FINANCIAL STATEMENT MISREPRESENTATION: COULD INVESTORS DETECT IT?

Deliah Leonie Kwasitsu
Bachelor of Management (B.Mgt.)
The University of Lethbridge, Alberta, Canada

Certified General Accountant (CGA)
Certified General Accountants Association of Alberta
Calgary, Alberta, Canada

A Research Project
Submitted to the School of Graduate Studies
of The University of Lethbridge
in Partial Fulfillment of the
Requirements for the Degree

MASTER OF SCIENCE IN MANAGEMENT

Faculty of Management
The University of Lethbridge
Lethbridge, Alberta, Canada

August 9, 2004

Financial Statement Misrepresentation: Could Investors Detect It?

DELIAH LEONIE KWASITSU

Approved:

Supervisor: Toni Nelson, Ph.D Date:

Reader: Khalil Torabzadeh, Ph.D Date:

External Examiner: Michael Wright, Ph.D Date:
University of Calgary, Calgary, Alberta

Chair, Project Examination Committee &
Director, Graduate Programs & Research: Michael Basil, Ph.D Date:

DEDICATION

Mobieka Nakiea Lindo

"the heights [that] great men reached and kept, were not attained by sudden flight, but they while their companions slept, were toiling upward in the night."

Henry Wadsworth Longfellow

ABSTRACT

The current study is designed to develop a model to improve investors' ability to identify firms that engage in financial statement misrepresentation by carefully analyzing published financial reports. Earnings management literature indicates that financial statement information is not fully utilized by investors and that fundamental analysis provides useful information about a firm's financial performance. The study examines accruals and the components that firms commonly use to violate GAAP in order to develop a probit regression model as an early detector of financial misrepresentation. The analysis consists of a matched-paired sample of 30 U.S. fraud firms and 30 non-fraud firms extracted from the GAO and Compustat databases. The results show that an investor who is comparing two firms from the same industry may use the lower Z score of the model and improve the chances of avoiding a fraud firm by at least 23%.

ACKNOWLEDGEMENTS

To my grandmother and grandfather, Pearly and Archie Johnson, who believed in me and always encouraged me to "try with yourself, my child." And to my dad, Archie Benjamin Johnson, who has always supported me. Dad you occupy a very special place in my heart; a million thanks to you!

To my dear aunt and uncle, Pansy and Lloyd Jones, you are the "wind beneath my wings."

To Dr. Toni Nelson, my supervisor, and Dr. Khalil Torabzadeh, my reader, both of whom I thank sincerely for their relentless efforts and sacrifices that made this project feasible.

To Dr. Lishi Kwasitsu, my dear husband and greatest supporter, who I specially thank and appreciate for standing by me throughout the period of my study. Also, to Michelle Cole, my daughter, who I thank for bombarding me with emails of cheer and encouragement. To the rest of my family and relatives, words cannot express my deep appreciation for your sacrifices and understanding during this period.

My special thanks also go to the congregations of the Beulah Church of Jesus Christ Apostolic, Edmonton, Alberta and the Palace of Praise, Portland, Oregon, for their prayerful support during this time.

Finally, and most importantly, I give thanks to the God of my salvation for establishing my goings throughout this time. "He raiseth up the poor out of the dust…that he may set him with princes…" (Ps. 113, vs 7-8). In Christ Jesus lies my strength.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EPIGRAPH

Graham's observations that investors pay too much for trendy, fashionable stocks and too little for companies that are out-of-favor, was on the money. . . . Why does this profitability discrepancy persist? because emotion favors the premium-priced stocks. They are fashionable. They are hot. They make great cocktail party chatter. There is an impressive and growing body of evidence demonstrating that investors and speculators don't necessarily learn from experience. Emotion overrides logic time after time.

Dreman, D. (1996). Ben Graham was Right--Again.

