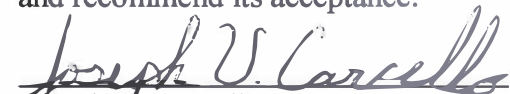


To the Graduate Council:

I am submitting herewith a dissertation written by Samuel Lockhart Tibbs entitled "The Ability of Earnings Management Models to Detect and Predict Public Discovery of Accounting-Fraud." I have examined the final paper copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.


Ronald E. Shrieves, Major Professor

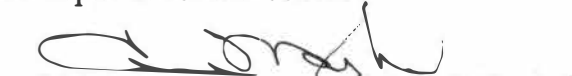
We have read this dissertation
and recommend its acceptance:


Joseph V. Carcello


Michael C. Ehrhardt


Deborah L. Murphy

Acceptance for the Council:


Vice Provost and Dean of Graduate Studies

Thesis
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The Ability of Earnings Management Models to Detect and Predict Public Discovery of Accounting-Fraud

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Samuel Lockhart Tibbs
December 2003

Dedication

This dissertation is dedicated to my wife and my father. Two people who I wish had been given the opportunity to meet.

Acknowledgements

I wish to thank all those who helped me complete my Doctor of Philosophy degree in Finance. I would like to thank Dr. Shrieves for his guidance and for acting as my committee chair. I would also like to thank Dr. Carcello, Dr. Ehrhardt, and Dr. Murphy for serving on my committee.

Lastly, I would like to thank my family and friends, whose encouragement and support made this work possible.

Abstract

The purpose of this study is to analyze and compare: 1) the ability of competing aggregate accrual and frequency distribution models to detect extreme earnings management, i.e. accounting-fraud, and 2) the ability of a composite model to predict accounting-fraud using only prior period information. Studies have used various models to detect earnings management in circumstances in which, a priori, some management is likely to exist. Events with incentives to manage earnings analyzed include issuing securities, maintaining positive earnings or an upward earnings trend, increasing an earnings-based bonus, increasing subsidies during import relief investigations, or decreasing penalties during antitrust investigations. However, few studies have tested such models when there existed a virtual certainty about which firms managed earnings. Using the Securities and Exchange Commission's (SEC) Accounting and Auditing Enforcement Releases (AAERs) to denote accounting-fraud firms, I establish a format of analysis in which relative certainty exists.

Using that format, I test various aggregate accrual, frequency distribution, and composite earnings management models' ability to distinguish between accounting-fraud and non-accounting-fraud matched firms. Aggregate accrual model results show that total accruals, the simplest model, performs best in detecting accounting-fraud. Also, those models calculated from the statement of cash flows always outperforms those calculated from the balance sheet. Frequency distribution models show a surprising lack of ability to detect accounting-fraud. The power of the test is adversely affected by an apparent targeting bias for the SEC to investigate firms that miss earnings thresholds.

As expected, the data intensive composite model shows the greatest ability to identify accounting-fraud firms from *ex ante* data. The composite model only uses prior period variables to represent financial condition of the firm, income-increasing accounting choices, and potentially opportunistic behavior to distinguish an accounting-fraud firm-year from a matched non-fraud firm-year. Significant variables include total accruals, sales growth, cash sales growth, a proxy for age of firm, inventory valuation method, straight-line depreciation, and merger/acquisition activity.

Overall, aggregate accrual models calculated from the balance sheet and frequency distribution models appear to have minimal ability to detect extreme earnings management. Aggregate accrual models calculated from the statement of cash flows appear to be more useful to distinguish accounting-fraud firms, although they exhibit relatively low explanatory power. Composite model results represent a particularly useful contribution since only prior period information is used to predict future accounting-fraud firms. Additionally, the significance of certain variables representing managerial behavior and incentives provide strong insight for accountants and regulators concerning the prediction/detection of accounting-fraud.

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I. Introduction

Earnings management models are techniques to estimate managerial discretion in reported earnings. Studies have used various models to detect/predict earnings management in various circumstances in which incentives for such management was hypothesized to exist, e.g., import relief investigations (Jones 1991), management buyouts (Perry and Williams 1994), initial public offerings (Aharony, Lin, and Loeb (1993) and Teoh, Welch, and Wong (1998a), and secondary equity offerings (Rangan 1998 and Teoh, Welch, and Wong 1998b). However, few have tested the efficacy of such models when enforcement actions filed by the SEC, or some other definitive descriptor, was used to establish certainty about which firms managed earnings (Dechow, Sloan, and Sweeney 1995, 1996, Beneish 1997, 1999, and Lee, Ingram, and Howard 1999).

This study's purpose is to extend prior research by analyzing earnings management methodologies' and models' ability to detect/predict an extreme form of earnings management, accounting-fraud. It is motivated by a lack of direct evidence that earnings management models can detect (recognize *ex post*) or predict (recognize *ex ante*) firm-years in which the SEC alleges that accounting-fraud occurred. This is an important issue, because improving the ability of market participants to recognize attempts by management to "mislead some stakeholders about the underlying economic performance of the company,"¹ reduces the incentive for firms to operate in such a manner, helping ensure the efficient allocation of capital.

I test the ability of various methodologies and models to identify firms that had

¹ Healy and Wahlen (1999)

enforcement actions filed against them by the SEC for accounting-fraud. Details of these SEC filed enforcement actions against firms have been published by the SEC since April 1982 in a series called Accounting and Auditing Enforcement Releases (AAERs). The database for this research uses AAERs to identify those firms that had enforcement actions filed against them for fraudulent financial reporting (i.e., accounting-fraud). There are two primary benefits of this AAER definitive descriptor format for analysis: first, it allows an opportunity to test the models under extreme circumstances; and second, the SEC, via the filing of AAERs, denotes with relative certainty which firms committed accounting-fraud. This establishes a “gold standard” testable situation in which the events are definitively partitioned from the universe of non-accounting-fraud firms and are of an unquestionably significant magnitude to promote detection.

The remainder of this dissertation is organized as follows: Section II provides the motivation; Section III discusses pertinent definitions of earnings management, motivations for earnings management, the role of accruals, including the methodologies and models to be tested; Section VI reviews earnings management and accounting-fraud literature; Section V discusses the accounting-fraud and control firm samples; Section VI contains the formal statements of hypotheses; Section VII contains the test methodologies and empirical results; Section VIII concludes.

II. Motivation

Earnings management and accounting-fraud have received significant media attention during the past five years. In a speech on September 28, 1998, the former Chairperson of the SEC, Arthur Levitt, stated that earnings management “can best be characterized as a game among market participants.” Levitt (1998) continues, “Increasingly, I have become concerned that the motivation to meet Wall Street earnings expectations may be overriding common sense business practices. Too many corporate managers, auditors, and analysts are participants in a game of nods and winks. In the zeal to satisfy consensus earnings estimates and project a smooth earnings path, wishful thinking may be winning the day over faithful representation.”

On November 9, 2000, the enforcement division of the SEC stated that corporate earnings management remains its “number one priority.” This desire to control improper earnings management in the financial markets is also evident in the November 14, 2000 issue of the “Current Issues and Rulemaking Projects” report by the Division of Corporate Finance of the SEC. The report stated, “market pressures are driving more public companies to use improper earnings management tricks” and discussed multiple rule changes concerning audit committee independence and reviews of interim financial statements proposed by the Earnings Management Task Force².

After many high profile accounting-fraud cases (e.g., Waste Management,

² This Task Force is a 12-member team created in May 2000 to supplement the SEC's fraud enforcement efforts and increase the pace of investigations. The team is comprised of a team of accountants and lawyers who focus exclusively on financial reporting and accounting investigations.

Sunbeam, Raytheon, Lucent, Enron, Worldcom, Cendant, Adelphia, Tyco, etc.), Arthur Levitt's speech seems more like a prophecy. These fraudulent events have been followed by increased governmental intervention and regulation. On July 9, 2002, the President of the United States issued an Executive Order for the establishment of the Corporate Fraud Task Force³. This ordered the Attorney General to immediately establish, within the Department of Justice, a Task Force providing direction for the investigation and prosecution in cases of "financial crimes." Also, on July 25, 2002, Congress responded by passing the Sarbanes-Oxley Act (with a vote of 423-3 in the House and 99-0 in the Senate⁴), which toughened corporate fraud and securities laws in the wake of the accounting scandals that had shaken confidence in Unites States' financial markets.

This study is motivated by the desire to determine whether market discipline can be a more efficient monitor of the financial markets than government intervention and regulation. The specific issue is whether rational investors can detect or predict an occurrence of accounting fraud using publicly available financial information. If so, it appears unlikely that regulatory action could improve upon the disciplinary force of informed securities markets; if not, then we are that much closer to a conclusion that current accounting standards are inadequate to the task. The results of this study will provide guidance to analysts, investors, regulators, researchers, and public policy makers about the efficacy of available tools to detect/predict accounting-fraud. As an example, let us consider the Enron scandal where accounting-fraud began in "at least early 1997"⁵ and continued until its financial implosion in 2001, ultimately costing investors over \$60

³ Website for the President of the United States,
<http://www.whitehouse.gov/news/releases/2002/07/20020709-2.html>

billion.^{6,7} Imagine if market participants had better insight into the prediction/detection of the fraud that was occurring. The question becomes could this scandal, or others, have been detected earlier, or with greater reliability, could some of this misallocation of capital been prevented?

⁴ CNN, <http://www.cnn.com/2002/ALLPOLITICS/07/25/corporate.reform/>

⁵ AAER 1617

⁶ CNN, <http://edition.cnn.com/2001/BUSINESS/12/02/enron.filing/index.html>

⁷ Additionally, Enron issued \$1.48 billion in stock during 1998 and 1999

III. Earnings Management Overview and Earnings Management Models

III.A. Definitions of Earnings Management

Academics, practitioners, and regulators have defined earnings management many ways:

1. Merchant (1987): “Earnings management can be defined as any action on the part of management which affects reported income and which provides no true economic advantage to the organization and may, in fact, in the long-term, be detrimental.”
2. Schipper (1989): “Earnings management is a purposeful intervention in the external financial reporting process, with the intent of obtaining some private gain.”
3. Dechow, Patel, and Zeckhauser (1999): “We label earnings management the strategic exercise of managerial discretion in influencing the earnings figure reported to external audiences.”
4. Healy and Wahlen (1999): “Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company, or to influence contractual outcomes that depend on reported accounting numbers.”

Although all of these definitions are relevant, the lack of concordance and substantiality provides a poor test structure for research. Dechow and Skinner (2000) supported this by stating in the “professional literature clear definitions of earnings management are difficult to discern from pronouncements and/or statements and speeches by regulators, although *an extreme form of earnings management – financial fraud* – is well defined⁸” (emphasis added). This “well defined” interpretation provides a

⁸ Financial fraud is defined as “the intentional, deliberate, misstatement or omission of material facts, or accounting data, which is misleading and, when considered with all the information made available, would cause the reader to change or alter his or her judgment or decision.” (National Association of Certified Fraud Examiners, 1993, 12)

format conducive to test the ability of methodologies and models to detect/predict extreme earnings management.

III.B. Motivations for Earnings Management

As Schipper (1989) states, earnings are managed “with the intent of obtaining some private gain.” In this context, any activity in which the owner/manager exercises influence over reported earnings to increase the compensation/wealth of the owner/manager are motivations to manage earnings. This includes the four most commonly cited circumstances leading to a motivation for earnings manipulation: 1) issue securities, 2) maintain positive earnings or an upward earnings trend, 3) increase size of earnings-based bonuses, and 4) increase the benefits of insider trading (Dechow, Sloan, and Sweeney 1996). Other common reasons to manipulate earnings are to avoid reporting a pre-tax loss (Beasley, Carcello, and Hermanson 1999), reducing political costs of the firm (e.g., during a government investigation) (Makar and Alam 1998), increase the political benefit of the firm (e.g., during import relief investigations) (Jones 1991), protect large insider holdings (Dechow, Sloan, and Sweeney 1996), or prevent a downward spiral (Beasley, Carcello, and Hermanson 1999). All of these motivations are hypothesized to provide an incentive to managers/owners to increase or protect their wealth by manipulating financial results.

III.C. The Role of Accruals

“[T]he principal goal of accrual accounting is to help investors assess the entity’s economic performance during a period through the use of basic accounting principles

such as revenue recognition and matching.”⁹ Although, the discretion that exists with accrual accounting provides a means for managers to reveal private information, it also enables managers to “mislead some stakeholders about the underlying economic performance of the company.”¹⁰

Earnings management literature often focuses on the total accruals of a firm; composed of a non-discretionary portion over which management has little control, and a discretionary portion over which management has greater ability to adjust.

$$\text{Total Accruals} = \text{Non-Discretionary Accruals} + \text{Discretionary Accruals}$$

Management has the ability to cause short-term changes in earnings¹¹ by adjusting total accruals since:

$$\text{Cash from Operations} + \text{Total Accruals} = \text{Earnings}$$

By varying the level of discretionary accruals, management has the ability to change the level of total accruals and thereby affect reported earnings. Sections III.D., III.E., and III.F. will describe the principal competing models for measuring earnings management.

III.D. Aggregate Accrual Earnings Management Models

Aggregate accrual earnings management literature attempts to develop models that calculate the discretionary portion of a firm’s total accruals. The methodology for these models is to establish a benchmark of non-discretionary accruals for firms in a

⁹ Dechow and Skinner (2000)

¹⁰ Healy and Wahlen (1999)

¹¹ Teoh, Welch, and Wong (1998a) state that accruals for their sample of IPOs reverse in 3 to 4 years.

specific industry¹². The portion of accruals estimated to be discretionary for a firm is the difference between the firm's total accruals and the industry's benchmark of non-discretionary accruals. Aggregate accrual models vary somewhat in their use of different explanatory variables and adjustments in a given fraudulent firm-year event period, which are explained in the following section.

Additionally, there are two sources of data to calculate total accruals: the balance sheet and the statement of cash flows. There are advantages and disadvantages to each source of data. When testing for earnings management using balance sheet data, accrual estimates are potentially contaminated by measurement error due to possible non-articulation between changes in working capital accounts and the accrual component of revenues and expenses on the income statement¹³. A fault with the cash flow from operations accrual estimation is the nonavailability of data prior to SFAS No. 95¹⁴, and the limited availability of the data in Compustat¹⁵ after SFAS No. 95. The primary tradeoff between the balance sheet and statement of cash flows approach is measurement error versus data availability.

¹² For example, this might be done by using a cross-sectional regression on a given year, across firms with the same two-digit SIC, of total accruals on changes in certain explanatory variables, such as change in sales, value of property, plant, and equipment, etc.

¹³ Collins and Hribar (2000) and Hribar and Collins (2002)

¹⁴ Companies were required to make the change for fiscal years ending after July 15, 1988, but earlier adoption was encouraged.

¹⁵ Also, this limitation may create a selection bias in the data.

III.D.1. Aggregate Accrual Models with Total Accruals Calculated from Balance Sheet

a. Jones Model

This model and the majority of subsequent literature calculate total accruals from year-over-year changes in the balance sheet. Total accruals is defined as:

$$TA_{it} = (\Delta CA_{it} - \Delta CL_{it} - \Delta Cash_{it} - \Delta STD_{it} - DEP_{it}) / A_{it-1}$$

where:

- TA_{it} = total accruals divided by lagged total assets in year t for firm i ;
- ΔCA_{it} = change in current assets from year $t-1$ to year t for firm i (Compustat #4);
- ΔCL_{it} = change in current liabilities in from year $t-1$ to year t for firm i (Compustat #5);
- $\Delta CASH_{it}$ = change in cash and cash equivalents from year $t-1$ to year t for firm i (Compustat #1);
- ΔSTD_{it} = change in debt included in current liabilities from year $t-1$ to year t for firm i (Compustat #34);
- DEP = depreciation and amortization expense in year t for firm i (Compustat #14);
- A_{it-1} = lagged total assets for firm i (Compustat #6);

Jones (1991) relaxes the assumption made by DeAngelo (1986) that non-discretionary accruals were constant. She proposes a model to account for changes in non-discretionary accruals based on changes in the economic circumstances of the firm. She assumes a linear relationship between total accruals of the firm and change in revenues and gross property, plant and equipment (PPE). Change in revenue is used to control for the economic growth of the firm and gross PPE is included to control for the portion of total accruals related to non-discretionary depreciation expenses¹⁶.

