies, we find that PCHGREC is the most significantly related to accounting fraud. It suggests that managers may apply more changes in receivables to commit fraudulent financial reporting (increasing revenues and gross margin). Therefore, auditors and regulators should focus more on fraud risks that are related to changes in receivables. In addition, auditors should use analytical procedures on the large differences between financial and NFMs because managers may manipulate financial measures but not NFMs.

Limitations

Even though this study provides some insight into the relationship between TA and fraud risk to researchers and practitioners, it still has several limitations. First, TA and fraud risk are measured by various proxies, which may not catch all the features of TA and fraud risk. In addition, it would be ideal to create a combined fraud risk index with all financial and nonfinancial proxies for an overall evaluation of firms' fraud risk level, but the binary nature of our NFM prevents us from doing so. As a robust check, we calculate the F scores from financial proxies and use those F scores to predict fraud in our matched fraud and nonfraud data set by following Dechow et al. (2011). Our prediction accuracy is similar to what is found in Dechow et al. (2011). However, we don't think the F-score method would be appropriate for regression analysis with our whole sample, where the non-fraud firms dominate. Also, TA is defined as a continuum of tax avoidance strategies, so it is difficult to separate TA strategies into different levels. Future studies could examine the relationship between specific tax avoidance strategies such as tax shelter and accounting fraud. Second, this study investigates the relationship between TA and fraud risk for publicly traded companies. The results may not be generalized to private companies since private companies may have different considerations when they conduct TA. Third, CASHETR, GAAPETR, and PBTD are used to measure the non-conformity between book and tax income. Future research could consider different proxies to measure the conformity between book and tax income for tax planning strategies. Fourth, as many companies do not disclose their NFM information, we use only one NFM variable (number of employees), which may not be able to measure fraud risk for all companies. Different industries have different NFMs. Future studies can consider including more industry-specific NFM variables for each industry for a more accurate measure of fraud risk.

Conclusion

Since accounting fraud is excessively harmful to corporations and society, a fraud risk assessment must be perform annually to detect accounting fraud before it occurs. According to the agency theory, managers may use various TA strategies for their own benefit at the expense of shareholders, thus increasing the risk of accounting fraud. In this research, we extend the literature on the consequences of TA by examining the relationship between TA and fraud risk. Using different proxies for TA and fraud risk, we find that TA is positively related to fraud risk. Among TA proxies, PBTD is most significantly associated with fraud risk proxies. Auditors and regulators should pay more attention to TA strategies that cause large differences between book and tax income. In addition, our results indicate that fraud risk proxies can be used to predict actual accounting fraud. Auditors and regulators should focus more on those high-fraud-risk areas that may lead to accounting fraud. Overall, we find that a higher level of TA could be considered a red flag for fraudulent financial reporting.

Table 1: Sample Description

Panel A: Sample Selection

Sample Requirement	# of Obs.
Firm-years from COMPUSAT database, 2000–2017	240,683
Less: firm years with negative and missing pretax income data	136,889
Less: firm years with missing tax avoidance data	30,599
Less: firm years of utility and finance industries	25,726
Less: firm years of foreign companies	449
Less: firm years with missing fraud data	11,785
Less: firm years with missing audit data	4,266
Less: firm years with missing BoardEx data	6,585
Less: firm years with outliers in TA and fraud risk variables	703
Firm-years in the final sample	23,681
Firms in the final sample	3,587
Minimum firm year	1
Maximum firm year	17

Panel B: Industry Distribution of Sample Firm-Years

Industry	# of observations	% of sample	cumulative %
Agriculture	89	0.38%	0.38%
Mining and Construction	659	2.78%	3.16%
Food and Tobacco	896	3.78%	6.94%
Textiles and Apparel	376	1.59%	8.53%
Lumber, Furniture and Printing	906	3.83%	12.36%
Chemicals	1034	4.37%	16.73%
Refining and Extractive	985	4.16%	20.89%
Durable Manufacturers	4995	21.09%	41.98%
Computers	3747	15.82%	57.80%
Transportation	1503	6.35%	64.15%
Retail	3593	15.17%	79.32%
Services	2992	12.63%	91.95%
Pharmaceuticals	1906	8.05%	100%

Table 2: Sample Description—Means of Main Variables by Industry

Industry	GAAPETR	CashETR	PBTD	PCHGREC	PCHGINV	DISCACC
Agriculture	0.341	0.303	0.048	0.098	0.132	0.022
Mining and Construction	0.312	0.266	0.049	0.185	0.167	0.010
Food and Tobacco	0.331	0.296	0.036	0.102	0.104	0.021
Textiles and Apparel	0.339	0.304	0.021	0.123	0.127	0.026
Lumber, Furniture and Printing	0.329	0.288	0.035	0.082	0.089	0.035
Chemicals	0.307	0.278	0.043	0.098	0.100	0.020
Refining and Extractive	0.342	0.249	0.081	0.186	0.169	0.064
Durable Manufacturers	0.303	0.262	0.036	0.126	0.127	0.020
Computers	0.278	0.224	0.045	0.152	0.125	0.043
Transportation	0.353	0.205	0.074	0.094	0.087	0.049
Retail	0.354	0.303	0.031	0.172	0.106	0.036
Services	0.354	0.274	0.043	0.151	0.073	0.041
Pharmaceuticals	0.303	0.258	0.034	0.165	0.161	0.026