I. INTRODUCTION

The Research Problem Statement

Recent, well-publicized, examples of fraudulent financial reporting have rocked North American markets with significant loss of shareholders' wealth and investors' faith in those same markets. The public press has pointed fingers at various players as having contributed to the market failures. Boards of directors, auditors, standard setters, the SEC, and investors themselves have been cited for a lack of due diligence. This project is designed to provide evidence by carefully analyzing financial reports as to whether investors could have determined that the firms were fraudulently reporting their financial position and performance. According to Lynn Turner, chief accountant of the SEC (as cited in Magrath & Weld, 2002), the "misapplication of GAAP and stretching the rules to achieve desired targets are fraudulent accounting practices" (p. 50).

The Research Purpose

The purpose of this research is to investigate selected U.S. firms that the SEC sanctioned for violating generally accepted accounting principles (GAAP), or firms that voluntarily restated their financial statements due to accounting irregularities, to determine whether investors could have detected the financial misrepresentation of these firms prior to public disclosure of the SEC censure.

The Research Objective

The objective of the current study is to attempt to answer the following research question: Could a model improve investors' ability to identify firms that engage in financial statement misrepresentation?

The Importance of the Research

Detection of financial fraud rests not only with corporate management, government regulators, and the accounting profession but also with investors. Investors are responsible for their own investment, and for investigating investment alternatives while companies are responsible for maximizing shareholders' wealth. It is the responsibility of investors not to accept financial reports purely at their face value as they know that managers may stretch the boundaries of fair reporting to the breaking point. According to Sloan (1996), investors apparently "fixate" on reported earnings. They tend to focus on earnings multipliers such as price-earnings ratios, and they have ignored the effects of cash flows. Dechow and Skinner (2000) argued that because of the way in which they respond to small discrepancies in earnings news, many investors seem to use heuristics (a simple rule of thumb indicating inability to process information) to determine firm value.

Many companies choose to manipulate earnings to meet or surpass market forecasts in order "to avoid investors' wrath and the inevitable impact on stock price when their earnings targets aren't met" (Phillips, Luehlfing, & Vallario, 2002, p. 48). They typically manipulate earnings to "grow market capitalization and increase the value of stock options"

(Levitt, 1998, ¶ 17). Serwer (2002) described this behavior as the cult of the shareholder, which started during the takeover and LBO boom of the 1980s, when corporate raiders forced CEOs to maximize shareholder value:

> the single biggest reason behind the recent spate of God-awful accounting has got to be the rise of the cult of the shareholder. Simply put, over time so much focus has been placed on levitating companies' stock prices that many executives will do almost anything--legal or otherwise--to make it happen (¶ 11).

The media and academic literature is replete with calls for investors to take ownership of their investment decisions. For example, Kahn (2002) challenged investors to become investigative, arguing that as investigators untangle the complicated accounting at Enron, the investor's own financial health depends on a good understanding of company earnings:

> The Enron collapse, the nagging questions about Tyco's accounting, the suspicion that many of America's most celebrated companies aren't nearly as profitable as they claim to be, make it imperative that you, the investor, get to the truth on earnings. When figures confound and experts confuse, you need to take a deep breath and do the math yourself. Can you? Sure (¶ 13).

This literature also discredits analysts' lack of independence and their conflict of interests. Analysts undermine their mediation role between management and the capital market by advising "management while at the same time evaluating their stocks" (Bing, 2002, p. 49). They compromise their position by owning stocks in the firms they represent and by talking "investors into buying all sorts of tech stocks they knew, or should have known, were dogs" (Norcea, 2002, ¶ 47). Dowen and Bauman (1995); Nutt, Easterwood, and Easterwood (1999); Cote (2000); and Sridharan, Dickes, and Caines (2002) discovered in their studies that analysts' reports are compromised due to optimism or economic incentives. Because analysts' reports are a major source of information for both big and small investors, these inaccurate forecasts undermine analysts' reputation and damage the efficient functioning of the capital market.

To mitigate this damage, the SEC urged investors not to rely totally on the recommendation of analysts but to do their own research. Nocera (2002) argued that "despite the constant reports of misconduct, investors can't cast all the blame for the market's troubles on the actions of CEOs and Wall Street analysts--much as they might like to" (¶ 6). Yet, investors continue to overlook their own role in business failures that deplete their wealth, typically pointing fingers at accountants and auditors (Phillips et al., 2002).