¹⁶ Jones (1991) does not discuss the possibility of discretion concerning choice of depreciation schedules, i.e., straight-line versus accelerated.

Calculation of the firm-specific parameters α_1 , α_2 , and α_3 are estimated by a cross-sectional regression for a given year, across firms with the same two-digit SIC, on the following model:

$$TA_{it} = \alpha_1 (1 / A_{it-1}) + \alpha_2 (\Delta REV_{it} / A_{it-1}) + \alpha_3 (PPE_{it} / A_{it-1}) + \varepsilon_{it} \quad (1)$$

Then industry-specific non-discretionary accrual proxy is generated with the following formula:

$$NDAP_{it} = \hat{\alpha}_1 (1 / A_{it-1}) + \hat{\alpha}_2 (\Delta REV_{it} / A_{it-1}) + \hat{\alpha}_3 (PPE_{it} / A_{it-1}) \quad (2)$$

The discretionary accruals proxy is estimated using the following formula:

$$DAP_{it} = TA_{it} - NDAP_{it} \quad (3)$$

where:

$\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3$ = industry-specific parameters;

ΔREV_{it} = change in revenues from year $t-1$ to year t for firm i (Compustat #12);

PPE_{it} = property, plant, and equipment in year t for firm i (Compustat #7);

$NDAP_{it}$ = predicted non-discretionary accruals divided by lagged total assets in year t for firm i ;

DAP_{it} = predicted discretionary accruals divided by lagged total assets in year t for firm i ;

b. Modified Jones Model

This version of the Jones model, by Dechow, Sloan, and Sweeney (1995), is designed to eliminate the hypothesized tendency of the Jones Model to measure discretionary accruals with error when managerial discretion is exercised over revenues. It is based on the reasoning that it is easier to manage earnings by exercising discretion over the recognition of revenue on credit sales, than to manage earnings by exercising discretion over the recognition of revenue on cash sales.

Calculation of the industry-specific parameters α_1 , α_2 , and α_3 are estimated by equation (1). Then firm-specific non-discretionary accrual proxy is generated with the following formula:

$$NDAP_{it} = \hat{\alpha}_1 (1 / A_{it-1}) + \hat{\alpha}_2 ((\Delta REV_{it} - \Delta REC_{it}) / A_{it-1}) + \hat{\alpha}_3 (PPE_{it} / A_{it-1}) \quad (4)$$

Then the discretionary accruals proxy is estimated using the equation (3).

where:

ΔREC_{it} = change in receivables in year t minus year $t-1$ for firm i (Compustat #151)

c. The Performance-Matched Discretionary Accrual Model

Kothari, Leone, and Wasley (2002) state, “[t]he use of performance-matched accruals appears essential to mitigate the concern of misspecification, and therefore spurious rejection (or failure to reject) of the null hypothesis” concerning the presence of earnings management. Dechow, Sloan, and Sweeney (1995), Krasznik (1999), and McNichols (2000) show that discretionary accrual estimates are correlated with earnings performance. Firms with higher (lower) earnings exhibit significantly positive (negative) discretionary accruals. This makes it more likely that one will detect earnings management that increases earnings for the most profitable firms and earnings management that reduces earnings for the least profitable firms. This model, by Kothari, Leone, and Wasley (2002), attempts to control for the misspecification exhibited by other models when applied to firms with extreme financial performance (e.g., Dechow, Sloan, and Sweeney 1995 and Guay, Kothari, and Watts 1996).

First, a firm suspected of managing its earnings is matched with a firm that is believed not to be managing its earnings by two-digit SIC and ROA. Next, using the Modified Jones model, the discretionary accruals of both firms are estimated. The discretionary accrual of the firm suspected of managing earnings is adjusted by the value of the discretionary accrual of the matched firm.

Calculation of the industry-specific parameters α_1 , α_2 , and α_3 , and the firm-specific non-discretionary accrual proxy are estimated using equation (1) and equation (4), respectively.

The adjusted discretionary accrual proxy is calculated by the following formulas:

$$DAP_{it, \text{ adjusted}} = DAP_{it, \text{ unadjusted}} - DAP_{it, \text{ matched firm}} \quad (5)$$

III.D.2. Aggregate Accrual Models with Total Accruals Calculated from Statement of Cash Flows

a. The Modified Jones Model using the Statement of Cash Flows

Usage of the statement of cash flows to calculate total accruals is supported by Collins and Hribar (2002) and eliminates many of the predictable biases which exist due to the existence of non-articulation events. Total accruals is defined as:

$$TA_{it} = - (\Delta AR_{it} + \Delta INV_{it} + \Delta AP_{it} + \Delta TAX_{it} + \Delta OTH_{it} + DEP_{it}) / A_{it-1} \quad (6)$$

where:

- TA_{it} = total accruals divided by lagged total assets in year t for firm i ;
- ΔAR_{it} = decrease (increase) in accounts receivable in year t for firm i (Compustat #302);
- ΔINV_{it} = decrease (increase) in inventory in year t for firm i (Compustat #303);
- ΔAP_{it} = decrease (increase) in accounts payable in year t firm i (Compustat #304);
- ΔTAX_{it} = decrease (increase) in taxes payable in year t firm i (Compustat #305);

ΔOTH_{it} = net change in other current assets in year t firm i (Compustat #307);
 DEP_{it} = depreciation expense in year t for firm i (Compustat #125);
 A_{it-1} = lagged total assets for firm i (Compustat #6);

This model addresses the measurement error generated by non-articulation events when balance sheet data items are used. They argue calculation of total accruals from the statement of cash flows corrects for errors caused by non-articulation events; such as mergers and acquisitions which can inflate the balance sheets, divestitures which can decrease the balance sheet, or foreign currency effects which can have either effect. By calculating total accruals from the statement of cash flows, Hribar and Collins (2002) shows the predictable biases generated by non-articulation events can be eliminated. The disadvantage with this method is that the data is effectively unavailable for fiscal years ending prior to July 15, 1988, and after July 15, 1988 the data suffers from limited availability¹⁷. Calculation of the industry-specific parameters α_1 , α_2 , and α_3 , and the firm-specific non-discretionary accrual proxy are estimated using equation (1) and equation (4), respectively. The discretionary accrual proxy is calculated using equation (3).

III.D.3. Discretionary Change in Receivables Adjustment to the Modified Jones

Model

As McNichols (2000) notes, the current construction of the Modified Jones model (equation (4)) considers all of the change in receivables to be discretionary. It is

¹⁷ For the period 1987 to 1997, there are 74,819 firm-years with sufficient data to calculate total accruals using the balance sheet method and 45,139 for the cash flow method (66% more for the balance sheet method). For the period 1989 to 1997, there are 62,959 firm-years with sufficient data to calculate total accruals using the balance sheet method and 40,914 for the cash flow method (54% more for the balance sheet method). Preliminary analysis shows no significant difference between log(market capitalization) and book-to-market ratios between samples.

reasonable to expect this method to be inappropriate since a portion of the change in receivables can be expected to be non-discretionary. Therefore, I propose an adjustment to this model to consider only the change in receivables that exceeds the expected change to be earmarked as discretionary. Where expected change is defined as the revenue growth rate, in other words this limits nondiscretionary receivables growth to the growth in revenue. The discretionary change in receivables adjustment to the Modified Jones model is calculated with following equations:

$$\text{Discretionary } \Delta \text{REC}_t = (\Delta \text{REC}_t - (\text{Revenue Growth Rate} * \text{REC}_{t-1})) \quad (7)$$

$$\text{NDAP}_{it} = \hat{\alpha}_1 (1 / A_{it-1}) + \hat{\alpha}_2 ((\Delta \text{REV}_{it} - \text{Discretionary } \Delta \text{REC}_{it}) / A_{it-1}) + \hat{\alpha}_3 (\text{PPE}_{it} / A_{it-1}) \quad (8)$$

Where:

Revenue Growth Rate = $(\text{Revenue}_t - \text{Revenue}_{t-1}) / \text{Revenue}_{t-1}$ (Compustat #12);

REC_{t-1} = Trade Receivables in year $t-1$ (Compustat #151);

The example below demonstrates the difference in the portion of receivables which are earmarked as discretionary by each method.

Example with company CMT:

CMT's sales were \$1B and \$1.1B, for the previous and current year, respectively. Trade Receivables were \$300M and \$350M, for the previous and current year, respectively.

With the Modified Jones model, the entire \$50M change in receivables for the firm is considered discretionary. When only considering the portion of change in receivables that exceeds revenue growth, \$20M¹⁸ is classified as discretionary.

¹⁸ Sales Growth was 10% $((\$1.1\text{B} - \$1\text{B}) / \$1\text{B})$, therefore Discretionary Change in Receivables is \$20M, $(\$50\text{M} - (10\% * \$300\text{M}))$.

III.E. Frequency Distribution Earnings Management Models

Frequency distribution models have also been used in attempts to detect earnings management. The means of detection is quite different from aggregate and specific accrual methods in that it does not calculate a value of discretionary accruals; instead, this approach hypothesizes that firms that narrowly exceed a threshold or target earnings level are engaging in earnings management. Test of this hypothesis analyzes the distribution of earnings around certain thresholds. For example, when the threshold is zero earnings, the model tests whether the frequency of earnings realizations in the region above (below) zero earnings is greater (less) than would be expected in the absence of earnings management. In other words, is there an abnormality in the distribution of earnings around zero? If so, then this provides support of earnings management to surpass that threshold.

III.E.1 Frequency Distribution Models Thresholds

The frequency distribution method has been proposed as evidence of earnings management by Burgstahler and Dichev (1997), and Degeorge, Patel, and Zeckhauser (1999). These studies analyze a universe of firms around the following thresholds¹⁹: (1) zero earnings; (2) past earnings and; (3) analysts' consensus earnings forecast. The authors postulate that clustering of earnings at, or slightly above, these thresholds support the existence of earnings management.

¹⁹ These thresholds were analyzed by Degeorge, Patel, and Zeckhauser (1999).

However, this testing method does not distinguish between firm decisions other than accrual management, which may affect the frequency of earnings around a given threshold. For instance, since the market response to beating a threshold by one cent per share is quite different to missing it by one cent per share, a firm may *ex ante* conservatively behave or structure contracts to increase the likelihood of being at or above the zero earnings threshold. To control for contemporaneous macroeconomic and industry influences upon decisions likely to affect the firm's distribution of earnings, a matched sample should be used. A test structure that compares the frequency of earnings realizations around a given threshold for the accounting-fraud sample relative to the control sample can be used to identify managed earnings *ex post*.

Research supports the hypothesis that frequency distribution analysis could be a means to identify extreme earnings managers. The study by Beasley, Carcello, and Hermanson (1999), which analyzed AAERs for firms from 1987 to 1997, states the most commonly cited reason why company representatives committed accounting-fraud was to avoid a pre-tax loss. This provides support for the hypothesized ability of frequency distribution analysis around the zero earnings threshold to detect extreme earnings management.

Dechow, Sloan, and Sweeney (1996) supports the hypothesis that frequency distribution analysis around the past earnings threshold could be a means to identify extreme earnings managers. Thirty-nine of the firms in their sample had the motivation for earnings manipulation reported in the enforcement releases filed by the SEC. The second most common motivation cited (28.2%), after supporting security price in anticipation of issuance (56.4%), was to maintain an "upwardly trending EPS." The

existence of such earnings trends, and its effect on the distribution of earnings, should facilitate the ability of frequency distribution analysis around the past earnings threshold to detect extreme earnings management.

Research does not clearly demonstrate that a common motivation to commit extreme earnings management is to meet or beat analysts' estimates. The positive stock price response to meeting/beating analysts' estimates versus the negative price response to missing has been well documented (Kasznik and McNichols 1999, Skinner and Sloan 2001, and Bartov, Givoly and Hayn 2002). Since these price responses greatly affect security issuance and insider trading activity, two commonly cited motivations for committing accounting-fraud, it seems reasonable to hypothesize that frequency distribution analysis around the analyst estimate threshold could be used to distinguish accounting-fraud firms from the matched sample.

III.F. Composite Model

Dechow, Sloan, and Sweeney (1996), Beneish (1997, 1999), and Lee, Ingram, and Howard (1999) develop composite models using variables representing the financial condition, management structure, and other variables in addition to earnings management estimates, to classify firms that had enforcement actions filed against them by the SEC. The importance of this methodology is that it allows for consideration of financial activities and managerial incentives to commit accounting-fraud in conjunction with a measure of accruals to predict accounting-fraud. My model builds upon these models and uses selected variables from Beneish (1997), to represent the accounting-fraud and

matched sample firms in three key areas: 1) accounting choices and behavior that inflates earnings, 2) financial condition of the firm, and 3) potential opportunistic behavior.

Beneish (1997), in addition to developing a composite model to detect extreme earnings managers, also identifies various financial characteristics which had ability to predict extreme earnings management firms. The variables represent the firm's age, assets, liquidity, leverage, profitability, cash flows, total accruals, and growth. These predictive variables are the foundation upon which my composite model was constructed.

III.F.1. Focus of Composite Model Variables

Usage of variables that inflate earnings is based on the assumption that firms that wish to increase reported earnings will first exhaust legal avenues prior to committing accounting-fraud. It is hypothesized that income-increasing accounting methods and accrual adjustments would be used more often by the accounting-fraud firms relative to a matched sample in the year prior to committing accounting-fraud. Also, variables representing the financial condition of the firm are important since avoidance of financial distress, maintenance of an earnings trend, and/or market premium may be motivations to commit accounting-fraud. Prior research hypothesizes that firms with financial distress, longer earnings trend, and/or market premium (lower book-to-market ratio) in the prior year are more likely to commit accounting-fraud relative to a matched sample. Finally, variables representing stock issuance and merger/acquisition activity are important since they represent a potentially opportunistic means to take advantage of an inflated stock price. It is hypothesized that accounting-fraud firms are more likely to attempt to raise capital or purchase other firms in the year prior to an accounting-fraud firm-year relative

to a matched sample. Therefore, by focusing on variables in these three areas, the composite model will be better adapted to distinguish accounting-fraud firms from a matched sample.

IV. Earnings Management and Accounting-Fraud Literature Review

Dechow, Sloan, and Sweeney (1995) evaluates the ability of alternative aggregate accrual models ability to detect earnings management. Using a regression-based model, they test various aggregate accrual models (the Healy, DeAngelo, Industry, Jones, and Modified Jones model) and find the Modified Jones model performs best in detecting earnings management. However, when analyzing firms with extreme financial performance (high growth), all models reject the null hypothesis of no earnings management at rates exceeding the specified test levels. This result highlights the importance of controlling for financial performance when investigating earnings management stimuli which are correlated with financial performance. Kothari, Leone, and Wasley (2002) propose a performance-based matching procedure to control this problem.

Dechow, Sloan, and Sweeney (1996) investigate firms subject to accounting and auditing enforcement actions (AAERs) for alleged violations of Generally Accepted Accounting Principles (GAAP). Using a logit model, they find the two most important motivations for earnings manipulation are the desire to attract external financing at low cost, and to continue an upward trending EPS. Additionally, they find that a stock issuance and the relative size of that issuance to market capitalization, are statistically significant variables to distinguish firms subject to AAERs. They analyze median total and discretionary accruals (generated by the modified Jones model) for 66 firms subject to AAERs to control firms matched by industry, total assets, and time period, and find that accruals gradually increased as the year of the alleged earnings manipulation approached. This increase implies potential predictive power to distinguish extreme

earnings managers. Dechow, Sloan, and Sweeney (1996) also shows that a larger percentage of firms subject to enforcement actions by the SEC use income-increasing accounting procedures (the combined choice of straight-line depreciation, FIFO inventory valuation method, and flow-through method for investment tax credits) relative to a matched sample and that their usage increases in the years prior to the firm committing accounting-fraud.

Beneish (1997) develops a composite model to detect earnings management among firms experiencing extreme financial performance and compares the model's performance to various discretionary accrual models. The model is tested on 64 firms that were either charged by the SEC or publicly admitted to violating GAAP during the period of 1983-1992. His control sample consists of the top decile of all firms with positive discretionary accruals (hereafter named aggressive accrualers) as estimated by the Modified Jones model. For the holdout sample, the probit model's mean (median) estimated probability for GAAP violators was 0.123 (.058) versus 0.026 (.009) for aggressive accrualers. He also compares mean and median values of selected financial characteristics for event and control firms one year prior to GAAP violation. Although several of these variables are statistically different between samples, Beneish (1997) never uses them in a prediction type model.