Table 3: Descriptive Statistics of TA, Fraud Risk, and Other Firm Characteristics

Variable	N	Mean	Median	Std. Dev.	Min	Max
GAAPETR	23681	0.319	0.342	0.125	0.000	0.996
CashETR	23681	0.250	0.248	0.168	0.000	1.000
PBTD	20748	0.046	0.032	0.099	-1.239	2.138
PCHGREC	22757	0.203	0.085	2.336	-1.000	194.818
PCHGINV	15614	0.117	0.074	0.299	-1.000	2.696
DISCACC	22976	0.032	0.034	0.084	-0.632	2.972
PCHGCASHSALE	23028	0.107	0.070	0.205	-1.000	1.252
CHGROA	17250	-0.001	0.001	0.071	-0.788	0.566
LnTA	23681	6.800	6.760	1.884	-0.580	13.590
DIFFBSE	22599	-0.027	0.036	5.281	-10.230	2.109
Lev	23588	0.179	0.139	0.201	0.000	3.730
MB	18564	0.473	0.408	0.481	-9.854	27.199
Loss	23681	0.010	0.000	0.102	0.000	1.000
PA	23659	0.246	0.177	0.217	0.000	0.971
PCHGSALES	23094	0.126	0.083	0.226	-1.125	2.038
Big4	23681	0.808	1.000	0.201	0.000	3.730
LnAuditfees	23609	13.866	13.901	1.282	7.450	18.362
AuditTenure	23644	23.756	19.930	19.086	0.230	105.470
ChairTenure	22580	8.067	6.700	6.140	0.000	34.800
ChairGender	22582	0.909	1.000	0.287	0.000	1.000

Table 4: Pearson's Coefficient of Correlation for Key Variables

	GAAPETR	CASHETR	PBTD	PCHGREC	PCHGINV	DISCACC	PSOFTASSET	PCHGCASHSALES	CHGROA	DIFFBSE
GAAPETR	1									
CASHETR	0.268***	1								
PBTD	-0.064***	-0.456***	1							
PCHGREC	0.007	-0.026***	0.04***	1						
PCHGINV	0.004	-0.052***	0.053***	0.197***	1					
DISCACC	-0.099***	0.065***	-0.013	0.124***	0.194***	1				
PSOFTASSET	-0.026***	0.075***	-0.125***	0.014*	0.057***	0.262***	1			
PCHGCASHSALES	0.075***	-0.048***	0.039***	0.156***	0.327***	0.058***	0.035***	1		
CHGROA	-0.096***	0.038***	0.196***	0.129***	0.147***	0.083***	-0.08***	0.301***	1	
DIFFBSE	0.024***	-0.012	0.003	-0.019**	-0.028***	0.030***	0.007	0.194***	0.057***	1

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

Table 5 (Panel A): TA and Fraud Risk-OLS Regression Results

Fraud Risk=PCHGREC	Model A1				Model A2				Model A3			
	TA=NEGCASHETR				TA=NEGGAAPETR				TA=PBTD			
	Coeff.		T-Stat	VIF	Coeff.		T-Stat	VIF	Coeff.		T-Stat	VIF
β0 (Intercept)	2.212	***	6.95	NA	2.342	***	7.28	NA	1.717	***	6.52	NA
β1 (TA)	0.232	***	2.48	1.08	0.42	***	3.41	1.07	0.017	***	3.76	1.07
β2 (LnAuditfees)	-0.104	***	-3.9	5.00	-0.113	***	-4.1	5.01	-0.002	***	-2.76	4.91
β3 (AuditTenure)	-0.001		-0.79	1.27	-0.001		-0.78	1.27	-0.001	***	-2.89	1.26
β4 (ChairTenure)	-0.007	***	-2.76	1.07	-0.007	***	-2.77	1.07	-0.001	***	-7.05	1.07
β5 (ChairGender)	-0.066		-1.24	1.03	-0.066		-1.24	1.03	0.004	***	2.9	1.03
β6 (LnTA)	0.043	**	2.36	5.09	0.044	**	2.43	5.09	0		-0.67	5.02
β7 (MB)	-0.078	**	-1.89	1.10	-0.071	**	-1.72	1.10	-0.007	***	-7.59	1.10
β8 (PCHGSALES)	0.747	***	8.65	1.15	0.768	***	8.9	1.15	0.116	***	7.48	1.15
β9 (Loss)	-0.056		-0.29	1.02	-0.021		-0.14	1.03	-0.024	***	-5.2	1.02
β10 (Restate)	-0.035		-0.59	1.04	-0.008		-0.16	1.04	0.001		1	1.04
β11 (PA)	-0.106		-1.16	1.60	-0.064		-0.74	1.60	-0.026	***	-12.33	1.58
β12 (Big4)	0.049		1.04	1.50	0.051		1.08	1.50	-0.004	***	-3.13	1.47
β13 (Lev)	0.023		0.28	1.25	0.033		0.4	1.24	0.002		1.15	1.26
β14 (ICME)	-0.005		-0.1	2.12	0.001		0.02	2.12	0.015		0.035	2.12
Industry effect	Yes				Yes				Yes			
Year effect	Yes				Yes				Yes			
N	21,517				21,517				19,363			
Adjusted R^2 %	1.19				1.22				1.43			