Auditors' role in business failures has also attracted adverse publicity. Since auditors often provide consulting services for the same firms that they audit, lack of independence and conflict of interests compromise the reliability of audited financial statements. For example, Madura (2004) reported that "The conflict of interests for auditors became very obvious during the demise of Enron. Its questionable accounting methods did not prevent Arthur Andersen from signing off on the audit" (p.49). The implication is that investors should do their own homework instead of relying totally on audited financial statements.

Nocera (2002) noted that the efficient functioning of the capital market requires the cooperation of everyone. This cooperative responsibility involves investors' vigilance, regulatory controls, the preparation of accurate analysts' reports, and financials that are the lifeblood of the capital market. Healy and Wahlen (1999) stated that earnings management research provides evidence of specimen firms with strong motivation to manage earnings by presenting fake financial statements prior to offering securities publicly. Prior earnings management research tended to focus on motivational factors of earnings management (Dechow, Sloan, & Sweeney, 1996), and the identification of the existence of earnings manipulation (Beneish, 1997, 1999). The current study attempts to extend this concern by examining whether ordinary investors ignored information which could have reduced their losses or prevented them from investing in the fraud firms.

The remainder of the current study is organized into five sections. The theory base for the research is stated in Section II, while section III reviews the extant literature to provide a context for the hypothesis and a framework for testing the empirical model. Section IV describes the research design and explains the sample selection procedures as well as the data collection. Section V analyzes the empirical results, and Section VI concludes the paper.

II. THEORY BASE FOR RESEARCH

Agency Theory

The theoretical framework of the current study includes both agency theory and efficient market theory. Agency theory states that as agents, managers act in ways that maximize their self-interest at cost to their principals or the owners outside the corporation, who lose shareholder value (Jensen & Meckling, 1976). The separation of ownership and control creates different risk preferences and divergent goals for managers and owners. The consequences of this divergence are referred to as agency costs. These costs include monitoring and bonding expenses incurred to prevent shirking by agents. Additional costs include cheating, oversight, laziness, excessive salaries, company expansion, and diversification that reduce the profit of owners (Donaldson, 2002). According to agency theory, there is a need for earnings management because of information asymmetry.[1] However, earnings management is two fold: one side is consistent with the interest of shareholders, while the other is not. First, earnings management is desirable when it is practised within the confines of GAAP to minimize contracting or political costs to the firm. It also enables managers to signal inside information about future cash flows through their accounting policy choices. For example, GAAP allows managers to choose different accounting treatment for the allocation of depreciation expense and inventory valuation. This discretionary authority helps managers to fulfill their responsibility for maximizing shareholders' wealth. Magrath and Weld (2002) reported that:

[1] Managers and other insiders within the firm have information advantage over outsiders, called adverse selection. Managers may shirk their responsibility and blame poor performance on factors beyond their control, called moral hazard (Scott, 2001).

> Companies have long used earnings management techniques to "smooth" earnings, a process that is typically rewarded in the stock market. For example, a 1994 *Wall Street Journal* article detailed the many ways in which General Electric smoothed earnings, including the careful timing of capital gains and the use of restructuring charges and reserves (p. 52).

Second, Healy and Wahlen (1999) argued that earnings mismanagement and fraudulent reporting occur:

> 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 (p. 368).

The SEC's definition quoted on page 1, which is applied to the current study, and that of Healy and Wahlen (1999) are consistent with the definition of the National Association of Certified Fraud Examiners (NACFE) (as cited in Dechow & Skinner, 2000). Well-publicized examples of fraudulent financial reporting have been reported by the media and academic literature. In his 2002 article, Sauer documented a fraudulent situation where:

> management at Midisoft Corporation falsely recognized as sales purchase orders obtained on an understanding that no product would be shipped until the customer gave further instructions. Midisoft then shipped product to a warehouse and obtained false documents to make it appear that the product had been delivered to customers. (p. 960).