Beasley, Carcello, and Hermanson (1999) analyze instances of fraudulent financial reporting as alleged by the SEC in AAERs issued from January 1987 to December 1997. With fraudulent financial reporting defined as a violation of Rule 10(b)-5 of the 1934 Securities Exchange Act and/or Section 17(a) of the 1933 Securities Act (both of which represent the primary antifraud provisions related to financial statement

reporting) 294 firms were identified. Focusing on 200 randomly selected firms from that sample of 294, the authors draw several key insights as to the type of firm that commits accounting-fraud. Specifically, the authors find many of the companies experienced net losses or were close to breakeven positions in periods before fraud. Thus, frauds may have been designed to reverse downward spirals for some companies and preserve upward trends for others.

DeGeorge, Patel, and Zeckhauser (1999) use the frequency distribution methodology to check for earnings management around three earnings thresholds. They find the most important threshold is that the firm report positive profits (earnings above zero). Once profitability is achieved, the next goal is to sustain recent performance (meet last years earnings), and finally, the last goal is to meet analysts' forecasts (meet consensus).

Lee, Ingram, and Howard (1999) demonstrates that the excess of earnings over operating cash flow (i.e., total accruals) was extreme in most fraud cases in the years prior to public discovery of financial fraud. This finding is based on a sample of 56 fraud cases from 1978-1991. Using a logit-based composite prediction model, they find that total accruals, market performance, firm size, leverage, and stock issuance are statistically significant explanatory variables to distinguish fraudulent financial reporting firms from all other firms in Compustat.

McNichols (2000) discusses the trade-offs associated with three research designs commonly used to detect earnings management: aggregate accruals, specific accruals, and frequency distribution of reported earnings. She concludes aggregate accruals models, such as the Modified Jones, that do not consider long-term earnings growth are

potentially misspecified and result in misleading inferences about earnings management behavior. This suggests the importance of the performance-matched discretionary accrual measure as described in Kothari, Leone, and Wasley (2002). McNichols suggests future progress in the earnings management literature would come from specific accrual and distribution-based tests, rather than from aggregate accrual tests.

Research by Kothari, Leone, and Wasley (2002) indicates extant discretionary accrual models were misspecified when applied to firms with extreme financial performance. Therefore, they examine the specification and power of a test based on a performance-matched (matching is on ROA and industry) discretionary accrual measure on stratified-random samples and compare it with traditional discretionary accrual measures (Jones, Modified Jones). Their results suggested inferences about earnings management using a performance-matched discretionary accrual measure are more reliable than a traditional measure of discretionary accruals.

Hribar and Collins (2002) find that previous studies that used balance sheet data items to test for earnings management are potentially contaminated by measurement error in accrual estimates. This error is based on the assumed articulation between changes in working capital accounts and the accrual component of revenues and expenses on the income statement. Using regression analysis, they find biases are induced by non-operating charges caused by three non-articulation events. Mergers and acquisitions induce a positive bias to estimated accruals; divestitures induce a negative bias to estimated accruals; and foreign currency translations induce a positive or negative bias in estimated accruals, depending on whether the dollar strengthened or weakened relative to the local currency of the countries in which a company operates. To correct these biases,

they calculated accruals using data items from the operating section of the statement of cash flows, since those data items are not affected by non-operating changes. They conclude that errors in balance sheet estimation of discretionary and non-discretionary accruals can confound regression results when those estimates are used as explanatory variables.

V. Data

The ideal situation to test models is to have two datasets that are perfectly partitioned, one fraud sample and one matched non-accounting-fraud sample, without any errors in classification of the firms. With the knowledge that perfect data does not exist, I use AAERs to attempt to minimize classification errors in my accounting-fraud and control sample. Figure A-1 identifies the potential sources of those errors. Per Figure A-2, my research focuses on the fiscal years of the “[a]ccounting fraud period described in the AAER” in which a fraudulent financial report was filed. Using the data from a fraudulent firm-year and/or years prior to that fraudulent firm-year (i.e., year that a fraudulent 10-K was filed), I test the ability of various models to detect or predict accounting-fraud.

The academic importance of this data set is that it represents a means to test earnings management models against a definitive partition, a “gold standard.” Under the null hypothesis that firms are not committing accounting-fraud, the statistical importance of having a “gold standard” is that it virtually eliminates the potential of having Type II errors when testing earnings management models²⁰. Therefore, the key to accurately testing these models is the validity of the assumption that the SEC has correctly identified firms that committed accounting-fraud.

Pincus, Holder, and Mock (1988) state that the SEC goes to great lengths to establish that earnings are manipulated knowingly and intentionally before taking an

²⁰ See Figure 1 concerning the potential sources of Type II errors

enforcement action. The SEC (1992) indicates that, out of the large number of cases brought to its attention, it only pursues cases involving the most significant and blatant incidences of earnings management. Also, Dechow, Sloan, and Sweeney (1995) report the mean (median) earnings restatement of 4.6% (2.3%) of assets for their sample of firm-years with earnings overstatements as alleged by the SEC. Finally, Dechow, Sloan, and Sweeney (1996) state that they believed the SEC identified extreme earnings management firms correctly because they verify the firm-years investigated by the SEC display managed earnings using constructs developed in the academic literature (for example, those firms employ more income increasing accounting procedures, have higher total accruals, and have higher discretionary accruals²¹). Based on this evidence, it is justifiable to suppose firms cited by the SEC in AAERs for fraudulent financial reporting, have indeed committed accounting-fraud. Therefore, under the null hypothesis that firms are not committing accounting-fraud, the potential for Type II errors is negligible.

There are three categories of papers that use models to estimate discretionary accruals. One analyzes in circumstances where, a priori, there is a belief earnings are being managed (e.g., IPOs, SEOs, Management buyouts, Antitrust investigations, Import relief investigations, etc.). The second group contains only five papers²² comparing earnings management models against AAERs, the most recent of which is from 1999. The remainder of research focuses on the universe of firm-years or randomly generated firm-years in which abnormal accruals are artificially induced. The problem with the universe of firm-years method is it does not quantify the ability of those models to detect

²¹ Dechow, Sloan, and Sweeney (1996) uses only the Modified Jones model calculated using total accruals from the balance sheet.

an actual event. The problem with the induced abnormal accrual method is that its performance is based on the assumption that it is an adequate depiction of true accrual behavior. This however is questionable, as it assumes the accruals are generated in one period and fully reverse in the next period. Dechow, Sloan, and Sweeney (1995) note this concern and state they recognize the validity of their results are contingent upon how representative their assumptions are of actual cases of earnings management.

V.A. Accounting-fraud Sample

The availability of the data set for my study is due to the generosity of Mark S. Beasley²³, Joseph V. Carcello²⁴, and the Committee of Sponsoring Organizations of the Treadway Commission (COSO)²⁵. These data contain information about firms that had Accounting and Auditing Enforcement Releases (AAERs) filed against them by the SEC. These fraudulent financial reporting occurrences involved violations of Rule 10(b)-5 of the 1934 Securities Exchange Act and/or Section 17(a) of the 1933 Securities Act, which represent the primary antifraud provisions related to financial statement reporting.

My initial data set (see Panel A of Table 1), a combination of the three sources aforementioned, includes 270 firms and 535 firm-years. The two requirements for my initial data set are: 1) the AAER must state that the firm filed at least one fraudulent 10-K

²² Dechow, Sloan, and Sweeney (1995, 1996), Beneish (1997, 1999) and Lee, Ingram, and Howard (1999)

²³ Mark S. Beasley allowed me access to the 75 firms, covering the period of 1978 to 1991, used in his “Empirical Analysis of the Relation between the Board of Director Composition and Financial Statement Fraud.”

²⁴ Joseph V. Carcello allowed me access to his database of AAERs, covering the period of 1998 to 2001.

²⁵ Committee of Sponsoring Organizations and John Flaherty allowed me data access to the study on “Fraudulent Financial Reporting: 1987-1997 An Analysis of U. S. Public Companies.”

(annual report)²⁶; and 2) I had to be able to identify a Cusip for the firm. After verifying that the firms had at least some data in Compustat, my sample dropped to 246 firms and 497 firm-years. Further, after verifying that firms had adequate data to calculate the previous year's ROA and Modified Jones model discretionary accruals using total accruals from the balance sheet, the sample dropped to 169 firms and 309 firm-years. Panel B of Table 1 reports the sample sizes and time periods covered by previous research. A comparison of Panel A and Panel B of Table 1 shows that my sample size is significantly larger.

Panel A of Table 2 shows that the average accounting-fraud firm had mean (median) Total Assets of \$2.488 billion (\$108.2 million) with mean (median) Market Capitalization of \$2.471 billion (\$132.1 million). Not surprisingly, the mean (median) total assets is larger than the \$533 million (\$15.7 million) reported in Beasley, Carcello, and Hermanson (1999) due to the additional data requirements of this study. The sample size drop in Panel A of Table 2 from the 309 firm-years reported in Panel A of Table 1 is driven by the capital market data requirement to calculate market capitalization and book to market ratio. When comparing median values relative to all firms meeting certain data requirements in Compustat, Panel B of Table 2, accounting-fraud firms have lower Total Assets, a similar Market Capitalization, lower Book-to-Market ratio, lower ROA, lower Profit Margin, higher Total Debt to Total Assets, higher Sales Growth, and a lower Z-Score. Overall accounting-fraud firms are growing faster, trading a premium (lower

²⁶ Many of the AAERs relate to the overstatement of quarterly earnings that are reversed before the fiscal year end.

book-to-market ratio), and less profitable, with a higher degree of financial leverage than non-accounting-fraud firms in Compustat.

The AAER filing dates range from April 1982 to December 2002 covering fraudulent financial reporting that occurred between August 1978 and December 2001. The accounting-fraud period for my sample averages 1.981 years and 71.5% of my sample committed accounting-fraud for 2 years or less. This is consistent with the Beasley, Carcello, and Hermanson (1999) average of 1.975 years and the Dechow, Sloan, and Sweeney (1996) average of 2.060 years. Panel C of Table 2 shows that 47.6% of the accounting-fraud firms only filed one fraudulent 10-K, with the remainder extending out to 7 years with one outlier of 12 years in length. Panel D of Table 2 reports the calendar year that the fraudulent 10-Ks were filed. There are a total of 497 fraudulent firm-years and 1993 has the most events with 39 firm-years (7.85%) of the sample. Panel E shows the distribution of firms that filed a fraudulent 10-K by industry. The largest percentage of firms is in manufacturing with 75 firms, equivalent to 30.5% of the sample. This is consistent with research by Beneish (1997) whose largest percentage was also manufacturing, at 28.12%.

V.B. Control Sample

A matched firm sample is constructed using the control firm methodology of Barber and Lyon (1996). Potential control firms will first have the same Compustat data item requirements as those of firms in the accounting-fraud sample. Next, to construct the sample of control firms with similar operating performance, I match on year and two-

digit SIC. Among these firms, potential control firms whose ROA²⁷ is within +/- 10% or within +/- 0.01 of the ROA of the sample firm are earmarked. Finally, among these firms, I choose that closest match that is not subject to an enforcement release.

Since not all firms that commit accounting-fraud are caught, there exists a potential source for error in my control sample²⁸. Without perfect insight, there is no way to eliminate all firms from the control sample that may have or currently are committing accounting-fraud, but have not been caught. If as before, we consider the null hypothesis that firms are not committing accounting-fraud, this problem could introduce Type I errors. However, if I am able to show a statistically significant difference exists in spite of this limitation, then I have shown these models have some usefulness to detect/predict accounting-fraud and therefore, have potential to improve market efficiency.

²⁷ Calculated as operating income in year minus 1 (Compustat #13) divided by the average of year minus 1 and year minus 2 book value of total assets (Compustat # 6). Note: Year 0 is the first year the AAER states that the fraudulent reporting occurred.

²⁸ See Figure 1

VI. Formal Statement of Hypotheses

A minimal criterion for the usefulness of earnings management models is their ability to detect/predict firms committing “an extreme form of earnings management – financial fraud.”²⁹ If these models cannot detect/predict the most egregious cases of earnings management, then how can they be expected to detect/predict less extreme cases? The advantage of my AAER sample is that it contains firms that were extreme earnings managers, and the fact the SEC filed an enforcement action against them provides an objective means to classify those events. The control sample provides the benchmark against which the accounting-fraud sample is compared. Testing the various earnings management models for their ability to detect/predict the most extreme form of earnings management and then comparing the results to the control firms, provides a measure of the relative abilities of those models.

The hypotheses I test concerning the ability of earnings management methodologies and models to detect and predict accounting-fraud are listed below.

H1: Aggregate accrual models can detect firms committing accounting-fraud. The purpose is to identify which, if any, aggregate accrual model can distinguish extreme earnings managers from a control sample. The various aggregate accrual models tested are the Jones, Modified Jones, Re-Modified Jones, Beneish, and the naïve Total Accruals model. These test results will then be used to determine the relative ability of such models to detect extreme earnings management.

²⁹ Dechow and Skinner (2000)

H2: Frequency distribution models can detect firms committing accounting-fraud. The issue is which, if any, threshold analyzed by the frequency distribution model can distinguish extreme earnings managers from a control sample. The thresholds analyzed include the zero earnings, past earnings, and analysts' estimate threshold. These test results will then be used to determine the relative ability of each threshold tested to detect extreme earnings management.

H3: Composite model structure can predict public discovery of firms committing accounting-fraud. Multiple variables are used in the composite model structure in order to determine their relative ability of such variables to predict extreme earnings managers.

VII. Data Analysis Methodology and Empirical Results

VII.A. Analysis of Aggregate Accrual Models

First, I construct a dataset of accounting-fraud firm-years and matched firms that had adequate data to calculate all aggregate accrual models using total accruals calculated by both the balance sheet and the statement of cash flow approaches. Using this dataset, which consists of 135 event and matched control firm-years³⁰, I calculate discretionary accrual estimates from various aggregate accrual models (Jones, Modified Jones, Re-Modified Jones, and Beneish) and naïve estimates of earnings management (Total Accruals model) using both the balance sheet and statement of cash flows. Next, I calculate the difference (event minus control) between the event and the matched firm measures of earnings management (discretionary accrual estimate and total accruals) in accordance with performance-based matching methodology from Kothari, Leone, and Wasley (2002). The average differences and the associated t-statistics are contained in Table 3³¹. The t-statistics are significant for some mean differences but not for others, but neither ANOVA, nor the Kruskal-Wallis non-parametric test are able to state that one model statistically outperforms the other models.

From Table 3, two important conclusions are drawn. First, the difference and its associated t-statistic shows that any aggregate accrual model performs better when using total accruals calculated from the statement of cash flows, relative to using total accruals calculated from the balance sheet. This is expected due to the inherent biases caused by

³⁰ The sample drops from the 309 firm-years to 135 firm-years due to the simultaneous balance sheet and statement of cash flows data restriction, and losses from control firm matching.

³¹ Test results were robust on 106 accounting-fraud firms and 106 control firms that were also matched on market capitalization.

calculating total accruals from the balance sheet due to non-articulation events as discussed in Hribar and Collins (2002) (merger/acquisition, discontinued operations, and currency translations). The second conclusion is that the naïve model, Total Accruals, always outperforms the more complicated models that attempt to partition accruals into discretionary and non-discretionary components. This provides strong support for Guay, Kothari, and Watts (1996) who conclude that aggregate accrual models “estimate discretionary estimates with considerable imprecision and/or misspecification” and that some models “randomly split” accruals into discretionary and non-discretionary components.

The first result is important because to date, no published research has tested earnings management measures calculated from the statement of cash flows. This research shows the potential biases that exist do affect aggregate accrual models’ ability to detect extreme earnings managers. Therefore, prior research should be reevaluated to check the validity of the results. The second result is important because it questions the future use of complex aggregate accrual models and advocates the use of the simplest measure of earnings management, total accruals. Additionally, to date no empirical aggregate accrual study utilizes simple total accruals as a measure of earnings management.