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

Model 1: $FRAUDRISK=\beta_0+\beta_1 TA+ \beta_2 AuditFees + \beta_3 AuditTenure + \beta_4 ChairTenure+\beta_5 ChairGender+ \beta_6 LnTA+ \beta_7 MB+ \beta_8 PCHGSales + \beta_9 Loss+ \beta_{10} Restate + \beta_{11} PA+ \beta_{12} Big4 + \beta_{13} Lev + \beta_{14} ICME+ Year\ Dummies + Industry\ Dummies +\varepsilon$

Table 5 (Panel B): TA and Fraud Risk-OLS Regression Results

Fraud Risk=PCHGINV	**Model B1**				**Model B2**				**Model B3**			
	TA=NEGCASHETR				**TA=NEGGAAPETR**				**TA=PBTD**			
	Coeff.		**T-Stat**	**VIF**	**Coeff.**		**T-Stat**	**VIF**	**Coeff.**		**T-Stat**	**VIF**
β0 (Intercept)	0.358	***	7.55	NA	0.344	***	7.15	NA	0.309	***	6.52	NA
β1 (TA)	0.058	***	3.87	1.07	0.048	**	2.52	1.10	0.129	***	4.42	1.06
β2 (LnAuditfees)	-0.026	**	-6.45	5.37	-0.011	***	-2.71	5.37	-0.028	***	-6.6	5.24
β3 (AuditTenure)	0	***	-3.9	1.26	0	***	-3.93	1.26	0	***	-3.78	1.26
β4 (ChairTenure)	-0.002	***	-4.31	1.06	-0.002	***	-4.38	1.06	-0.002	***	-4.01	1.06
β5 (ChairGender)	0.009		1.15	1.04	0.012		1.55	1.06	0.008		1.03	1.04
β6 (LnTA)	0.017	***	6.05	5.34	0.012	***	4.56	5.34	0.018	***	6.38	5.24
β7 (MB)	0.013	*	1.85	1.20	0.012	*	1.81	1.20	0.019	**	2.55	1.19
β8 (PCHGSALES)	0.509	***	42.98	1.19	0.499	***	43.31	1.18	0.481	***	39.66	1.19
β9 (Loss)	-0.059	*	-2.26	1.02	-0.06	**	-2.31	1.03	-0.067	**	-2.3	1.02
β10 (Restate)	0.007		0.95	1.04	0.003		0.38	1.04	0.006		0.72	1.05
β11 (PA)	-0.027	***	-2.64	1.49	-0.029	**	-2.29	1.49	-0.045	***	-3.33	1.50
β12 (Big4)	-0.009		-1.18	1.48	-0.009		-1.18	1.48	-0.008		-1.01	1.45
β13 (Lev)	0.041	***	3.22	1.26	0.044	***	3.45	1.25	0.052	***	3.5	1.28
β14 (ICME)	0.017	**	2.24	2.36	0.017	**	2.24	2.36	0.014	*	1.71	2.36
Industry effect	Yes				Yes				Yes			
Year effect	Yes				Yes				Yes			
N	14,824				14,824				13,394			
Adjusted R^2 %	16.4				16.3				15.9			

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

Model 1: $FRAUDRISK=\beta_0+\beta_1 TA+ \beta_2 AuditFees + \beta_3 AuditTenure + \beta_4 ChairTenure+\beta_5 ChairGender+ \beta_6 LnTA+ \beta_7 MB+ \beta_8 PCHGSales + \beta_9 Loss+ \beta_{10} Restate + \beta_{11} PA+ \beta_{12} Big4 + \beta_{13} Lev + \beta_{14} ICME+ Year\ Dummies + Industry\ Dummies +\varepsilon$

Table 5 (Panel C): TA and Fraud Risk-OLS Regression Results

Fraud Risk=DISCACC	Model C1				Model C2				Model C3			
	TA=NEGCASHETR				TA=NEGGAAPETR				TA=PBTD			
	Coeff.		T-Stat	VIF	Coeff.		T-Stat	VIF	Coeff.		T-Stat	VIF
β0 (Intercept)	0.05	***	4.58	NA	0.089	***	8.17	NA	0.036	***	3.09	NA
β1 (TA)	0.004		1.34	1.08	0.099	**	23.54	1.07	0.045	***	7.71	1.07
β2 (LnAuditfees)	-0.002	**	-2.18	4.95	-0.003	***	-3.09	4.95	-0.001		-0.98	4.85
β3 (AuditTenure)	0	***	4.65	1.27	0	***	4.8	1.27	0	***	4.43	1.26
β4 (ChairTenure)	0	***	4.23	1.07	0	***	4.86	1.07	0	***	3.84	1.07
β5 (ChairGender)	-0.002		-1.27	1.03	-0.002		-1.06	1.03	-0.003		-1.58	1.03
β6 (LnTA)	-0.002	***	-3.77	5.03	-0.002	***	-3.53	5.03	-0.003	***	-3.96	4.96
β7 (MB)	0.007	***	7.12	1.10	0.008	***	7.83	1.10	0.007	**	6.35	1.09
β8 (PCHGSALES)	0.01	***	4.2	1.15	0.01	***	4.14	1.15	0.008	***	3.22	1.15
β9 (Loss)	-0.006		-1.2	1.02	0.004		0.87	1.03	-0.007	**	-1.25	1.02
β10 (Restate)	0.003	*	0.95	1.04	0.003		1.78	1.04	0.003		1.62	1.04
β11 (PA)	-0.062	***	-20.44	1.60	-0.066	***	-22.31	1.59	-0.066	***	-20.65	1.58
β12 (Big4)	-0.016		-9.5	1.50	-0.014		-8.83	1.50	-0.016	***	-9.07	1.47
β13 (Lev)	0.02	***	7.14	1.25	0.019	***	6.59	1.24	0.022	***	6.77	1.26
β14 (ICME)	-0.013	***	-7.83	2.12	-0.012	**	-6.96	2.12	0.014	*	1.71	2.12
Industry effect	Yes				Yes				Yes			
Year effect	Yes				Yes				Yes			
N	21,731				21,731				19,566			
Adjusted R^2 %	9.38				11.63				9.69			