In an exploratory study of this nature, Table 1 gives a reasonably good illustration of how earnings management progresses into fraudulent reporting (Dechow & Skinner, 2000).

TABLE 1
Earnings Management Versus Fraudulent Reporting

	Accounting Choices	"Real" Cash Flow Choices
Within GAAP		
"Conservative" Accounting	Exaggerated restructuring charges and asset write-offs Overestimation of acquired in-process R&D in purchase acquisitions Excessively aggressive recognition of provisions or reserves	Postponing sales Increasing R&D or advertising expenditures
"Neutral" Earnings	Earnings that result from the impartial process of operations	
"Aggressive" Accounting	Bad debts provision understated Provisions or reserves drawn down in an excessively aggressive way	Delaying R&D or advertising expenditures Increasing sales
GAAP Violation		
"Fraudulent" accounting	Recording false inventory Recording sales prematurely Sales invoices backdated	

Source: Adapted from Dechow and Skinner , 2000

Agency literature has informed the investigation of fraudulent firms. For example, Dechow et al. (1996) found that fraud is associated with weak internal governance structures. Using variables associated with corporate governance to proxy for agency costs, they examined corporate governance structures and identified some of the characteristics that are generally associated with earnings manipulators. They found that the fraud firms had weak internal governance structure where the founder or the CEO served as a chairman of the board or the board of directors consisted chiefly of insiders or had no audit committee or external blockholder monitoring management. This association between weak internal governance structure and earnings manipulation means that investors should pay attention to signals pertaining to governance issues.

Other empirical works on agency theory indicate that managers tend to use their discretionary authority to signal inside information or to manipulate earnings opportunistically. Since opportunistic earnings management adversely impacts the efficient functioning of the capital market, one of the main concerns of the current study is that managers could use their information advantage to deceive investors. Thus, the current study attempts to determine the extent to which asymmetric information allows managers to misrepresent their financial operations and positions in ways that investors cannot detect.

Efficient Market Theory

Efficient market theory (EMT) or efficient market hypothesis (EMH) states that the stock market may have weak, semi-strong, or strong forms of efficiency (Fama, 1970). A semi-strong form of efficiency states that all historical data and publicly available information are reflected in current prices. As new favorable or adverse information is introduced about the economy, industries, and companies, it is instantaneously impounded into the current share price. This means that an investor cannot manipulate this information to obtain abnormally high returns (Scott, 2001). Because the stock price compounds all immediate information, no stock is really overvalued or undervalued and trading enhanced by forecasting of future stock price is futile as abnormally high returns can only depend on luck (Donaldson, 2002).

Because the concept of market efficiency is controversial, it has implications for fundamental analysis. In fundamental analysis, financial variables are used to estimate the intrinsic value of a security. This analysis makes it possible to make buy or sell recommendations based on whether the current market price of a security is less or greater than its intrinsic value (Cleary & Jones, 2000). Evidence from EMT anomalies indicates that superior fundamental analysis may enable sophisticated investors to derive abnormal returns (Cleary & Jones, 2000). These anomalies arise when information in the public domain can be used to obtain abnormal returns. However, the proponents of EMT do not believe in the concept of market anomaly, claiming that investors cannot outperform the market consistently (Brown, 2001). The controversy surrounding the concept of market efficiency is due to the fact that some researchers have produced empirical results suggesting that investors have the ability to earn abnormal returns (Ou & Penman, 1989; Ou, 1990; Sloan, 1996; Nutt et al., 1999; Abarbanell & Bushee, 1997, 1998). These works largely assumed adherence to GAAP. If the EMT is descriptive of the market, then the market price should reflect all publicly available information. A finding to the contrary is anomalous to the EMT as shown in the results of the current study.

III. LITERATURE REVIEW

The following section provides an overview of the relevant research on bankruptcy, fundamental analysis, and earnings management in order to give a methodological focus to the study.