VII.B. Analysis of Frequency Distribution Models

To compare the distribution of earnings³² for accounting-fraud firm-years versus the matched sample, I construct frequency plots of earnings per share around three thresholds. Tables 4 Panels A and B, Table 5 Panels A and B, Table 6 Panels A and B, report the distribution of earnings per share around thresholds in certain ranges. Figures A-4A, A-4B, A-5A, A-5B, A-6A, and A-6B are frequency plots of the distribution of earnings per share around thresholds in the -0.05 to +0.05 range. Overall, the results are contrary to hypothesized, showing a larger amount of clustering around the thresholds for control firm-years than for the accounting-fraud firm-years. Research by Feroz, Park, and Pastena (1991) helps explain this confounding result. They state “GAAP violators also experience poor performance subsequently, and this likely leads to detection, as the SEC targets firms with bad news to minimize the likelihood of falsely accusing a firm.” This target bias created by the SEC’s selection method³³ reduces the ability of frequency distribution analysis to detect extreme earnings managers. Therefore, to mitigate this confounding effect, I also analyze earnings distributions for all but the last fraud firm-year (which should be noted also eliminates all one-year events). This corrective action is based on the hypothesis that poor performance during the last year of the fraud causes the firm to become the target of an SEC investigation.

³² Both Earnings per Share (Fully Diluted)-Excluding Extraordinary Items (Compustat #57) and Earnings per Share (Fully Diluted)-Including Extraordinary Items (Compustat #169) were analyzed to verify robustness.

³³ The SEC’s targeting bias to investigate firms after experiencing poor performance increases the potential of type I errors. Thereby decreasing the ability of frequency distribution analysis to detect extreme earnings managers.

VII.B.1. Zero Earnings Threshold

Clustering of accounting-fraud firms at or above the zero earnings threshold is supported by Beasley, Carcello, and Hermanson (1999), who state the most commonly cited reason for financial fraud was to avoid a pre-tax loss. Using all accounting-fraud firm-years with earnings data (Compustat data item # 57 –Earnings per share excluding extraordinary items) and a matched sample with the same data requirement, I construct tables and frequency plots showing the distribution of earnings around zero. Table 4A and Figure A-4A show that results are contrary to the hypothesis, a larger amount of matched firms cluster around the threshold relative to the event firms. Additionally, the means for the distributions are contrary to hypothesized. The mean earnings per share (EPS) of the event firms at 0.0241 is significantly lower than the mean EPS of the control firms at 0.7176. Both ANOVA and Kruskal-Wallis³⁴ test reject the hypothesis that these two samples come from identical populations at the 1% level of significance. Nevertheless, it may be noted though, that both samples exhibit similar distribution shapes around the threshold.

However, the SEC's targeting bias is potentially confounding this result. To control for this, I eliminate any accounting-fraud firm-year that is the last year of the accounting-fraud. When the last year of the fraud is removed, the event firm mean EPS raises to 0.2672 and the control firm mean EPS drops to 0.6706 and neither ANOVA, nor Kruskal-Wallis test are able to reject that these two samples come from identical populations. There is little change in earnings distribution in proximity to the zero

³⁴ The Kruskal-Wallis test is a non-parametric test used when the assumption of normality or equality of variance is not met. This test, like many other non-parametric tests, uses the ranks of the data rather than

earnings threshold, as indicated by Figure A-4B. Additionally, Panel A of Table 4 shows that a larger number of event firms miss the zero earnings threshold by a larger margin relative to the control firms. Panel B of Table 4 indicates that this difference between the event and control firms is mitigated when the last fraud firm-years are eliminated. These results, compared to the analysis of all fraud firm-years, support research that the SEC is more likely to investigate firms that miss the zero earnings threshold.

VII.B.2. Past Earnings Threshold

Clustering of earnings manipulators at or above the past earnings threshold is supported by Dechow, Sloan, and Sweeney (1996), who found that for their sample 28.2% of the earnings manipulations are motivated by a desire to portray an upward earnings trend. Using all accounting-fraud firm-years with earnings data (Compustat data item # 57 –Earnings per share excluding extraordinary items) for the year of, and the year prior to the accounting-fraud firm-year and a matched sample with the same data requirement, I construct tables and frequency plots showing the distribution of earnings around past earnings threshold. Table 5A and Figure A-5A show results that are contrary to the hypothesis, with more clustering around the threshold for matched firms. The mean past earnings adjusted EPS of the event firms at -0.2855 is significantly lower than the mean past earnings adjusted EPS of the control firms at 0.1428. Both ANOVA and Kruskal-Wallis test are able to reject that these two samples come from identical populations at the 1% level of significance. However, it may be noted that both samples

their raw values to calculate the statistic. Since this test does not make a distributional assumption, it is not as powerful as the ANOVA.

exhibit similar distribution shapes around the threshold, with the matched sample showing the higher frequency of operating earnings at or slightly above the threshold.

However, once again, the SEC's targeting bias is potentially confounding this result. To control for this, I eliminate any accounting-fraud firm-year that is the last year of the accounting-fraud. When the last year of the fraud is removed, the event firm mean past earnings adjusted EPS increases to -0.0766 and the control firm mean past earnings adjusted EPS drops to 0.1176 and neither ANOVA, nor Kruskal-Wallis test are able to reject that these two samples come from identical populations. There was little change relative to all firm-years in earnings distribution in proximity to the past earnings threshold, as indicated by Figure A-5B. Additionally, Panel A of Table 5 shows that a larger number of event firms miss the past earnings threshold and by a larger margin relative to the control firms. Panel B of Table 5 indicates that this difference between the event and control firms is mitigated when the last fraud firm-years are eliminated. These results, when compared to the analysis of all fraud firm-years, supports the hypothesis that the SEC has a targeting bias to investigate firms that miss the past earnings threshold.

VII.B.3. Analysts' Estimate Threshold

Although there is no research that has investigated meeting/beating analysts' estimates as a motivation to commit accounting-fraud, there are obvious incentives for firms to do so. Firms that are motivated to commit accounting-fraud for securities issuance or to maintain an upward earnings trend (two commonly cited motivations) would certainly benefit from meeting/beating analysts' estimates. Additionally, Skinner and Sloan (2001) shows that growth stocks (defined as firms having a low book-to-

market ratio) suffer abnormally large negative price responses to missing analysts' estimates relative to non-growth stocks. Therefore, since firms in the accounting-fraud sample have above average revenue growth rate and are trading at a premium (low book-to-market ratio), there appears to be incentives for those firms to manage earnings to meet/beat analysts' estimates.

Using all accounting-fraud firm-years with earnings data (Compustat data item # 57 –Earnings per share excluding extraordinary items) and IBES median analysts' earnings estimate data for the accounting-fraud firm-year and a matched sample with the same data requirement, I construct tables and frequency plots showing the distribution of earnings around consensus analysts' estimate threshold³⁵. Table 6A and Figure A-6A show that contrary to the hypothesis, the matched sample shows a larger amount of clustering at and above the threshold than accounting-fraud firms. The mean analysts' forecast error of the event firms at -0.6971 is significantly lower than the mean analysts' forecast error of the control firms at 0.3246. Both ANOVA and Kruskal-Wallis are able to reject the hypothesis that these two samples come from identical populations. Also, in this case, unlike the zero and past earnings threshold analysis, the samples do not exhibit similar distribution shapes around the threshold. There exists a significantly larger number of accounting-fraud firms barely missing the threshold by one or two cents relative to the matched sample, 10 versus 3 respectively. Also, there exists a significantly larger number of control firms meeting or beating the threshold by one or two cents, 12 versus 6 respectively.

³⁵ The IBES analysts' estimate data restriction caused the sample size to drop markedly.

Again, the SEC's targeting bias is potentially confounding this result. To control for this, I eliminate any accounting-fraud firm-year that is the last year of the accounting-fraud. A comparison of Figure A-6A and A-6B shows that even though the last year of the fraud was removed from the sample the distribution of earnings in proximity of the threshold is similar. Additionally, Tables 6A and 6B indicate that accounting-fraud firms miss earnings estimates more often than matched firms in either case. In support of this, unlike previous thresholds, even though sample size decreased to 47 firm-years, ANOVA and Kruskal-Wallis are able to reject that these two samples come from identical populations with p-values at 11% and 12%, respectively.

Unlike the results with zero and past earnings thresholds, when using the earnings estimate threshold, the hypothesis that the event and control firms come from identical populations can be rejected, even after controlling for the SEC's targeting bias. This implies that the targeting bias is less pronounced for missing analysts' estimates than it is for missing zero and past earnings thresholds. This hypothesis is supported by the pecking order of thresholds espoused by DeGeorge, Patel, and Zeckhauser (1999), where the order of importance is first the zero, then past earnings, and lastly analysts' estimate threshold. This also agrees with Beasley, Carcello, and Hermanson (1999) who state that pressures of financial strain or distress may have provided incentives for fraudulent activities. In other words, the firms' main concern was viability, not meeting analysts' estimates.

VII.B.4. Overview of Threshold Analysis

Missing the zero and past earnings threshold appears to be used by the SEC as a means to identify potential firms to be investigated. Once the targeting bias that exists is controlled by removing the last year of fraud from the analysis, the accounting-fraud and matched sample earnings distributions are not statistically different, although there are a larger number of matched sample firms than accounting-fraud firms at or slightly above the thresholds. This provides little support for frequency distribution analysis around the zero and past earnings threshold to detect accounting-fraud firms.

A question for future research is what motivates the analysts' excessive optimism concerning earnings estimates for accounting-fraud firms. Analyzing 33 event and 33 control firms that had adequate Compustat and IBES data for two years prior to the first year of accounting-fraud provides some insight. Preliminary results indicate that two years prior to the first year of fraud, the accounting-fraud firms on average beat analysts' estimates by a greater margin than the matched firms. One year prior to the first year of accounting-fraud, the accounting-fraud firms and matched firms are approximately equal in meeting analysts' estimates. One year later, i.e., in the first year of fraud, accounting-fraud firms miss estimates more often and by a larger margin than the matched sample. This implies that the analysts' optimism may be fueled by prior earnings performance and that the fraud was perpetrated to prevent missing estimates by an even wider margin. This suggests that analysts' do not adjust for accruals when making estimates consistent with Bradshaw, Richardson, and Sloan (2000). These preliminary results relate directly to section VII.C.1 which discusses the selection of Composite model variables that inflate earnings.

VII.C. Composite Models

Two key issues exist concerning predictive composite models: 1) whether prior period variables have the ability to predict accounting-fraud and 2) if measures of earnings management, such as total accruals, are important relative to other variables. By adding to the predictive variables suggested from Beneish (1997), a logit model is constructed to predict accounting-fraud by using only data from periods prior to the accounting-fraud firm-year in question. Variables for composite model are selected from three areas based on managers' utility-maximizing behavior. Therefore, variables covering income-increasing choices, financial condition and opportunistic behavior of the firm are chosen.

VII.C.1. Variables that Inflate Earnings

Based on managerial utility-maximizing behavior, it is reasonable that managers' would first pursue legal income-increasing options prior to committing fraud. Therefore, the presence of accounting choices that inflate earnings is more likely in years prior to fraudulent activity. Total accruals the year prior to accounting-fraud is the variable used, since within the confines of GAAP, a firm has some leeway to inflate earnings for a short period of time. Dechow, Sloan, and Sweeney (1996) and Beneish (1997) support this by showing that total accruals increase in the years approaching the fraud year as identified by the AAER. Lee, Ingram, and Howard (1999) state that total accruals peak sometime in the three years prior to the beginning of fraudulent accounting activity. It is expected that total accruals in years prior to accounting-fraud would be greater for the event firms than for the matched sample. Therefore the odds ratio, which is greater than one if the variable

increases the probability of fraud, or below one if the variable decreases the probability of fraud, is expected to be greater than one for total accruals.

The Accounting Change Binary is 1 if the firm institutes an accounting change the year prior to an accounting-fraud firm-year, 0 otherwise. Due to the potential of such changes to inflate earnings, it is expected that the odds ratio would be greater than one.

The Flow Through Investment Tax Credit Binary is 1 if the firm uses the credit the year prior to an accounting-fraud firm-year, 0 otherwise. The flow through method reduces taxes by the entire amount of the credits allowed in the year the asset that is placed into service, thereby temporarily inflating earnings. The expected use of this tax credit should be higher for the event versus the control firms in periods prior to committing fraud, therefore it is hypothesized that the odds ratio will be greater than one.

The Straight-line Depreciation Binary is 1 if the firm uses straight-line depreciation the year prior to the accounting-fraud firm-year, 0 otherwise. Since the use of straight-line depreciation relative to accelerated depreciation, *ceteris paribus*, inflates earnings, it is hypothesized that the odds ratio will be greater than one.

Various binary variables are used to represent the inventory valuation method. If a particular inventory valuation method is used the year prior to the accounting-fraud firm-year then the binary is equal to 1, 0 otherwise. Since FIFO and Specific Identification methods have the greatest potential to inflate earnings relative to other methods, it is hypothesized the odds ratio for those variables will be greater than one. The odds ratios for other inventory valuation methods are expected to be less than or equal to one. Finally, managers may use discontinued operations (defined as discontinued operations

gain or loss deflated by total assets) as a means to write-off losses to portray higher operating earnings, therefore it is hypothesized that the odds ratio will be less than one.

VII.C.2. Variables that Represent Financial Condition

Since accounting-fraud is often committed by firms under financial distress, variables that represent the financial condition of the firm the year prior to the accounting-fraud firm-year are chosen. Since low working capital over total assets, low profit margin, low cash flow over total assets, low cash sales growth, and a low Z-Score could represent financial distress, it is expected that the odds ratio would be less than one for those variables. Also, since high leverage can represent financial distress it is expected that the odds ratio would be greater than one for the total debt to total assets variable.

According to the opinion of the former Chief Accountant of the SEC's enforcement program (Diacont 1995), in his experience, many of the companies which became the subject of an enforcement action, did so in the context of an initial public offering or as a result of financial statement manipulations shortly after their initial public offering. Beneish (1997) goes on to state that, "[y]ounger firms may thus be subject to closer scrutiny if the SEC perceives them as higher risks." This perception is consistent with evidence from Dopuch, Holthausen, and Leftwich (1987), which states that younger firms are more likely to experience financial distress. Therefore, since younger firms may be subject to closer scrutiny and/or financial distress, it is expected that my proxy variable for firm age, time covered by Compustat, would have an odds ratio less than one.

Since firms with a lower book-to-market ratio are largely valued by future growth opportunities, a reversal in expectations about future firm performance would have a marked effect on the value of the firm. Firms trading at a premium have a greater incentive to commit fraud to prevent a reversal. Therefore, it is expected that the odds ratio for the book-to-market ratio would be less than one.

Additionally, according to Barth, Elliott, and Finn (1997), firms that maintain earnings trends trade at a premium and experience an asymmetric price drop when that trend is broken. Since it is hypothesized that the motivation to commit fraud would be positively related to the length of the earnings trend experienced, it is expected that for the length of a zero and past earnings trend variables that the odds ratio would be greater than one.

VII.C.3. Variables that Represent Potential Opportunistic Behavior

If firms have inflated earnings and/or are trading at a premium, managers have an incentive to act opportunistically by issuing equity or to purchase other firms. Fraudulent firms may undergo mergers/acquisitions to take advantage of the firm's inflated stock price to purchase other firms. Or they may use complicated merger/acquisition accounting to build reserves which are improperly reversed later. Levitt (1998) states "[s]ome acquirers, particularly those using stock as an acquisition currency, have used this environment as an opportunity to engage in another form of 'creative' accounting." Levitt (1998) calls it "merger magic" and continues on to say "troubling is the creation of large liabilities for future operating expenses to protect future earnings -- all under the mask of an acquisition." Therefore, the odds ratio for merger/acquisition binary is

expected to be greater than one. Also, since a firm in such a position would want to buy firms that would have the greatest contribution to its income and sales, it is hypothesized that merger/acquisition contribution to income and sales would have an odds ratio greater than one.

Finally, firms that have inflated their earnings and/or are trading at a premium (lower market-to-book ratio relative to their peers) because of fraud are expected to issue shares to take advantage of such a situation. Therefore, it is hypothesized that the odds ratios for a stock issuance binary and the ratio of stock issuance proceeds to market capitalization would be greater than one.