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

Model 1: $FRAUDRISK=\beta_0+\beta_1 TA+ \beta_2 AuditFees + \beta_3 AuditTenure + \beta_4 ChairTenure+\beta_5 ChairGender+ \beta_6 LnTA+ \beta_7 MB+ \beta_8 PCHGSales + \beta_9 Loss+ \beta_{10} Restate + \beta_{11} PA+ \beta_{12} Big4 + \beta_{13} Lev + \beta_{14} ICME+ Year\ Dummies + Industry\ Dummies +\varepsilon$

Table 5 (Panel D): TA and Fraud Risk-OLS Regression Results

Fraud Risk=PCHGCASHSALES	**Model D1**				**Model D2**				**Model D3**			
	TA=NEGCASHETR				**TA=NEGGAAPETR**				**TA=PBTD**			
	Coeff.		**T-Stat**	**VIF**	**Coeff.**		**T-Stat**	**VIF**	**Coeff.**		**T-Stat**	**VIF**
β0 (Intercept)	0.307	***	11.24	NA	0.3	***	10.71	NA	0.275	***	9.54	NA
β1 (TA)	0.08	***	10.01	1.08	0		0.01	1.07	0.115	***	7.88	1.06
β2 (LnAuditfees)	-0.004	*	-1.65	4.94	-0.004	*	-1.91	4.95	-0.004	*	-1.75	4.85
β3 (AuditTenure)	0	***	-5.04	1.26	0	***	-5.04	1.26	0	***	-4.84	1.26
β4 (ChairTenure)	-0.002	***	-7.92	1.06	-0.002	***	-8.31	1.06	-0.002	***	-7.37	1.07
β5 (ChairGender)	0.01	**	2.23	1.03	0.01	**	2.12	1.03	0.01	**	2.18	1.03
β6 (LnTA)	-0.007	***	-4.17	5.03	-0.006	***	-4.11	5.03	-0.006	***	-3.83	4.95
β7 (MB)	-0.041	***	-15.81	1.09	-0.041	***	-15.81	1.09	-0.04	**	-15.08	1.08
β8 (Loss)	-0.095	***	-7.39	1.02	-0.099	***	-7.63	1.02	-0.082	***	-5.72	1.02
β9 (Restate)	-0.01	**	-2.37	1.04	-0.01	**	-2.42	1.04	-0.01	**	-2.38	1.04
β10 (PA)	-0.074	***	-9.88	1.58	-0.068	***	-9.14	1.58	-0.066	***	-8.27	1.57
β11 (Big4)	-0.003		-0.68	1.5	-0.004		-1.01	1.5	-0.002		-0.37	1.47
β12 (Lev)	-0.07	***	-9.76	1.25	-0.064	***	-8.98	1.24	-0.071	***	-8.98	1.26
β13 (ICME)	-0.017	***	-4.07	2.12	-0.017	***	-4.15	2.12	-0.018	***	-4.14	2.11
Industry effect	Yes				Yes				Yes			
Year effect	Yes				Yes				Yes			
N	21,764				21,764				19,599			
Adjusted R^2 %	12.07				11.66				12.01			

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

Model 1: $FRAUDRISK=\beta_0+\beta_1 TA+ \beta_2 AuditFees + \beta_3 AuditTenure + \beta_4 ChairTenure+\beta_5 ChairGender+ \beta_6 LnTA+ \beta_7 MB+ \beta_8 Loss+ \beta_9 Restate + \beta_{10} PA+ \beta_{11} Big4 + \beta_{12} Lev + \beta_{13} ICME+ Year\ Dummies + Industry\ Dummies +\varepsilon$