Bankruptcy Prediction Literature

Predicting the future profitability of a firm is central to its valuation and it is of primary interest to investors and stakeholders. Prior research has verified the effectiveness of fundamental financial statement analysis in determining firm performance by developing models that segregate firms into fail and non-fail categories. These models are beneficial to various stakeholders including investors, creditors, and auditors, who are susceptible to significant losses when companies fail abruptly (Boritz, 1991). In their bankruptcy models, Beaver (1966), Altman (1968), and Ohlson (1980) used financial ratios, obtained from published annual financial statements, to show that business failure can be predicted with a high degree of accuracy one to five years prior to failure. More recent publications have incorporated industry-relative data (Hill & Perry, 1996; Platt & Platt, 2002) and content analysis (Stiner, 2002) in predicting bankruptcy. Ohlson (1980), in particular, found that current liquidity, financial structure, performance, and financial ratios could predict failure within a year. In addition to financial ratios, other signals of potential business failure include changes in the market price of stocks (Beaver, 1968), poor earnings quality due to declining operating performance, and EPS (Fairfield & Whisenant, 2001). This means that astute investors, who can identify undervalued (overvalued) firms, could outperform the market by employing an investment strategy that buys (shorts) expected winners (losers).

One limitation of bankruptcy models is that they assume adherence to GAAP. Therefore, extending the bankruptcy prediction models to a situation of non-adherence to GAAP would benefit various stakeholders including investors, creditors, and auditors, who sustain significant losses when businesses fail because of non-adherence to GAAP. Such a model would operate as an early warning signal and enable investors to protect themselves by discriminating between firms that comply with GAAP vis-à-vis those firms that do not.

Fundamental Analysis Literature

The proponents of EMT claim that published financial statement information cannot be used to obtain abnormal returns while advocates of market anomalies claim otherwise. Numerous studies provide evidence showing that financial statements provide information that can be used to predict firm value. For example, investment analysis and bankruptcy models use financial statement ratios to predict firm value. Similarly, early earnings-forecasting researchers using fundamental analysis, which includes ratio analysis, found financial statement information to be significant in predicting future firm performance. Ou and Penman (1989) found that the market did not impound information contained in financial statement ratios on a timely basis nor did the market properly value qualitative information contained in annual reports (Ou 1990). In a similar study, Holthausen and Larcker (1992) documented abnormal returns based on financial ratios, although they did not succeed in replicating the Ou and

Penman (1989) model. In a subsequent study, Greig (1992) argued that abnormal returns in the models of both Ou and Penman (1989) and Holthausen and Larcker (1992) were a consequence of firm size. Abnormal returns with a six-year duration were, however, documented in a later study by Stober (1992). Lev and Thiagarajan (1993) simplified the methodological problems encountered in some of the prior studies by using 12 fundamental variables identified by analysts. After controlling for factors such as firm size effects, they concluded that the fundamentals were value-relevant in relation to excess returns. Abarbanell and Bushee (1997) compared the association between fundamental signals and changes in stock price based on nine fundamental signals developed by Lev and Thiagarajan (1993). Testing the relation between one-year-ahead change in earnings and five-year earnings growth, Abarbanell and Bushee (1997) concluded that the fundamental signals and future-earnings changes were related. In similar studies, Abarbanell and Bushee (1998) as well as Piotroski (2000) showed that fundamental signals can be used to predict future abnormal returns. This means that a careful analysis of financial statements information may help investors to earn abnormal returns. In addition, investors may earn abnormal returns by understanding the information content available from sources other than earnings. According to Sloan (1996), if investors could strategically differentiate between high and low performing firms, then they could maximize on the market's inability to distinguish between cash flows and accruals components of earnings.