VII.D. Composite Model Data

VII.D.1. Composite Model Data Description

The descriptive statistics for the 162 accounting-fraud firm-years and the 162 firm-years in the control sample are shown in Table 8 (see Table 7 for variable definitions), which presents the means, medians, and the significance of their difference. The sample size drops from 309 firm-years due to the increased data requirements for the event and control firms. As shown in Table 8, accounting-fraud firms are younger firms with higher total accruals, more total assets, more leverage, higher sales growth, and a lower book-to-market ratio. They use income increasing accounting choices such as straight-line depreciation, FIFO or Specific identification inventory valuation, or flow through investment tax credit more often than the control firms.

One particularly interesting point is that 35.2% of event firms undergo a merger/acquisition the year prior to the accounting-fraud firm-year analyzed versus

14.2% for the control firms, statistically different with a p-value of < 1%. Those mergers/acquisitions increase sales by an average of 5.0% for the event sample versus 2.4% for the control sample. Another interesting point is that 13.0% of the event sample issues equity the year prior to the accounting-fraud firm-year analyzed versus 4.9% for the control sample. Accounting-fraud firm issuances are also larger, increasing market capitalization by 2.2% for the event sample, versus 0.9% for the control sample.

VII.D.2. Composite Model Logistic Regression

Table 9 reports the results of the logistic regression's ability to distinguish accounting-fraud firms from the control firms. The model is defined as follows:

$$M = \beta'X,$$

Where M is a binary that is equal to 1 for the accounting-fraud firms and M is equal to 0 for the control firms, β is a matrix of coefficients, and X is a matrix of explanatory variables. The extended version of the logistic regression is defined as follows:

$$\begin{aligned} M = & \beta_1*(Total\ Accruals\ by\ B/S) + \beta_2*(Working\ Capital\ over\ Total\ Assets) + \\ & \beta_3*(Total\ Assets) + \beta_4*(Total\ Debt\ to\ Total\ Assets) + \beta_5*(Profit\ Margin) + \beta_6*(Cash\ Flow \\ & over\ Total\ Assets\ by\ B/S) + \beta_7*(Sales\ Growth) + \beta_8*(Cash\ Sales\ Growth) + \beta_9*(Book\ to \\ & Market) + \beta_{10}*(Altman's\ Z-Score) + \beta_{11}*(Time\ covered\ by\ Compustat) + \beta_{12}*(Zero \\ & Earnings\ String) + \beta_{13}*(Past\ Earnings\ String) + \beta_{14}*(Discontinued\ Operations\ over \\ & Total\ Assets) + \beta_{15}*(Merger/Acquisition\ Contribution\ to\ Income) + \\ & \beta_{16}*(Merger/Acquisition\ Contribution\ to\ Sales) + \beta_{17}*(Accounting\ Change\ Binary) + \\ & \beta_{18}*(Flow\ Through\ Investment\ Tax\ Credit\ Binary) + \beta_{19}*(Straightline\ Depreciation \\ & Binary) + \beta_{20}*(Replacement\ Cost\ Inventory\ Binary) + \beta_{21}*(Standard\ Cost\ Inventory \end{aligned}$$

$$\begin{aligned} & \text{Binary}) + \beta_{22} * (\text{Retail Method Inventory Binary}) + \beta_{23} * (\text{Average Cost Inventory Binary}) \\ & + \beta_{24} * (\text{Specific Identification Inventory Binary}) + \beta_{25} * (\text{FIFO Inventory Binary}) + \\ & \beta_{26} * (\text{Stock Issuance Binary}) + \beta_{27} * (\text{Stock Issuance Proceeds over Market Cap.}) \end{aligned}$$

The logistic regression is stacked to test a certain sequence of explanatory variables. First, to test the predictive ability of the model that exhibits the best ability to detect accounting-fraud (as reported in Table 3) is estimated (column 1 of Table 9), total accruals calculated from the balance sheet.³⁶ The second stacked regression (column 2 of Table 9) adds the predictive variables, excluding the proxy for firm age (time listed in Compustat) which is included later, recommended in Beneish (1997). The following stacked regressions add various variables in stages representing book-to-market ratio and Altman's bankruptcy score (columns 3 of Table 9), proxy for age of the firm and earnings trends (columns 4 of Table 9), discontinued operations and mergers/acquisitions (columns 5 of Table 9), accounting and inventory valuation methods (columns 6 of Table 9), and stock issuance information (columns 7 of Table 9). Using data only from years prior to the accounting-fraud firm-year to be predicted, the model that includes all the explanatory variables properly classifies 64.2% of the event firm-years and 67.3% of the control firm-years, with an overall percentage of correctly classified at 65.7%. Each statistically significant variable has its hypothesized odds ratio value, above or below one³⁷.

³⁶ Total accruals from the statement of cash flows was not used since that additional data restriction caused a significant drop in sample size, from 162 to 68 event and control firm-years.

³⁷ Results are consistent when events and controls were also matched by year, 2-digit SIC, ROA, and market capitalization. This additional market capitalization restriction of +/- \$250 million or +/- 10% caused the sample to drop from 162 to 129 event and control firm-years.

Total accruals by B/S has the expected odds ratio and is statistically significant at the 10%, or better, for the majority of the regressions in Table 9. Sales growth and Cash Sales Growth have the anticipated odds ratios which state that firms with high Sales Growth, but low Cash Sales Growth are more likely to be accounting-fraud firms. This implies that firms are supporting sales growth through the use of credit to their customers. Time Covered by Compustat has its hypothesized less than one odds ratio implying that younger firms are more likely to commit accounting-fraud, agreeing with Dopuch, Holthausen, and Leftwich (1987), and Diacont (1995).

The existence of a merger/acquisition the year prior to the accounting-fraud firm-year to be analyzed is a highly significant variable to properly classify accounting-fraud and matched sample firms. Additionally, Mergers/Acquisitions Contribution to Sales odds ratio is greater than one as hypothesized, but is only significant at the 10% level. This implies that accounting-fraud firms are more likely to undergo mergers/acquisitions that contribute the greatest to current firm sales.

Straight-line Depreciation Binary has the expected odds ratio of greater than one, implying that firms exercise legal options to increase earnings in periods prior to committing accounting-fraud, but is only marginally significant with a p-value of 13.6% or 11.6% depending on the model analyzed. Consistent with inflating earnings legally prior to committing accounting-fraud, Specific Identification Binary and FIFO Binary are statistically significant and have odds ratios greater than one, and significance at the 3% and 7% level, respectively. Although the stock issuance variables odds ratios are greater than one, they are not statistically significant in the logistic regression.

Neither the zero, nor past earnings strings variable were significant, implying that maintaining an earnings trend is not a sufficient motivation to commit accounting-fraud. This may be explained by the fact that Table 8 shows that average earnings trends are actually shorter for event firms, implying that their premium (lower book-to-market ratio), if it existed, may have been due to other factors. Also, although the Book-to-Market has the expected odds ratio, it is not statistically significant.

VII.D.3. Composite Model Conclusion

The logistic regression provides evidence of firm characteristics and behaviors that help distinguish accounting-fraud firms from a matched sample, based upon data available in the year prior to the filing of a fraudulent annual report, per the AAER. The significance of variables representing income-increasing accounting choices, financial condition of the firm, and potentially opportunistic behavior by management demonstrates the importance of considering measures of earnings management in conjunction with managerial incentives to commit accounting-fraud. Overall, the composite model indicates younger firms, with higher total accruals and sales growth, using income-increasing accounting choices, with merger/acquisition activity are more likely to commit accounting-fraud. Concerning the use of Beneish's predictive variables, my results support research reported in Beneish (1997). The statistical significance of total accruals as a predictor of accounting fraud supports Lee, Ingram, and Howard (1999). The lack of statistical significance of the variables representing earnings trends is contrary to expected based on the motivations for extreme earnings management discussed in Beasley, Carcello, and Hermanson (1999) and Dechow, Sloan, and Sweeney

(1996). The significance of FIFO inventory valuation methods is consistent with hypotheses presented in Dechow, Sloan, and Sweeney (1996) and Beneish (1997), but contrary to previous research, my results provide statistical support to those hypotheses. The marginal significance of Straightline Depreciation is consistent with an hypothesis presented in Dechow, Sloan, and Sweeney (1996), but my research is the first to provide statistical evidence of its significance. However, the lack of significance of the stock issuance variables in the logit model was contrary to Dechow, Sloan, and Sweeney (1996), however the test of means between the event and control firms supports prior research.

My results add to the body of knowledge by showing that maintaining an earnings trend is not a sufficient motivation to commit accounting-fraud. Additionally, it shows that the use of the Specific Identification inventory valuation method the year prior to an accounting fraud firm-year is statistically significant variable in predicting extreme earnings management. It also shows that merger/acquisition activity the year prior to committing accounting fraud is highly statistically significant. Implying that accounting-fraud firms act opportunistically to benefit from complicated acquisition accounting and/or possibly an inflated stock price.

Results indicate that variables other than total accruals add significant power to the model's ability to distinguish accounting-fraud firm-years from matched firm-years. Table 9 shows that, as variables representing managerial incentives to commit fraud are added, the statistical significance of total accruals decreases (from a p-value of 0.1% to

11.4%), while the model's percent properly classified increases from 55.6% to 65.7%³⁸.

Including these additional variables increases the model's performance and provides better insight into the condition and behavior of the firm prior to a fraudulent firm-year.

By recognizing certain firm characteristics and behaviors; investors, regulators, and accountants can enhance their ability to predict fraudulent accounting. This can help investors improve the allocation of their capital and help accountants recognize fraudulent activities that would misallocate such capital. Additionally, such knowledge provides a means for the SEC to improve their prediction of accounting-fraud. This may lessen the SEC's targeting bias to investigate firms only after the fraud is so severe that financial implosion is probable. If the SEC can discover violators earlier, it reduces the benefits that current and future firms may receive by acting fraudulently, thereby decreasing occurrences of such fraudulent activity.

³⁸ This result is robust even when total accruals from the statement of cash flows is used.

VIII. Conclusion and Additions to Literature

Over the last five years, accounting-fraud scandals have had a tremendous effect on U.S. financial markets and the U.S. economy. Government has responded with the passage of the Sarbanes-Oxley Act by Congress, the establishment of the Corporate Fraud Task Force by the President of the United States, and the redoubled focus of the SEC on fraudulent activities. This confirms the intent of lawmakers and regulators to improve accounting practices and provide tougher penalties for those who commit financial crimes.

Simultaneously, academia has developed methodologies and models in an attempt to improve the transparency of the financial markets and reduce the amount of misallocated capital. The majority of the academic literature focused on using accruals to assess the extent to which firms managed their earnings, commonly analyzing instances in which earnings management was likely (such as Initial Public Offerings, Secondary Equity Offerings, Import Relief Investigations, management buyouts, etc.), but not definite. Unfortunately, little direct evidence has been provided to distinguish which methods worked best when there existed a virtual certainty about which firms were extreme earnings managers.

Many of the papers addressing the use of accruals to manage earnings have not dealt with the most egregious abuses of investors – abuses deemed serious enough to bring about charges of fraud by the SEC. This research attempts to further the evaluation of earnings management models as tools for detecting and predicting financial fraud. Using the Securities and Exchange Commission's (SEC) Accounting and Auditing Enforcement Releases (AAERs) to establish relative certainty, accounting-fraud firms are

definitively partitioned from non-accounting-fraud firms. This “gold standard” for distinguishing between fraud and non-fraud firms provides a robust situation to contribute to the literature by testing the ability of aggregate accrual, frequency distribution, and composite models to distinguish accounting-fraud firms from a matched sample.

Broadly speaking my strategy focuses on two separate goals: the detection and prediction of extreme earnings management. The research goal to detect accounting-fraud is supported by two subcategories: the aggregate accrual and frequency distribution analysis models. Their purpose is to detect accounting-fraud using the current and past period data available. The research goal to predict accounting-fraud includes the composite model structure whose purpose is predict the public discovery of accounting-fraud using data only available the year prior to the fraudulent event.

Concerning detection with aggregate accrual models, my research has contributed by being the first to utilize total accruals from the statement of cash flows and performance-matched aggregate accrual models using cash flow data items using a “gold standard,” AAER dataset. Results indicate all discretionary accrual models with total accruals calculated using the statement of cash flows resulted in statistically significant differences between fraud and non-fraud firms (at the 5% level of significance). However, only the naïve model of Total Accruals resulted in statistically significant differences when calculated using total accruals from the balance sheet. These results provide support for the theoretical work by Hribar and Collins (2002) concerning non-articulation event induced biases and noise in total accruals calculated from the balance sheet. Additionally, my results indicated that total accruals, my non-partitioned naïve

measure of earnings management, always outperformed discretionary accrual models. Although tests did not indicate that model results were statistically different, the fact that a naïve measure could marginally outperform the partitioned measures of accruals provides unique empirical support for Guay, Kothari, and Watts (1996) conclusion that aggregate accrual models “estimate discretionary estimates with considerable imprecision and/or misspecification” and that some models “randomly split” accruals into discretionary and non-discretionary components. Furthermore, it is important to consider that total accruals is also the easiest to calculate. Based on the apparent imprecision with which discretionary accrual models partition accruals, and the cost of calculation of those models, it is difficult to justify the future usage of such models. Therefore, investors, regulators, and accountants can enhance their ability to detect accounting-fraud firms and reduce their computational cost to detect fraudulent accounting by using the simplest model, total accruals, calculated using the statement of cash flows.

Utilizing a previously unused matched firm perspective for frequency distribution analysis, my research compares accounting-fraud and matched sample earnings distributions around three earnings thresholds. Initial results of frequency distribution analysis are unable to support a hypothesis that accounting-fraud firms were meeting/beating thresholds more often than matched firms. However, when analyzing the zero and past earnings thresholds for all but the last year of a multi-year fraud, evidence of a targeting bias was discovered, providing empirical support for the hypothesized SEC targeting bias by Feroz, Park, and Pastena (1991). This is shown since prior to controlling for the SEC’s targeting bias, earnings distributions were statistically negatively skewed for the accounting-fraud firms as compared to the matched sample, but after removing the

last year of all frauds from analysis to control for the targeting bias the two distributions were statistically indistinguishable.

In concordance with Guay, Kothari, and Watts (1996) and Beneish (1997), who conjectured that models that also consider managers' incentives have a better chance to identify extreme earnings managers, my composite model uses variables to represent firms' financial condition, use of income-increasing accounting choices, and potentially opportunistic behavior the year prior to accounting-fraud to distinguish fraud and non-fraud firms. My composite model analysis, using a larger sample than used in prior research, supports research by Dechow, Sloan, and Sweeney (1996), Beneish (1997) and Lee, Ingram, and Howard (1999) that firms made income-increasing accounting choices prior to an enforcement action being filed. This implies fraud was committed because the offending firms' had already exhausted legal options to better represent their firms' performance.

This research also contributes to the literature by showing that potentially opportunistic merger/acquisition activity in periods prior to public discovery of accounting-fraud statistically distinguishes extreme earnings managers. Such behavior is hypothesized to be opportunistic, based on Levitt (1998) discussion concerning creation of large liabilities for future operating expenses to protect future earnings, aptly named "merger magic." Merger/acquisition activity may also be opportunistic through the use of inflated stock prices to acquire other firms due to the use of income-increasing accounting choices during the purchase period. The statistically larger sales contribution

of the merged/acquired firms for accounting-fraud firms relative to the matched firms³⁹ supports this hypothesis implying that future accounting-fraud firms, realizing that their stock is overvalued, used it to buy larger firms relative to the matched sample. However, future research of purchase method and characteristics of the firm purchased are needed to definitively state that mergers/acquisitions are opportunistic.

In summary, the analysis employing the composite model for distinguishing between fraud and non-fraud firms offers potentially important insights for the prediction of fraudulent accounting. Future accounting-fraud firms are younger, higher growth, more leveraged firms that trade at a premium (lower book-to-market ratio) relative to their peers. They are more likely to choose income-increasing accounting choices (such as straight-line depreciation, FIFO or Specific Identification inventory valuation methods, and Flow Through Investment Tax Credits) and more likely to participate in potentially opportunistic merger/acquisition activity in the year prior to filing a fraudulent annual report relative to a matched sample.