Table 5 (Panel E): TA and Fraud Risk-OLS Regression Results

Fraud Risk=CHGROA	Model E1				Model E2				Model E3			
	TA=NEGCASHETR				TA=NEGGAAPETR				TA=PBTD			
	Coeff.		T-Stat	VIF	Coeff.		T-Stat	VIF	Coeff.		T-Stat	VIF
β0 (Intercept)	0.236	***	26.26	NA	0.262	***	29.09	NA	0.212	***	23.26	NA
β1 (TA)	0.007	***	2.73	1.08	0.069	***	19.87	1.07	0.185	***	40.25	1.07
β2 (LnAuditfees)	-0.009	***	-11.46	4.93	-0.009	***	-12.43	4.94	-0.008	***	-10.75	4.83
β3 (AuditTenure)	0	***	4.93	1.27	0	***	5.04	1.26	0	***	5.23	1.26
β4 (ChairTenure)	0		-1.46	1.07	0		-1.12	1.07	-0.002		-0.11	1.07
β5 (ChairGender)	-0.003	*	-1.85	1.03	-0.003	*	-1.72	1.03	-0.003	*	-1.72	1.03
β6 (LnTA)	0.002	***	3	5.02	0.002	***	3.33	5.02	0.002	***	4.76	4.94
β7 (MB)	-0.032	***	-38.08	1.1	-0.032	***	-37.86	1.1	-0.03	***	-35.31	1.09
β8 (PCHGSALES)	0.08	***	39.51	1.15	0.08	***	40.13	1.15	0.076	***	37.14	1.15
β9 (Loss)	-0.098	***	-23.16	1.02	-0.091	***	-21.63	1.03	-0.096	***	-21.12	1.02
β10 (Restate)	-0.003	**	-2.31	1.04	-0.003	**	-2.29	1.04	-0.003	***	-21.12	1.04
β11 (PA)	-0.008	***	-3.23	1.59	-0.011	***	-4.33	1.59	-0.016	***	-6.56	1.58
β12 (Big4)	-0.004		-0.32	1.5	0		0.22	1.5	0.002		1.37	1.47
β13 (Lev)	-0.044	***	-18.84	1.25	-0.045	***	-19.31	1.24	-0.059	***	-23.6	1.26
β14 (ICME)	0.014	***	9.8	2.12	0.015	***	10.66	2.13	0.013	***	9.18	2.12
Industry effect	Yes				Yes				Yes			
Year effect	Yes				Yes				Yes			
N	21,815				21,815				19,639			
Adjusted R^2 %	21.15				22.53				27.22			

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

Model 1: $FRAUDRISK=\beta_0+\beta_1 TA+ \beta_2 AuditFees + \beta_3 AuditTenure + \beta_4 ChairTenure+\beta_5 ChairGender+ \beta_6 LnTA+ \beta_7 MB+ \beta_8 PCHGSales + \beta_9 Loss+ \beta_{10} Restate + \beta_{11} PA+ \beta_{12} Big4 + \beta_{13} Lev + \beta_{14} ICME+ Year\ Dummies + Industry\ Dummies +\varepsilon$

Table 5 (Panel F): TA and Fraud Risk-Logistic Regression Results

Fraud Risk=DIFFBSE	**Model F1**			**Model F2**			**Model F3**		
	TA=NEGCASHETR			**TA=NEGGAAPETR**			**TA=PBTD**		
	Odds ratio		**Z-Stat**	**Odds ratio**		**Z-Stat**	**Odds ratio**		**Z-Stat**
β0 (Intercept)	2.735	***	3.4	2.973	***	3.6	0.811	***	-0.62
β1 (TA)	1.507	***	3.85	1.419	***	2.48	2.792	***	5.48
β2 (LnAuditfees)	0.879	***	-4.77	0.873	***	-5	0.985	***	-5.03
β3 (AuditTenure)	0.998		-1.02	0.998		-1.05	0.997	***	-2.08
β4 (ChairTenure)	0.976	***	-7.88	0.976	***	-8.01	0.974	***	-7.75
β5 (ChairGender)	1.327	***	4.12	1.328	***	4.15	1.305	***	3.51
β6 (LnTA)	0.976		-1.31	0.908		-1.18	0.868		-1.23
β7 (MB)	0.904	***	-2.91	0.904	***	-2.9	0.905	***	-2.63
β8 (PCHGSALES)	5.141	***	15.81	5.172	***	15.94	5.338	***	15.21
β9 (Loss)	0.979		-0.12	0.995		-0.03	0.996		-0.13
β10 (Restate)	1.052		0.87	1.053		0.88	1.028		0.45
β11 (PA)	1.111		1.21	1.136		1.46	1.155		1.43
β12 (Big4)	1.019		0.37	1.019		0.39	0.941		-0.95
β13 (Lev)	1.61	***	3.99	1.619	***	4.03	1.63	***	4.08
β14 (ICME)	0.514	***	-16	0.512	***	-16.07	0.703	***	-7.41
Industry effect	Yes			Yes			Yes		
Year effect	Yes			Yes			Yes		
N	22,271			22,271			19,648		
Pseudo R^2	0.0394			0.039			0.034		

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%. No VIF is for Logit model.