Earnings Management Literature

Discretionary financial reporting is acceptable within the confines of GAAP. This type of reporting enables managers to accomplish their responsibilities to stakeholders. For example, managers may smooth earnings or manage earnings to maintain firm value when their firm's stock price is sensitive to earnings news or dramatic reactions from the market in meeting or failure to meet market-based expectations (Myers & Skinner, 1999; Abarbanell & Lehavy, 2000; Payne & Robb, 2000; Bartova, Givolyb & Haync, 2002). The example of General Electric's earnings smoothing activities, already cited on page 7, is another case in point (Magrath & Weld, 2002, p. 52). Smoothing stabilizes a firm's earnings stream thereby increasing its value. Smoothing also leads to increased accuracy in predicting future cash flows from which firm value is derived. Smoothing exists because of the importance of net income to the investment decision making of stakeholders. As a result, managers smooth earnings for various reasons including the need to meet market expectations and to prevent debt covenant violation. They also smooth earnings for external reporting purposes. For example, through external reporting, a firm can convey inside information concerning plans for long term earnings growth to its stakeholders. This sort of reporting helps the market to esteem the firm as being credible, transparent, and less risky. The market typically rewards the process of smoothing with higher market value and lower cost of capital. The EMT claims that earnings smoothing is reflected in a firm's stock price and that the market cannot be deceived by either earnings smoothing or earnings manipulation.

Smoothing, however, may evolve into abusive earnings management. See Table 1 (p. 8) for an illustration of how conservative accounting choices may deviate into GAAP non-compliance. As described above, smoothing earnings is not necessarily opportunistic. However, it becomes opportunistic when GAAP is contravened by the presentation of misleading financial results in an attempt to fool investors and other stakeholders. Managers may contravene GAAP in various ways through activities such as (1) timing of transactions, (2) method of accounting allocations, (3) classifying income as operating/non-operating income. For example, managers may record fictitious sales and create fraudulent invoices or shipping documents to conceal their act from auditors. Managers may also achieve income smoothing by switching methods of inventory valuation and depreciation allocation to other methods. But, because of disclosure requirements, this method of deception is generally ineffective. They may also capitalize advertising cost (instead of expensing it) when sales are down in order to boost the bottom line. Another smoothing technique is to classify nonoperating income, like investment income, as operating income to boost declining operating income. Myers and Skinner (1999), and Abarbanell and Lehavy (2000) found that abusive earnings management in fraud firms is not transparent to investors and analysts. As a consequence, these firms had more analysts following, reduced analyst's forecast errors, less revision of analyst's forecast, and less negative earnings. The lack of transparency on the part of analysts may be attributed to "forecast optimism".[2] Auditors who may be expected to detect GAAP violation tend to be onstrained by conflict of interests (Madura, 2004) and by restrictive audit plans (Hemraj, 2003).

[2] Analysts tend to overreact or underreact to new information which leads to a "serial correlation of surprises." This means that bad news is accompanied by more bad news; the reciprocal also holds. According to Abarbanell and Bushee (1997), "though analysts use the fundamental signals in revising their forecasts, they do not use the information in all of the signals efficiently" (p. 17).

It requires investors' vigilance to uncover earnings management and to prevent managers from exploiting the information asymmetry. Dechow, et al. (1996) noted that investors could estimate a firm's value by carefully examining the signals of accruals. Using the modified Jones Model (1995) to estimate discretionary accruals, they reported that accruals prior to AAER sanctioning were higher for the fraud firms. Figure 1 (p.18) of their paper graphically described the different behavior of accruals in the fraud firms and the non-fraud firms. The authors also pointed out that some earnings manipulators fraudulently overstated their revenue to obtain external financing at low cost or to avoid debt covenant restrictions. These are important factors that investors should pay attention to.

Although fraudulent reporting may be carefully camouflaged, this information can be ferreted out by fundamental analysis. Lee, Ingram, and Howard (1999) showed that earnings relative to operating cash flows were extremely high for the fraud firms in the prediscovery years relative to the non-fraud firms in their sample of 56 fraud cases from 1978 to 1991. They examined five years of data (three years of prediscovery fraud data and two years of postdiscovery data) to identify the period that maximizes the effect between fraud and accruals. They found that earnings minus cash flows are a useful indicator of financial fraud. Lee et al. tested a new measure of accruals (see p. 34) as a "potential indicator of fraud rather than examining variables that might be correlated with accruals" (p. 764) for the purpose of clarifying mixed results pertaining to the importance of accruals in signaling fraud. They used level variables because they were concerned about the comparative differences between the variables rather than changes in their value from one period to the next. A level variable or fundamental ratio is defined as the value of a certain indicator at a specific time. A change variable is the difference in the level ratio from one period to the next. The main difference between the current study and that of Lee et al. is that they used level variables. Change variables are used in the current study because it is assumed that fraud exacerbates and its persistence would cause the ratio to be higher. Three years of prediscovery fraud data are used to capture the distortion if fraud persists.