Using a significantly larger database than that used in prior research, my research contributes to the body of knowledge by testing previously analyzed methodologies and models, testing previously untested methodologies and models, and providing unique extensions and results related to the performance of those tests. My research shows that: 1) the simplest aggregate accrual model using total accruals from the statement of cash flows works best to detect accounting-fraud, 2) the frequency distribution analysis has no

³⁹ When only the first year of fraud is analyzed both contribution to sales and contribution to income variables were statistically larger. This indicates that accounting-fraud firms merged/acquired larger firms that contributed the most to net income. Results were robust using both total accruals from the balance sheet and the statement of cash flows.

ability to detect extreme earnings management, and 3) the composite model provides unique insight into different variables that can aid in the prediction of accounting-fraud.

Future research should focus on merger/acquisition behavior in periods prior to accounting-fraud firm-years. A key unanswered question from this research is whether merger/acquisition activity by the accounting-fraud firm is opportunistic. Is the purpose to take advantage of overvalued stock prices due to income-increasing accounting choices used by the firm or an attempt to fuel the growth of the firm and reverse a downward spiral of the firm's performance? Or is it simply that a merger/acquisition provided another opportunity for firms take advantage of accounting procedures to obfuscate their firm's true performance. Future research should also focus on extending the composite model research to include management structure and holdings. Combining variables representing governance of the firm, as used by Dechow, Sloan, and Sweeney (1996), will likely add to the ability of the model to distinguish managerial incentives to commit accounting-fraud.

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Appendix

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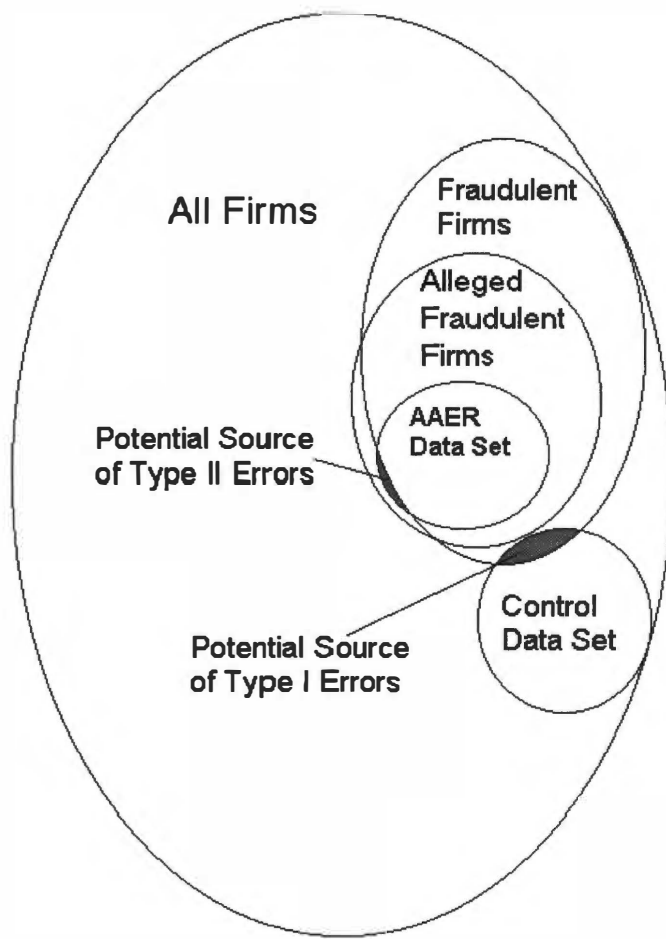


Figure A-1. Potential Sources of Type I and Type II Errors.
The shaded portions indicate the potential sources of Type I and Type II errors.

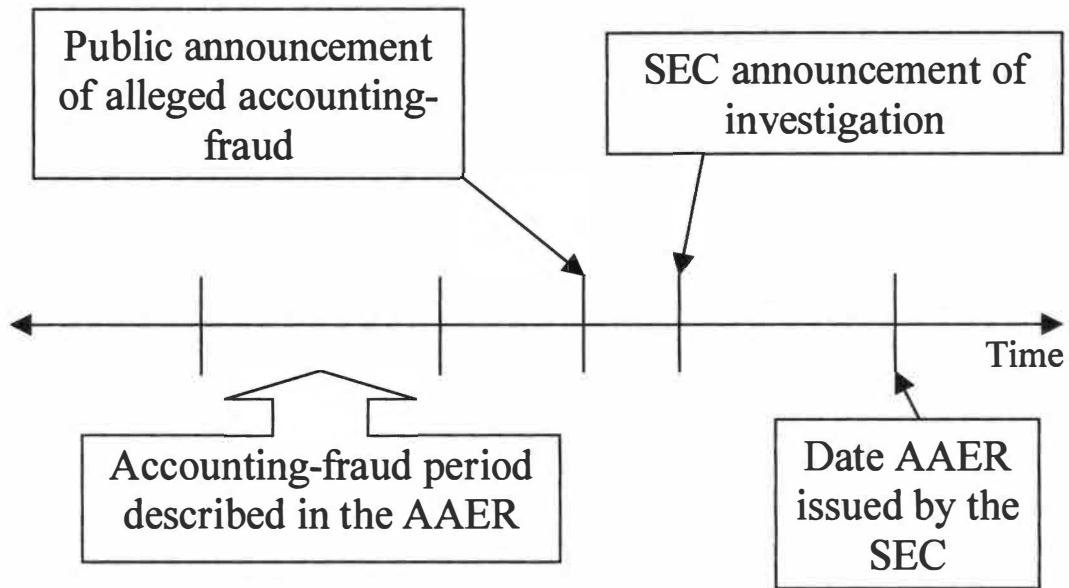


Figure A-2. Chronological Order of AAER Events.

Chronological order of events for a typical firm subject to an Accounting and Auditing Enforcement Release (AAER).

**Table 1. Compustat Data Comparison with Prior Research.
Panels A and B**

Panel A: Dissertation's Sample Size				
Study	time period	fraud firms	fraud firm-years	matching criteria
Starting sample with a Cusip	1978-2001	270	535	Industry and ROA
Sample with data in Compustat	1978-2001	246	497	Industry and ROA
Sample after data restriction*	1978-2001	169	309	Industry and ROA
* Restricted on the most complex discretionary accrual calculation used in previous literature				
Panel B: Prior Studies' Sample Size				
Study	time period	fraud firms	fraud firm-years	matching criteria
Dechow, Sloan, and Sweeney (1995)	1982-1992	32 92	56	All other firms in industry
Dechow, Sloan, and Sweeney (1996)	1982-1992	(66 used)	N/A	SIC and Market Cap. All firms in highest decile of discretionary accruals
Beneish (1997)	1983-1991	64	N/A	
Summers and Sweeney (1998)	1980-1987	51	N/A	SIC and Market Cap.
Lee, Ingram, and Howard (1999)	1978-1991	56	N/A	All other firms

Table 2. Accounting-Fraud and Compustat Summary Statistics.**Panels A and B**

Accounting-fraud and Compustat firm-year summary statistics for 1978-2001. Firm-years included have adequate data to calculate total accruals by the balance sheet, with sales and assets greater than \$10 million. The sample size drop in Panel A from the 309 firm-years reported in Panel A of Table 1 is driven by the capital market data requirement to calculate market capitalization and book to market ratio. Additionally, the top 0.05% and bottom 0.05% values were removed from Panel B to minimize outliers in Compustat.

Panel A: Accounting-fraud firm-year summary statistics (n = 239)						
Variable ^a	mean	median	std dev	minimum	maximum	n
Total Assets (\$millions)	2488.4	108.2	7788.9	10.3	65503.0	239
Market Cap. (\$millions)	2470.7	132.1	9751.3	1.8	93490.4	239
Book to Market	0.61	0.60	0.29	0.06	2.00	239
ROA	10.6%	13.0%	19.1%	-93.0%	75.3%	239
Profit Margin	-4.9%	2.7%	33.5%	-214.8%	29.6%	239
Total Debt to Total Assets	0.52	0.52	0.24	0.07	1.20	239
Sales Growth	63.2%	28.8%	152.7%	-58.2%	1751.6%	238
Cash Sales Growth	59.6%	31.2%	136.9%	-71.1%	1398.7%	221
Altman's Z-Score	4.34	2.91	4.63	-10.12	35.47	238
Years covered by Compustat	8.62	6	7.43	1	34	239

Panel B: Compustat firm-year summary statistics (n = 99884)						
Variable ^a	mean	median	std dev	minimum	maximum	n
Total Assets (\$millions)	1356.1	133.3	5877.3	10.0	244192.5	99884
Market Cap. (\$millions)	1324.0	103.4	8000.7	0.0	596475.8	99884
Book to Market	0.79	0.80	0.33	0.03	2.90	99823
ROA	13.1%	13.8%	13.7%	-111.8%	84.9%	99870
Profit Margin	-0.9%	3.6%	32.5%	-847.4%	101.9%	99878
Total Debt to Total Assets	0.47	0.46	0.23	0.02	2.80	99767
Sales Growth	26.8%	11.2%	153.7%	-85.9%	11283.9%	99602
Cash Sales Growth	24.9%	10.4%	167.5%	-4538.9%	11055.7%	91649
Altman's Z-Score	4.40	3.24	6.03	-15.40	137.61	98723
Years covered by Compustat	11.63	10	8.20	1	39	99884

Variable	* Variable Definition
Total Assets	Total Assets of the firm (#6)
Market Cap.	Market Capitalization = Share Price _t (#24) x Number of Common Shares Outstanding _t (#25)
Book to Market	Ratio of book value of total assets to the sum of book value of liabilities and preferred stock and the market value of common equity at the fiscal year-end prior to the announcement [Book to Market = Total Assets _t (#6) / (Total Assets _t (#6) - (Shareholders' Equity _t (#216) - Preferred Stock Value _t (#56, unless missing, then #10 unless missing, then #130)) + Market Capitalization _t (#24 * #25))]
ROA	Return on Assets = Operating Income Before Depreciation _t (#13) / Total Assets _t (#6)
Profit Margin	Income Before Extraordinary Items _t (#18) / Sales _t (#12)
Total Debt to Total Assets	Current Liabilities _t (#5) + Long-Term Debt _t (#9) / Total Assets _t (#6)
Sales Growth	Sales Growth Rate _t = (Sales _t (#12) - Sales _{t-1}) / Sales _{t-1}
Cash Sales Growth	Cash Sales Growth Rate _t = (Cash Sales _t - Cash Sales _{t-1}) / Cash Sales _{t-1} , where: Cash Sales _t = (Sales _t (#12) - (Receivables _t (#2) - Receivables _{t-1}))
Altman's Z-Score	Altman's Z-Score _t = ((Earnings Before Interest and Taxes _t (#178) / Total Assets _t (#6)) x 3.3) + ((Sales _t (#12) / Total Assets _t (#6)) x 0.999) + (Market Capitalization _t (#24 * #25) / Total Liabilities _t (#181) x 0.6) + (Current Assets _t (#4) - Current Liabilities _t (#5) / Total Assets _t (#6) x 12) + (Retained Earnings _t (#36) / Total Assets _t (#6) x 14)
Years covered by Compustat	As a proxy for age of the firm, the variable represents number of years that the firm reported data in Compustat.

Table 2. Continued.**Panels C, D, and E**

Number of fraudulent annual reports per firm, and the number of fraudulent firm-years per calendar year, and distribution by 2-digit SIC of fraudulent firm-years and all firm-years in Compustat.

Panel C: Number of Annual Reports (10-Ks) with reporting violations													
	Number of Annual Reports (10-Ks) per accounting-fraud firm												
# of 10-Ks	1	2	3	4	5	6	7	8	9	10	11	12	Total:
# of firms	117	59	39	20	8	1	1	0	0	0	0	1	246
Panel D: Calendar years in which firms committed accounting-fraud													
	Fiscal year-end of accounting fraud violation												
year of violation	'79	'80	'81	'82	'83	'84	'85	'86	'87	'88	'89	'90	
# of firm-years	2	3	6	13	13	13	13	20	19	25	37	26	
year of violation	'91	'92	'93	'94	'95	'96	'97	'98	'99	'00	'01		Total:
# of firm-years	36	36	39	35	33	29	34	25	20	13	7		497
Panel E: SIC distribution of firm-years													
2-digit SIC	Industry description		# of accounting-fraud firm-years		%		# of Compustat firm-years		%				
01-09	Agriculture, Forestry, Fishing		1		0.2%		1171		0.5%				
10-19	Mining and construction		15		3.0%		19797		7.9%				
20-29	Commodity production		68		13.7%		35874		14.4%				
30-39	Manufacturing		140		28.2%		69441		27.9%				
40-49	Transportation and utilities		34		6.8%		27107		10.9%				
50-59	Wholesale and retail		61		12.3%		29022		11.7%				
60-69	Financial services (excl. 60-63)		63		12.7%		21916		8.8%				
70-79	Personal and business services		80		16.1%		32057		12.9%				
80-89	Health and other services		26		5.2%		9907		4.0%				
90-99	Public administration		9		1.8%		2801		1.1%				
			497		100.0%		249093		100.0%				

Table 3. Comparison of Aggregate Accrual Estimates Mean Differences.

Comparison of aggregate accrual estimates mean differences (event firms' mean minus control firms' mean)

	TA B/S	TA CF	Jones B/S	Jones CF	Mod. Jones B/S	Mod. Jones CF	ReMod. Jones B/S	ReMod. Jones CF	Beneish B/S	Beneish CF
event firms' mean	0.1206	0.0913	0.0877	0.1220	0.1032	0.1230	0.0895	0.1192	0.1513	0.1311
control firms' mean	-0.0336	-0.0591	0.0207	0.0097	0.0235	0.0099	0.0178	0.0081	0.0816	0.0084
mean difference	0.1542	0.1504	0.0670	0.1123	0.0797	0.1132	0.0717	0.1112	0.0697	0.1228
t statistic	2.65	3.70	1.07	2.06	1.28	2.18	1.12	2.13	0.75	2.24
p-value	0.0091	0.0003	0.2862	0.0410	0.2020	0.0308	0.2639	0.0347	0.4550	0.0265
percent positive	65.2%	68.9%	63.7%	59.3%	62.2%	60.0%	63.0%	60.0%	62.2%	60.0%
z statistic	3.44	4.30	3.10	2.07	2.75	2.24	2.93	2.24	2.75	2.24
p-value	0.0003	0.0000	0.0010	0.0194	0.0029	0.0126	0.0017	0.0126	0.0029	0.0126

Note 1: Even though the t-statistics are significant for some mean differences but not for others, neither ANOVA, nor Kruskal-Wallis tests were able to say that the mean differences were statistically significant from one another.

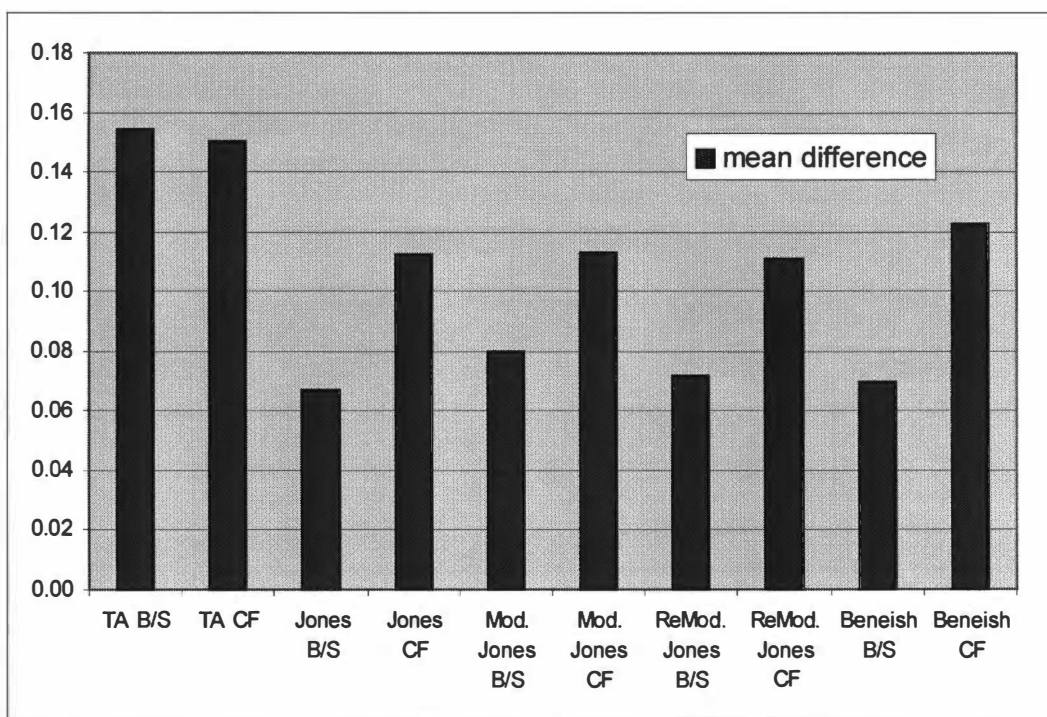


Figure A-3. Graph of Aggregate Accrual Estimates Mean Differences.
 Graph of aggregate accrual estimates mean differences (event firms' mean minus control firms' mean). Y-axis is the aggregate accrual estimates mean difference and the X-axis is the type of aggregate accrual model used.