Model1: $Logit(FRAUDRISK)=\beta_0+\beta_1TA+\beta_2AuditFees+\beta_3AuditTenure+\beta_4ChairTenure+\beta_5ChairGender+\beta_6LnTA+\beta_7MB+\beta_8PCHGSales+\beta_9Loss+\beta_{10}Restate+\beta_{11}PA+\beta_{12}Big4+\beta_{13}Lev+\beta_{14}ICME+Year\ Dummies+Industry\ Dummies+\varepsilon$

Table 6: Fraud Risk and Fraud-Logistic Regression Results

FRAUD =1	**Model 2a (PCHGREC)**			**Model 2b (DISCACC)**			**Model 2c (PCHGCASHSALES)**			**Model 2d (PSOFTASSET)**		
	Odds ratio		**Z-Stat**	**Odds ratio**		**Z-Stat**	**Odds ratio**		**Z-Stat**	**Odds ratio**		**Z-Stat**
β0 (Intercept)	381.61	***	4.52	630.05	***	4.75	381.61	***	4.52	147.89	***	4.26
β1 (Fraud risk)	15.9	**	2.25	8.82	**	2.37	0.063	**	-2.25	1.53	**	1.84
β2 (PCHGSALES)	0.749		-1.36	0.997		-0.02	11.917	**	2.23	0.707	*	-1.7
β3 (LnTA)	1.383	***	3.68	1.428	***	3.91	1.383	***	3.68	1.272	***	2.9
β4 (LnAuditfees)	0.549	***	-4.8	0.526	***	-4.97	0.549	***	-4.8	0.59	***	-4.56
β5 (AuditTenure)	1.00		0.35	0.999		-0.21	1.00		0.35	1.00		0.61
β6 (Loss)	0.914		-0.11	0.849		-0.19	0.914		-0.11	0.773		-0.31
β7 (PA)	0.364	**	-2.11	0.284	**	-2.55	0.364	**	-2.11	0.364	**	-2.11
β8 (Restate)	1.295		0.94	1.438		1.3	1.295		0.94	1.373		1.17
β9 (Big4)	1.168		0.61	1.308		1.03	1.168		0.61	1.17		0.62
β10 (ICME)	2.387	**	2.41	2.454	**	2.49	2.387	**	2.41	2.446	**	2.54
N	532			527			532			536		
Pseudo R^2	0.0512			0.0607			0.0512			0.0392		

Notes: *, **, and *** indicate significance at 10%, 5%, and 1%.

The logistic regression model is

$Logit(FRAUD)=\beta_0+\beta_1 Fraudrisk+\beta_2 PCHGSales+\beta_3 LnTA+\beta_4 Auditfees+\beta_5 AuditTenure+\beta_6 Loss+\beta_7 PA+\beta_8 Restate+\beta_9 Big4+\beta_{10} ICME$ With Fraud risk = PCHGREC, Fraud risk = DISCACC, Fraud risk = PCHGCASHSALES, Fraud risk=PSOFTAS in Model 2a, Model 2b, Model 2c, and Model 2d, respectively.

Appendix A: Definitions of Main Variables and Control Variables.

Variable	Definition
Cash effective tax rate (CashETR)	=Cash taxes paid/pretax income=TXPD/PI =#317/#170 CashETR is considered missing if pretax income <=0; CashETR is shortened to the range [0,1]
GAAP effective tax rate (GAAPETR)	=Total income taxes/pretax income=TXT/PI =#16/#170 GAAPETR is considered missing if pretax income <=0; GAAPETR is shortened to the range [0,1]
Permanent book-tax difference (PBTD)	= (total book-tax difference - temporary book-tax difference)/lagged assets. = {PI – (TXC+TXFO)/STR – (TXDI/STR)}/lag AT = {#170 – (#63+#64)/STR – (#50/STR)}/lag #6;
Negative CashETR (NEGCASHETR)	= - CashETR
Negative GAAPETR (NEGGAAPETR)	= - GAAPETR
Percentage change of accounts receivable (PCHGREC)	= (current receivable – prior receivable) / prior receivable=(RECT-lagRECT)/lag RECT = (#2 – lag #2)/lag #2
Percentage change of inventory (PCHGINV)	= (current inventory – prior inventory)/prior inventory= (INVT-lag INVT)/lag INVT = (#3 – lag #3)/lag #3
Discretionary accrual (DISCACC)	See Appendix B
Percentage change of sales (PCHGSALES)	= (current sales – prior sales)/prior sales= (SALE-lag SALE)/lag SALE = (#12 – lag #12)/lag #12
Percentage change of cash sales (PCHGCASHSALES)	= (current cash sales – prior cash sales)/prior cash sales= {SALE - RECT – (lag SALE – lag RECT)}/ (lag SALE – lag RECT) = {#12 - #2 – (lag#12 – lag#2)}/ (lag#12 – lag#2)
Percentage of soft assets (PSOFTASSET)	= (total assets – PPE – cash) / total assets = (AT-PPENT-CH)/AT = (#6 - #8 - #1)/#6
Employee growth rate (PCHGEMPL)	= (current employee # - prior year employee #)/prior year employee # = (EMP-lag EMP)/lag EMP = (#29 – lag #29)/lag #29
Difference between sales growth rate and employee growth rate (DIFFBSE)	= PCHGSALES – PCHGEMPL = (SALE-lag SALE)/lag SALE – (EMP-lag EMP)/lag EMP = (#12 – lag #12)/lag #12 - (#29 – lag #29)/lag #29
Large fraud risk from NFM (LargeRisk)	= 1 if DIFFBSE is greater than 20% and 0 otherwise
Change of Return on Assets (CHGROA)	= net income / total assets – prior year net income/prior year total assets = IBC/AT – lag IBC/lag AT = #172/#6 – lag #172/lag#6
Leverage (Lev)	=long-term debt/total assets = DLTT/AT =#9/#6
Market to book value (MB)	= market value of total equity/book value of total equity = PRCCD*CSHOC/CEQ = #199*#25/#60
Plant assets (PA)	= Property, plant, Equipment/total assets = PPENT/AT = #8/#6