If opportunistic earnings management can "fool" the majority of the market, then this creates opportunity for astute investors, who can detect earnings management, to profit from the market. Detecting earnings management is, however, not easy because firms can mask operational problems with aggressive accounting techniques. Once the manipulation is detected, these firms suffer from significant price decline, implying that a prediscovery of earnings manipulation could result in abnormal returns to vigilant investors. Dechow et al., (1996) found that the stock price of manipulators fell by approximately 9%, their cost of capital increased, analysts' following decreased, short term interest rate increased, and dispersion in analysts' forecast errors increased. Perhaps, a fundamental analysis of financial reports during this period of market anomaly could be advantageous.

Because public corporations in the U.S. are characterized by a separation of ownership and control that gives rise to agency cost, information asymmetry will persist. Since investors generally rely on financial information to predict firm value, the accuracy of stock prices (a major cause of many corporate control problems) has become a controversial issue. Despite contrary claims by the EMT advocates, mixed evidence from bankruptcy, fundamental analysis, and earnings management research findings indicate that the market is anomalous and that the use of ratio analysis can earn abnormal returns. The bankruptcy and fundamental analysis literatures, however, assume that the firms are GAAP compliant. Consequently, fundamental analysis, which is employed as an analytical tool in the current study, is used to determine whether investors could differentiate between firms that engage in fraudulent financial reporting and those that do not.

Hypothesis Formulation

The hypothesis, stated in the null, is that fraudulent reporting cannot be distinguished from fairly pervasive earnings management if managers deliberately attempt to hide or distort their inside information. For example, if managers record fictitious sales and create false invoices or shipping documents, then it may be impossible for the market to uncover the deception.

H_O: Diligent investors could not detect fraudulent accounting using fundamental financial statement analysis.

IV. RESEARCH DESIGN

The objective of this section is to design a model that investors may use to detect financial statement misrepresentation from publicly available information. To avoid the complexity of sophisticated accruals-based models with inadequate applicability, this model is designed to accommodate the ordinary investor. A matched-pair design is used in the analysis to simulate the investment strategy of an individual investor. This split sample is important to the study in determining whether investors are negligent in detecting firms whose financial reporting is fraudulent. To demonstrate the opportunities available to ordinary investors, data are extracted from the SEC database that is publicly accessible.

Sample Selection and Description

This section focuses on the sample selection and the matching of the fraud firms and the non-fraud (control) firms. A criterion for the research sample is that the fraud firms and the non-fraud firms should have ten years of data prior to the first public disclosure of the manipulation. Because the first year of fraud discovery varied for the firms and the maximum number of restatements is five years, the fifth year following or the tenth year in which no fraud occurred, is chosen to match all the firms. For example, one sample firm that violated GAAP from 1995 to 1999 and whose infraction was discovered in the year 2000 is matched on financial statement data extracted from the year 1990. The aim is to match the fraud firms and the non-fraud firms before the fraud firms were likely to have engaged in aggressive earnings management. As a consequence, the sample contains only mature firms. This means that the difference in the current sample and that of Beneish (1997, 1999) and Lee et al. may impact the comparability of the results because the samples of these researchers contained a disproportionate of number of start-up firms.

a. Selection and Description of the Fraud Firms

The sample consists of 60 publicly traded U.S. firms, including 30 fraud firms and 30 non-fraud firms. The 30 fraud firms are randomly selected from the United States General Accounting Office (GAO) Financial Statement Restatement Database 2002, GAO-03-395R. The database contains 919 announced financial statement restatements[3] for the period January 1, 1997 through to June 30, 2002. In some cases, the restatements are prompted by the fraud firms, independent auditors, or the SEC. Irrespective of the restatement initiator, the SEC investigates all accounting irregularities.[4] The GAO report includes only financial statement restatements that have material impact on a firm's financial outcome. In addition, the report includes the reasons for the restatements, the initial and subsequent announcement dates, the stock market where the company traded, the ticker symbol, and the source that instigated the restatement. The GAO stated that its database was released to the public in response to numerous requests from academics and researchers, who found the database to be a useful resource for financial statement restatement information.