Table 4. Distribution of Earnings Around the Zero Earnings Threshold.**Panels A and B**

Panel A contains the distribution operating earnings (Compustat #57) for all event and control firm-years around the zero earnings threshold. Panel B contains the distribution of operating earnings (Compustat #57) for all event and control firm-years, excluding the last firm-specific fraudulent firm-years and control firm-years, around the zero earnings threshold.

Panel A: All Fraud Firm-Years (See Note 1)					
EPS:	< -0.05	-0.05 to -0.01	At zero	0.01 to 0.05	> 0.05
Events:	113	8	4	16	180
	35.2%	2.5%	1.2%	5.0%	56.1%
Controls:	82	7	11	17	204
	25.5%	2.2%	3.4%	5.3%	63.6%
321 event firm-years and 321 control firm-years					
Panel B: All But Last Fraud Firm-Years (See Note 2)					
EPS:	< -0.05	-0.05 to -0.01	At zero	0.01 to 0.05	> 0.05
Events:	44	7	1	10	107
	26.0%	4.1%	0.6%	5.9%	63.3%
Controls:	43	2	9	8	107
	25.4%	1.2%	5.3%	4.7%	63.3%
169 event firm-years and 169 control firm-years					

Note1: Both ANOVA and Kruskal-Wallis test are able to reject that these two samples come from identical populations at the 1% level of significance.

Note 2: Neither the ANOVA, nor Kruskal-Wallis tests are able to reject that these two samples come from identical populations.

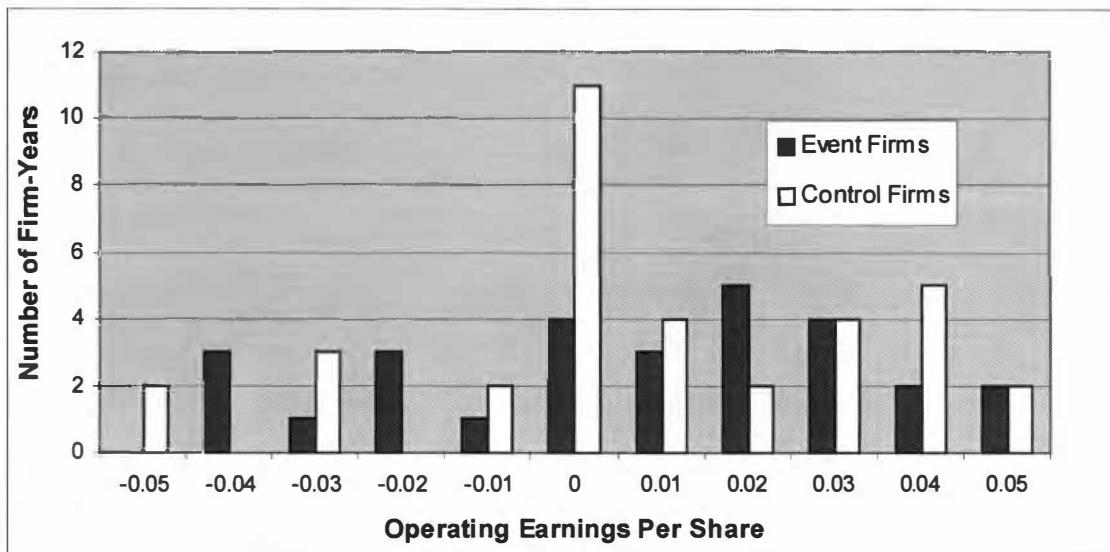


Figure A-4A. Frequency Plot of Annual Operating Earnings for All Firm-Years. Frequency plot of annual operating earnings (Compustat #57) for all event and matched control firm-years that were within +/- 5 cents of the zero earnings threshold.

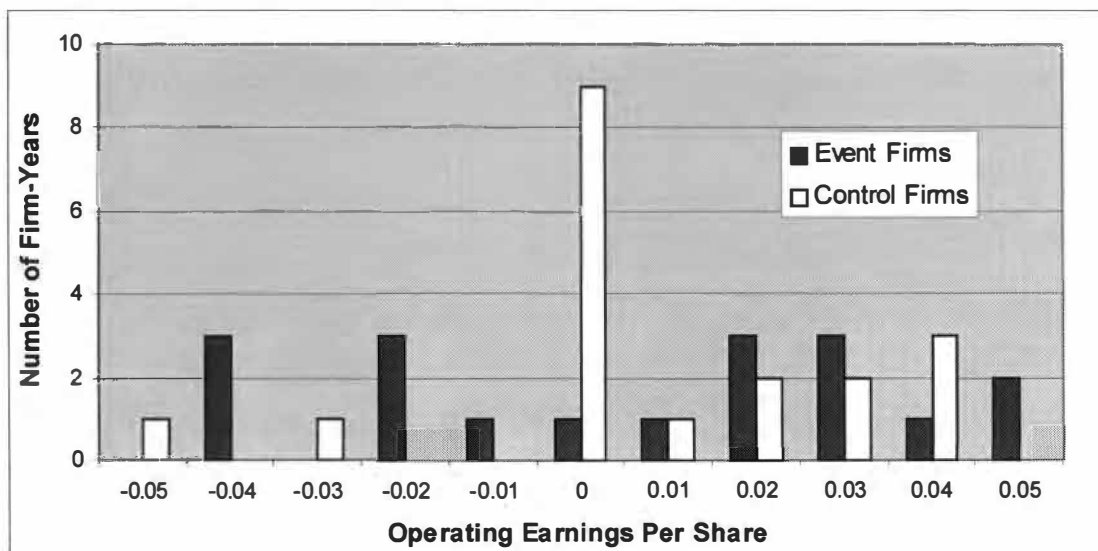


Figure A-4B. Frequency Plot of Annual Operating Earnings for All But the Last Fraud Firm-Years. Frequency plot of operating earnings (Compustat #57) for all event and control firm-years, excluding the last firm-specific fraudulent firm-years and matched control firm-years, that were within +/- 5 cents of the zero earnings threshold. .

Figure A-4. Frequency Plots of Annual Operating Earnings.

Table 5. Distribution of Earnings Around the Past Earnings Threshold.**Panels A and B**

Distribution of earnings around the past earnings threshold for event and matched control firms are presented. Past earnings adjusted EPS is calculated by current annual operating earnings (Compustat #57) minus the previous year's annual operating earnings. Panel A reports results for all event and control firm-years. Panel B reports results for all firm-years, excluding the last firm-specific fraudulent firm-year for events and controls.

Panel A: All Fraud Firm-Years (See Note 1)					
EPS:	< -0.05	-0.05 to -0.01	At zero	0.01 to 0.05	> 0.05
Events:	161	8	5	16	125
	51.1%	2.5%	1.6%	5.1%	39.7%
Controls:	117	20	8	20	150
	37.1%	6.3%	2.5%	6.3%	47.6%
315 event firm-years and 315 control firm-years					

Panel B: All But Last Fraud Firm-Years (See Note 2)					
EPS:	< -0.05	-0.05 to -0.01	At zero	0.01 to 0.05	> 0.05
Events:	72	5	2	10	77
	43.4%	3.0%	1.2%	6.0%	46.4%
Controls:	63	10	7	9	77
	38.0%	6.0%	4.2%	5.4%	46.4%
166 event firm-years and 166 control firm-years					

Note1: Both ANOVA and Kruskal-Wallis test are able to reject that these two samples come from identical populations at the 1% level of significance.

Note 2: Neither the ANOVA, nor Kruskal-Wallis tests are able to reject that these two samples come from identical populations.

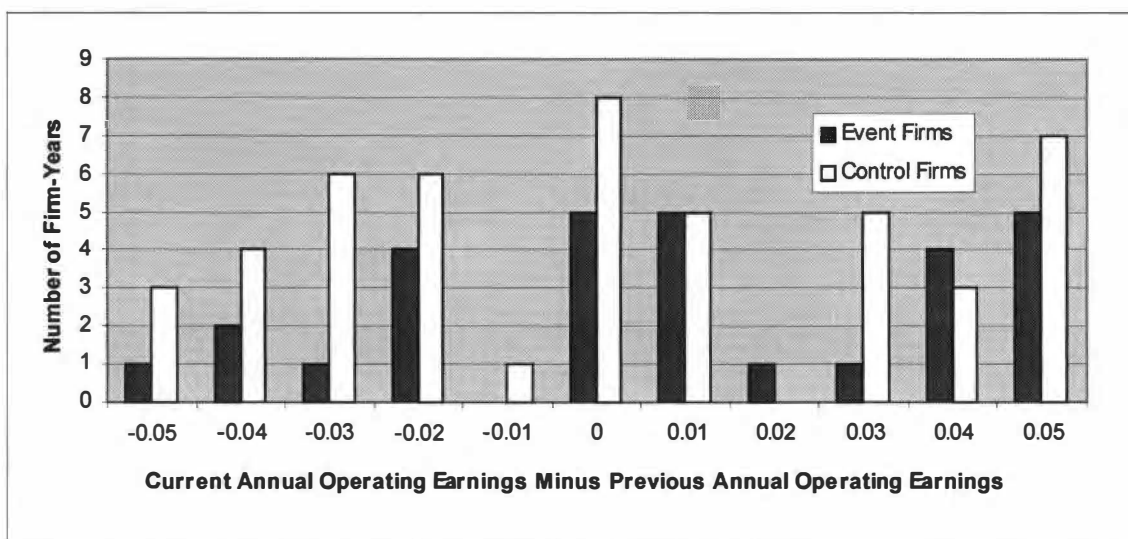


Figure A-5A. Frequency Plot of Annual Operating Minus Past Operating Earnings for All Firm-Years.

Frequency plot of current annual operating earnings (Compustat #57) minus past annual operating earnings for all event and matched control firm-years that were within +/- 5 cents of the past earnings threshold.

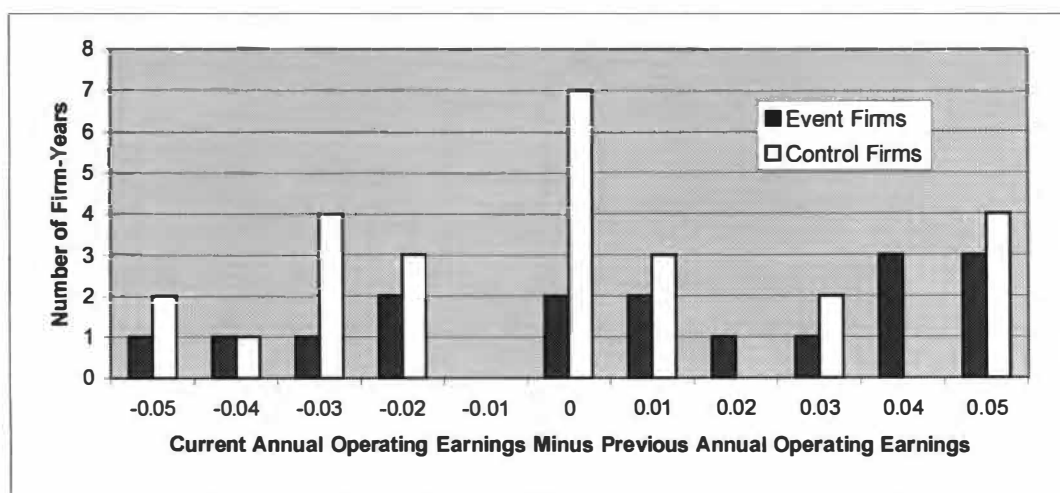


Figure A-5B. Frequency Plot of Annual Operating Minus Past Operating Earnings for All Firm-Years.

Frequency plot of current annual operating earnings (Compustat #57) minus past annual operating earnings for all event and control firm-years, excluding the last firm-specific fraudulent firm-years and matched control firm-years, that were within +/- 5 cents of the past earnings threshold.

Figure A-5. Frequency Plots of Annual Operating Earnings Around the Past Earnings Threshold.

Table 6. Distribution of Analysts' Forecast Errors.**Panels A and B**

Distribution of analysts' forecast errors for event and matched control firms are presented. Forecast errors are calculated by IBES median earnings estimate minus operating earnings (Compustat #57). Panel A reports results for all fraud firm-years. Panel B reports results for all firm-years, excluding the last firm-specific fraudulent firm-year for events and matched controls.

Panel A: All Fraud Firm-Years (See Note 1)					
EPS:	< -0.05	-0.05 to -0.01	At zero	0.01 to 0.05	> 0.05
Events:	62	14	3	7	29
	53.9%	12.2%	2.6%	6.1%	25.2%
Controls:	32	10	5	15	53
	27.8%	8.7%	4.3%	13.0%	46.1%
115 event firms and 115 control firms					

Panel B: All But Last Fraud Firm-Years (See Note 2)					
EPS:	< -0.05	-0.05 to -0.01	At zero	0.01 to 0.05	> 0.05
Events:	15	9	1	4	18
	31.9%	19.1%	2.1%	8.5%	38.3%
Controls:	14	4	2	5	22
	29.8%	8.5%	4.3%	10.6%	46.8%
47 event firms and 47 control firms					

Note1: Both ANOVA and Kruskal-Wallis test are able to reject that these two samples come from identical populations at the 1% level of significance.

Note 2: ANOVA and Kruskal-Wallis test are able to reject that these two samples come from identical populations with p-values of 11% and 12%, respectively.

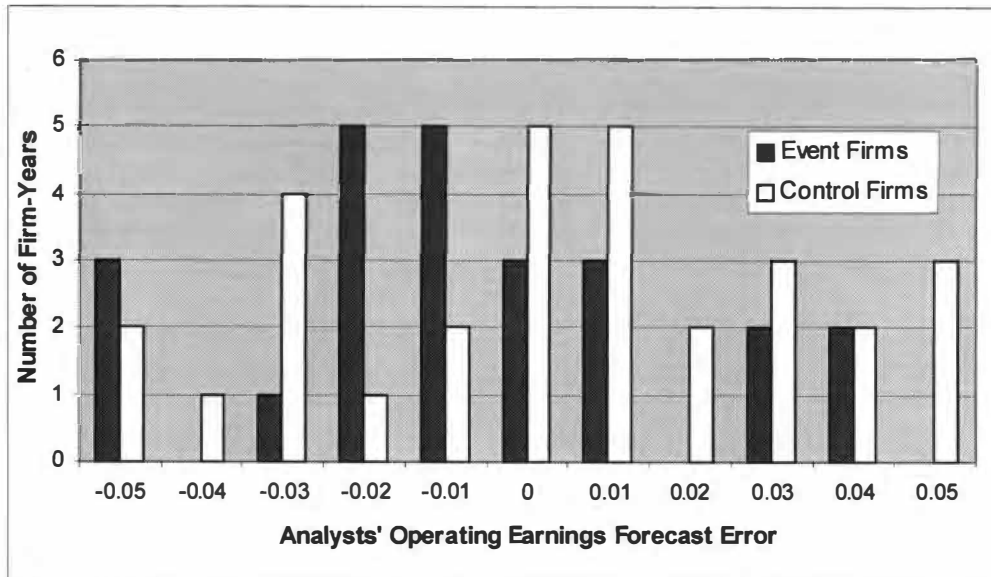


Figure A-6A. Frequency Plot of Analysts' Forecast Error for All Firm-Years. Frequency plot of analysts' forecast errors for all event and matched control firm-years that were within +/- 5 cents of the forecast error threshold. Analysts' forecast errors are calculated by IBES median earnings estimate minus operating earnings (Compustat #57).