Appendix B: Discretionary Accrual

The modified Jones model by Dechow et al. (1995) is used to estimate discretionary accrual.
First, we use the following model to estimate the values of α_0, β_1, and β_2.
$ACC_{j,t}/ Assets_{j,t-1} = \alpha_0 * 1/Assets_{j,t-1} + \beta_1 * \Delta Sales_{j,t}/ Assets_{j,t-1} + \beta_2 * GPPE_{j,t}/ Assets_{j,t-1} + \varepsilon_{j,t}$
Total accruals (ACC) are calculated as (Income before extraordinary items and discontinued operations– operating cash flows).
Next, we estimate discretionary accrual by using the following model.
$Discacc_{j,t} = ACC_{j,t}/ Assets_{j,t-1} - \{\alpha_0 * 1/Assets_{j,t-1} + \beta_1 * (\Delta Sales_{j,t} - \Delta receivables_{j,t}) / Assets_{j,t-1} + \beta_2 * GPPE_{j,t}/ Assets_{j,t-1}\}$
The variables are defined as the following:
Total accruals (ACC) = {#123 – (#308 - #124)}/ lag #6
Percentage change in sales ($\Delta Sales_{j,t}$) = (#12 – lag #12) / lag #6
Gross property, plant and equipment = #7 /lag #6
Percentage change in receivables = (#2 – lag #2) / lag #6

Appendix C: Descriptive Statistics of Matched Sample

Industry	Fraud vs Non-Fraud #	Max LnTA (Fraud vs Non-Fraud)	Min LnTA (Fraud vs Non-Fraud)	SCI Codes Range
Agriculture	2-2	5.09-5.02	4.92-4.67	0100–0999,
Construction	8-8	8.42-8.46	4.71-4.86	1000–1299 1400–1999
Food	17-17	9.65-9.52	3.60-3.47	2000–2141
Textiles	4-4	7.02-7.04	6.51-6.51	2200–2399,
Chemicals	2-2	7.47-7.46	5.12-5.19	2800–2824 2840–2899,
Refining	5-5	6.22-6.22	1.39-1.23	1300–1399 2900–2999,
Manufacturers	72-72	12.02-12.01	2.90-2.90	3000–3569, 3580–3669 3680–3999,
Computers	85-85	11.39-11.48	2.36-2.36	3570–3579, 3670–3679 7370–7379
Transportation	9-9	11.43-11.00	7.51-7.35	4000–4899
Retail	47-47	8.89-8.87	2.35-2.64	5000–5999,
Services	45-45	13.38-13.38	2.76-2.68	7000–7369 7380–9999,
Pharmaceuticals	28-28	10.23-10.22	3.62-3.62	2830–2836 3829–3851

Note: Not all industries are included as some industries don't have listed fraud cases on AAER.

References

Abbott, L. J., S. Parker, G. F. Peters. 2004. Audit Committee Characteristics and Restatements. *AUDITING: A Journal of Practice and Theory*, 23(1): 69–87.https://doi.org/10.2308/aud.2004.23.1.69

ACFE Occupational Fraud 2024. A Report to the Nations. ACFE Publication. Retrieved October 2, 2025, from https://www. acfe.com/rttn/docs/2024-report-to-nations.pdf

Armstrong, C. S., J. L. Blouin, A. D. Jagolinzer. and Larcker, D. F. 2015. Corporate Governance, Incentives, and Tax Avoidance. *Journal of Accounting and Economics*, 50(1): 1–17.

Balakrishnan, K., J. Blouin, and W. Guay. 2012. Does Tax Aggressiveness Reduce Corporate Transparency? Working paper, London Business School, and University of Pennsylvania.

Barton, J and P. J. Simko. 2002. The Balance Sheet as an Earnings Management Constraint. Available at SSRN:https://ssrn.com/abstract=320641orhttp://dx.doi.org/10.2139/ssrn.320641

Bell, T. B., and J. V. Carcello. 2000. A Decision Aid for Assessing the Likelihood of Fraudulent Financial Reporting. Auditing: A Journal of Practice and Theory 19(1):169–184.

Behn, B. K., and R. A. Riley, Jr. 1999. Using nonfinancial information to predict financial performance: The case of the U.S. airline industry. *Journal of Accounting, Auditing and Finance* 14(1): 29–56.

Brazel, J., K. Jones, and M. Zimbelman. 2009. Using Nonfinancial Measures to Assess Fraud Risk. *Journal of Accounting Research*. 47(5): 1135–1166.

Brazel, J. and J. Schmidt. 2019. Do Auditors and Audit Committee Lower Fraud Risk by Constraining Inconsistencies between Financial and Nonfinancial Measures? *Auditing: Journal of Practice and Theory* 38 (1): 103–122.

Chen, S., X. Chen, Q. Cheng, and T. Shevlin. 2010. Are Family Firms More Tax Aggressive than Non-family Firms? *Journal of Financial Economics* 95(1): 41–61.

Cheng, C., K. Hennes, and P. Sapkota. 2022. The Nonlinear Relation between Effective Tax Rates and Tax-Related Restatements. *Accounting Horizons* 36(4): 1–26.

Cook, K. A., G. R. Huston, and T. C. Omer. 2008. Earnings Management through Effective Tax Rates: The effects of Tax-planning Investment and the Sarbanes-Oxley Act of 2002. *Contemporary Accounting Research* 25(2): 447–71.

Cressey, D. 1953. Other People's Money: A Study in the Social Psychology of Embezzlement, Free press, Glencoe, IL.

Desai, M. A. 2005. The Degradation of Reported Corporate Profits. *Journal of Economic Perspectives* 19(1): 171–192.

Desai, M. A., and D. Dharmapala. 2006. Tax Avoidance and High-Powered Incentives. *Journal of Financial Economics* 79(1): 145–179.

Desai, M. A., and D. Dharmapala. 2009. Tax Avoidance and Firm Value. *Journal of Economics and Statistics* 91(3): 537–546.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting Earnings Management. *The Accounting Review* 70(2): 193–226.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1996. Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC. *Contemporary Accounting*; Research 13(1): 1–36.

Dechow, P., W. Ge, C. Larson, and R. Sloan. 2011. Predicting Material Accounting Misstatements. *Contemporary Accounting Research* 28(1): 17–82.

DeFond, M. L., and J. Jiambalvo. 1994. Debt covenant violation and misstatement of accruals. *Journal of Accounting and Economics* 17(1): 145–76.

DeFond, M.L., and J. R. Francis. 2005. Auditing research after Sarbanes-Oxley. *Auditing: Journal of Practice and Theory* 24 (Supplement): 5–30.

Dhaliwal, D. S., C. A. Gleason, and L. F. Mills. 2004. Last-chance Earnings Management: Using the Tax Expense to Meet Analysts' Forecasts. *Contemporary Accounting Research* 21(2): 431–59.

Dyck, A., Morse, A. and Zingales, L. 2023. How Pervasive is Corporate Fraud? Review of Accounting Studies29, 736–769. https://doi.org/10.1007/s11142-022-09738-5

Dyreng, S., Hanlon, M., and Maydew, E. (2008). Long-run Tax Avoidance. *The Accounting Review*, 83(1): 61–82.

Erickson, M., Hanlon, M., Maydew, E. 2004. How Much Will Firms Pay for Earnings that Do Not Exist? Evidence of Taxes Paid on Allegedly Fraudulent Earnings. *The Accounting Review* 79(4): 387–408.

Frank, M. M., L. J. Lynch, S. O. Rego. 2009. Tax Reporting Aggressiveness and its Relation to Aggressive Financial Reporting. *The Accounting Review* 84(2): 467–496.

Graham, J., and A. Tucker. 2006. Tax Shelters and Corporate Debt Policy. *Journal of Financial Economics* 81, 563–594.

Hanlon, M., and S. Heitzman. 2010. A Review of Tax Research. *Journal of Accounting and Economics* 50(2):127–178.

Hanlon, M., G. Krishnan and L. F. Mills. 2012. Audit Fees and Book-Tax Differences. *Journal of the American Taxation Association* 4 (1): 55–86.

Kothari, S. P., A. Leone, and C. Wasley. 2005. Performance-matched discretionary accrual measures. *Journal of Accounting and Economics* 39(1): 163–97.

Lawrence, A., M. Minutti-Meza, and P. Zhang. 2011. Can Big 4 versus non-Big 4 Differences in Audit Quality Proxies be Attributed to Client Characteristics? *The Accounting Review*. 86(1):259–586.

Lennox, C., P. Lisowsky, J. Pittman. 2012. Tax Aggressiveness and Accounting Fraud. *Journal of Accounting Research* 51(4): 739–778.

Nicholas, S. 2021. What is Accounting Fraud? https://www.investopedia.com/ask/answers/032715/what-accounting-fraud.asp

Phillips, J., M. Pincus, and S. Rego. 2003. Earnings management: New evidence based on the deferred tax expense. *The Accounting Review* 178(2): 491–522.

Public Company Accounting Oversight Board (PCAOB). PCAOB Standing Advisory Group Meeting: Meeting Agenda (September 8–9, 2004). Web site, http://pcaobus.org/News_and_Events/Events/2004/09-08-09

Rego, S. O. (2003). Tax-Avoidance Activities of U.S. Multinational Corporations. *Contemporary Accounting Research*, 20, 805–833. https://doi.org/10.1506/VANN-B7UB-GMFA-9E6W

Reichelt, K. J., and D. Wang. 2010. National and Office-Specific Measures of Auditor Industry Expertise and Effects on Audit Quality. *Journal of Accounting Research*, 48(3), 647–686.

Robinson, J. R., S. A. Sikes, and C. D. Weaver. (2010). Performance Measurement of Corporate Tax Departments. *The Accounting Review*, 85(3), 1035–1064.

Ross, S. (1973) The Economic Theory of Agency: The Principal's Problem. *American Economic Review*, 63, 134–139.

Shackelford, D., and T. Shevlin. 2001. Empirical tax research in accounting. *Journal of Accounting and Economics* 31(1–3): 321–387.

Thompson, R. A. 2023. Reporting Misstatements and Revisions: An Evaluation of Managers' Use of Materiality Discretion. *Contemporary Accounting Research* 40(4): 2745–2784.