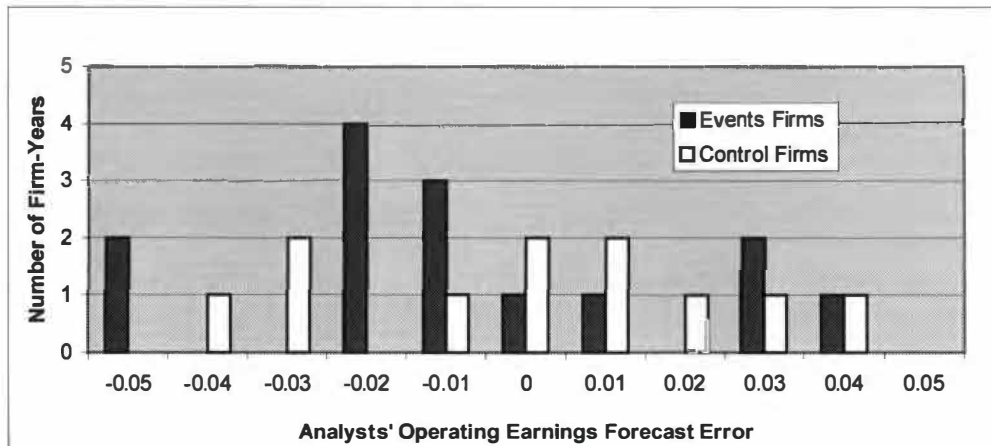


Figure A-6B. Frequency Plot of Analysts' Forecast Error for All But the Last Fraud Firm-Years.

Frequency plot of analysts' forecast errors for all event and control firm-years, excluding the last firm-specific fraudulent firm-years and matched control firm-years, that were within +/- 5 cents of the forecast error threshold. Analysts' forecast errors are calculated by IBES median earnings estimate minus operating earnings (Compustat #57).

Figure A-6. Frequency Plots of Analysts' Forecast Error Threshold.

Table 7. Composite Model Variable Definitions.

Summary statistics of event and matched sample firms one year prior to an accounting-fraud firm-year

Variable	Variable Definitions
Total Assets	Total Assets of the firm _{t-1} (#6)
Market Cap.	Market Capitalization = Share Price _{t-1} (#24) x Number of Common Shares Outstanding _{t-1} (#25)
Book to Market	Ratio of book value of total assets to the sum of book value of liabilities and preferred stock and the market value of common equity at the fiscal year-end prior to the announcement [Book to Market _{t-1} = Total Assets _{t-1} (#6) / (Total Assets _{t-1} (#6) - (Shareholders' Equity _{t-1} , (#216) - Preferred Stock Value _{t-1} (#56, unless missing then #10, unless missing then (#130)) + Market Capitalization _{t-1} (#24*#25))]
ROA	Return on Assets = Operating Income Before Depreciation _{t-1} (#13) / Total Assets _{t-1} (#6)
Profit Margin	Income Before Extraordinary Items _{t-1} (#18) / Sales _{t-1} (#12)
Total Debt to Total Assets	(Current Liabilities _{t-1} (#5) + Long-Term Debt _{t-1} (#9)) / Total Assets _{t-1} (#6)
Sales Growth	Sales Growth Rate = (Sales _{t-1} (#12) - Sales _{t-2}) / Sales _{t-2}
Cash Sales Growth	Cash Sales Growth Rate = (Cash Sales _{t-1} - Cash Sales _{t-2}) / Cash Sales _{t-2} , where: Cash Sales _{t-1} = (Sales _{t-1} (#12) - (Receivables _{t-1} (#2) - Receivables _{t-2}))
Altman's Z-Score	Altman's Z-Score = ((Earnings Before Interest and Taxes _{t-1} (#178) / Total Assets _{t-1} (#6)) x 3.3) + ((Sales _{t-1} (#12) / Total Assets _{t-1} (#6)) x 0.999) + (Market Capitalization _{t-1} (#24*#25) / Total Liabilities _{t-1} (#181) x 0.6) + (Current Assets _{t-1} (#4) - Current Liabilities, (#9)
Years covered by Compustat	As a proxy for age of the firm, the variable represents number of years that the firm reported data in Compustat.
Zero Earnings String	Number of consecutive years that operating earnings (#57) was greater than or equal to zero as of t-1.
Past Earnings String	Number of consecutive years that operating earnings (#57) was greater than or equal to the prior year's operating earnings as of t-1.
Discontinued Operations over Total Assets	Discontinued Operations over Total Assets = Discontinued Operations _{t-1} (#66) / Total Assets _{t-1} (#6)
Merger/Acquisition Binary	Merger/Acquisition Binary = 1 if the firm underwent a merger/acquisition year t-1 (footnote code #1), 0 otherwise
Merger/Acquisition Contribution to Income	Merger/Acquisition Contribution to Income = Merger/Acquisition Contribution to Income _{t-1} (#248) / Net Income _{t-1} (#172)
Merger/Acquisition Contribution to Sales	Merger/Acquisition Contribution to Sales = Merger/Acquisition Contribution to Sales _{t-1} (#249) / Sales _{t-1} (#12)
Accounting Change Binary	Accounting Change Binary = 1 if the firm underwent an accounting change (footnote code #1, 5, 6, 9, 10, 12, 20, 23, and 30) in year t-1, 0 otherwise
Flow Through Investment Tax Credit Binary	Flow Through Investment Tax Credit Binary = 1 if the firm used Flow Through Investment Tax Credit (footnote code #8) year t-1, 0 otherwise
Straightline Depreciation Binary	Straightline Depreciation Binary = 1 if the firm used Straightline Depreciation (footnote code #15) year t-1, 0 otherwise
Replacement Cost Inventory Binary	Replacement Cost Inventory Binary = 1 if the firm used Replacement Cost Inventory Valuation Method (#59) year t-1, 0 otherwise
Standard Cost Inventory Binary	Standard Cost Inventory Binary = 1 if the firm used Standard Cost Inventory Valuation Method (#59) year t-1, 0 otherwise
Retail Method Inventory Binary	Retail Method Inventory Binary = 1 if the firm used Retail Method Inventory Valuation (#59) year t-1, 0 otherwise
Average Cost Inventory Binary	Average Cost Inventory Binary = 1 if the firm used Average Cost Inventory Valuation Method (#59) year t-1, 0 otherwise
Specific Identification Inventory Binary	Specific Identification Inventory Binary = 1 if the firm used Specific Identification Inventory Valuation Method (#59) year t-1, 0 otherwise
FIFO Inventory Binary	Replacement Cost Inventory Binary = 1 if the firm used Replacement Cost Inventory Valuation Method (#59) year t-1, 0 otherwise
Stock Issuance Binary	Stock Issuance Binary = 1 if the firm issued equity the year t-1, 0 otherwise
Stock Issuance Proceeds over Market Cap.	Stock Issuance Proceeds over Market Cap. = Equity issued the year prior to an Accounting-Fraud Firm-Year / Market Capitalization _{t-1} (#24*#25)

Table 8. Composite Model Variable Summary Statistics.

Summary statistics of event and matched sample firms one year prior to an accounting-fraud firm-year

	Accounting Fraud Firms		Matched Firms		t statistic mean test (p value, two-tailed)		z score median test (p value, two-tailed)	
Variable	(n = 162)		(n = 162)					
	mean	median	mean	median				
Total Accruals by B/S	0.014	0.000	-0.036	-0.027	3.90	(0.0001)	2.44	(0.0147)
Working Capital over Total Assets	0.279	0.281	0.303	0.312	-0.93	(0.3533)	-0.67	(0.5056)
Total Assets	1584.9	72.3	508.7	66.0	2.45	(0.0152)	0.22	(0.8244)
Total Debt to Total Assets	0.500	0.517	0.449	0.422	2.06	(0.0412)	2.66	(0.0078)
Profit Margin	-0.035	0.038	0.001	0.036	-1.41	(0.1614)	0.22	(0.8244)
Cash Flow over Total Assets	0.018	0.045	-0.025	0.022	2.57	(0.0110)	1.33	(0.1831)
Sales Growth	0.412	0.271	0.175	0.091	4.26	(0.0000)	4.66	(0.0000)
Cash Sales Growth	0.365	0.271	0.250	0.121	1.61	(0.1094)	3.33	(0.0009)
Book to Market	0.625	0.598	0.716	0.710	-2.74	(0.0069)	-2.66	(0.0078)
Altman's Z-Score	5.438	3.198	5.256	3.385	0.15	(0.8820)	-0.67	(0.5056)
Time covered by Compustat	7.660	6	9.846	7	-4.66	(0.0000)	-2.37	(0.0176)
Zero Earnings String	3.840	3	5.352	3	-2.87	(0.0046)	0.12	(0.9017)
Past Earnings String	0.840	0	0.914	1	-0.60	(0.5461)	-0.67	(0.5055)
Discontinued Operations over Total Assets	-0.005	0	-0.004	0	-0.37	(0.7139)	0.02	(0.9838)
Merger/Acquisition Binary	0.352	0	0.142	0	4.66	(0.0000)	4.37	(0.0000)
Merger/Acquisition Contribution to Income	-1.025	0	-0.028	0	-0.97	(0.3357)	0.44	(0.6601)
Merger/Acquisition Contribution to Sales	0.050	0	0.024	0	1.88	(0.0614)	2.17	(0.0301)
Accounting Change Binary	0.136	0	0.154	0	-0.52	(0.6030)	-0.47	(0.6365)
Flow Through Investment Tax Credit Binary	0.333	0	0.278	0	1.74	(0.0833)	1.08	(0.2785)
Straightline Depreciation Binary	0.833	1	0.759	1	1.67	(0.0962)	1.65	(0.0984)
Replacement Cost Inventory Binary	0	0	0.006	0	-1.00	(0.3188)	-1.00	(0.3173)
Standard Cost Inventory Binary	0.006	0	0.037	0	-1.91	(0.0586)	-1.91	(0.0564)
Retail Method Inventory Binary	0.006	0	0.006	0	0.00	(1.0000)	0.00	(1.0000)
Average Cost Inventory Binary	0.093	0	0.099	0	-0.19	(0.8534)	-0.19	(0.8504)
Specific Identification Inventory Binary	0.037	0	0.006	0	1.91	(0.0586)	1.91	(0.0564)
FIFO Inventory Binary	0.642	1	0.512	1	2.40	(0.0177)	2.36	(0.0184)
Stock Issuance Binary	0.130	0	0.049	0	2.54	(0.0119)	2.53	(0.0115)
Stock Issuance Proceeds over Market Cap.	0.022	0	0.009	0	1.95	(0.0533)	2.53	(0.0115)

Table 9. Composite Model Logistic Regression Results.

Logistic regression results to distinguish accounting-fraud firms (n = 162) from a matched sample (n = 162)

Independent variables		predicted odds ratio value		Dependent variable = 1 for accounting fraud firms, 0 for matched firms						
Intercept	odds ratio	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	p-value		72.6%	35.5%	55.6%	54.5%	88.1%	40.2%	39.7%	
Total Accruals by B/S	odds ratio	> 1	34.854	178.156	190.318	90.344	93.853	72.822	62.162	
	p-value		0.1%	3.2%	2.7%	6.7%	6.6%	10.1%	11.4%	
Working Capital over Total Assets	odds ratio	< 1		1.000	0.913	0.753	1.096	1.488	1.401	
	p-value			100.0%	89.4%	68.2%	89.8%	59.2%	65.2%	
Total Assets	odds ratio	< 1		1.000	1.000	1.000	1.000	1.000	1.000	
	p-value			5.1%	5.4%	1.4%	1.0%	0.4%	0.4%	
Total Debt to Total Assets	odds ratio	> 1		1.478	1.995	2.156	2.399	1.765	1.703	
	p-value			58.3%	36.2%	31.8%	26.3%	48.6%	51.3%	
Profit Margin	odds ratio	< 1		0.924	1.220	1.252	1.238	1.096	1.075	
	p-value			91.1%	77.7%	75.8%	77.4%	91.0%	92.9%	
Cash Flow over Total Assets	odds ratio	< 1		0.123	0.086	0.160	0.163	0.188	0.204	
	p-value			21.1%	14.3%	30.6%	31.1%	37.2%	39.6%	
Sales Growth	odds ratio	> 1		11.225	13.505	12.621	8.497	6.890	6.171	
	p-value			0.1%	0.0%	0.1%	0.4%	1.0%	1.7%	
Cash Sales Growth	odds ratio	< 1		0.270	0.210	0.185	0.187	0.224	0.237	
	p-value			2.6%	0.6%	0.4%	0.4%	1.1%	1.5%	
Book to Market	odds ratio	< 1			0.637	0.658	0.601	0.596	0.597	
	p-value				27.7%	32.6%	24.5%	25.0%	25.6%	
Z-Score	odds ratio	< 1			1.023	1.028	1.032	1.022	1.021	
	p-value				30.9%	25.5%	18.9%	37.4%	39.2%	
Time covered by Compustat	odds ratio	< 1				0.919	0.921	0.918	0.920	
	p-value					0.4%	0.7%	1.2%	1.4%	
Zero Earnings String	odds ratio	> 1				0.999	0.992	0.999	0.997	
	p-value					96.7%	79.6%	98.4%	92.1%	
Past Earnings String	odds ratio	> 1				0.937	0.969	0.968	0.956	
	p-value					53.5%	76.9%	76.9%	69.0%	
Discontinued Operations over Total Assets	odds ratio	> 1					0.858	0.470	0.483	
	p-value						96.2%	81.8%	82.5%	
Merger/Acquisition Binary	odds ratio	> 1					2.377	2.972	3.005	
	p-value						1.0%	0.3%	0.2%	
Merger/Acquisition Contribution to Income	odds ratio	> 1					0.997	1.000	0.999	
	p-value						95.1%	99.9%	99.1%	
Merger/Acquisition Contribution to Sales	odds ratio	> 1					6.616	8.116	8.263	
	p-value						8.6%	6.5%	6.3%	

Table 9. Continued.

Independent variables		predicted odds ratio value		Dependent variable = 1 for accounting fraud firms, 0 for matched firms					
Accounting Change Binary	odds ratio	> 1						0.867	0.859
	p-value							70.4%	69.1%
Flow Through Investment Tax Credit Binary	odds ratio	> 1						1.113	1.088
	p-value							71.8%	77.9%
Straightline Depreciation Binary	odds ratio	> 1						1.637	1.691
	p-value							13.6%	11.6%
Replacement Cost Inventory Binary	odds ratio	< 1						0.000	0.000
	p-value							99.0%	99.0%
Standard Cost Inventory Binary	odds ratio	< 1						0.524	0.539
	p-value							57.7%	59.4%
Retail Method Inventory Binary	odds ratio	< 1						1.536	1.645
	p-value							78.1%	74.7%
Average Cost Inventory Binary	odds ratio	< 1						0.685	0.685
	p-value							50.7%	50.9%
Specific Identification Inventory Binary	odds ratio	> 1						13.247	11.641
	p-value							3.0%	3.8%
FIFO Inventory Binary	odds ratio	> 1						1.773	1.772
	p-value							7.0%	7.1%
Stock Issuance Binary	odds ratio	> 1							1.331
	p-value								75.4%
Stock Issuance Proceeds over Market Cap.	odds ratio	> 1							3.158
	p-value								77.4%
Likelihood Ratio			13.686	47.240	50.626	64.230	75.358	93.621	94.752
	p-value		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Percent Correctly Classified			55.6%	59.0%	60.2%	65.1%	66.0%	65.7%	65.7%

Vita.

Samuel Lockhart Tibbs was born in Charlotte, NC on February 6, 1973. He was raised in Charlotte, NC and Dunlap, TN. After High School he joined the U.S. Navy, completing his undergraduate degree while in the service. Later he went on to complete his Ph. D. in Business Administration from the University of Tennessee.