[3] According to the GAO, "financial statement restatement occurs when a company, either voluntarily or prompted by auditors or regulators, revises public financial information that was previously reported" (p. 1).

[4] The GAO defines accounting irregularity as "an instance in which a company restates its financial statements because they were not fairly presented in accordance with GAAP. This would include material errors and fraud" (p. 2).

TABLE 2
Sample Selection Procedure and Industry Distribution for the Fraud Firms

Financial statement restatements issued between 1997 and 2002 (GAO 2002 database)	919
Eliminate multiple financial statement restatements	(79)
Total number of firms available	840

SIC Codes	Industry Distribution	Total Firms Available	%	Firms Available Readjusted	%	Research Sample	%
1000-1999	Mining, oil, and construction	21	2.50%	13	4.39%	1	3.33%
2000-2999	Commodity production	105	12.50%	46	15.54%	5	16.67%
3000-3999	Manufacturing	213	25.36%	87	29.39%	9	30.00%
4000-4999	Transportation and utilities	66	7.86%	31	10.47%	3	10.00%
5000-5999	Wholesale and retail trade	90	10.71%	35	11.82%	4	13.33%
6000-6999	Financial services	111	13.21%	33	11.15%	3	10.00%
7000-7999	Business and personal services	183	21.79%	41	13.85%	4	13.33%
8000-8999	Health and other services	48	5.71%	10	3.38%	1	3.33%
9000-9999	Public administration	3	0.36%	0	0.00%	0	0.00%
Total Firms		840	100.00%	296	100.00%	30	100.00%
	Further eliminated:						
	firms missing from Compustat	(137)					
	firms with incomplete informati	(407)					
	Total sample of firms available	296					

Because of the exploratory nature of the study, only 30 fraud firms are selected from the GAO database for empirical analysis. The small number of firms keeps the analysis at a reasonably manageable level. The sample selection procedure and the industry classification of the 30 fraud firms are summarized in Table 2. First, the total sample of 919 GAO financial statement restatements is imported into the Compustat database (Table 2). Seventy-nine (79) financial statement restatements are eliminated because these firms made more than one restatement announcements. To avoid duplicate count, only the restatement made prior to the first public disclosure is maintained for each firm. Consequently, the research sample is selected from 840 firms. Second, 137 firms missing from the Compustat database are further eliminated. Third, the remaining sample of 703 firms is checked in the Compustat database for availability of financial statement information. Four hundred and seven (407) firms with incomplete financial information are further eliminated by this procedure thereby reducing the GAO list to 296 firms (Table 2). This elimination is partly due to the ten years of data used to ensure that the fraud firms are matched to the non-fraud firms prior to income manipulation (see p.18). The 296 firms are stratified into eight strata using a two-digit SIC code and the 30 frauds firms are selected from this list. Table 2 illustrates how the 30 firms are selected from each stratum based on the strata's percentage representation of the remaining sample population.

The fraud firms are distributed across 64 two-digit SIC industries in the selected sample. Table 2 illustrates the industry distribution of the firms. In the "Total Firms Available" column, the manufacturing industries group (SIC 3000-3900) is the most prominent with 25% or 213 firms. This is followed by the business and personal services industry (SIC 7000-7900) with 21% or 183 firms. Financial services (SIC 6000-6900) is next with 13% or 111 firms, followed by commodity production (SIC 2000-2900) with 12% or 105 firms. Of the two-digit SIC code, computers (SIC 35; part of the manufacturing sector) is the most prominent, followed by electrical equipment ex computer (SIC 36) in second place. In the business and personal services sector, 185 firms belong to SIC 73 of which software (SIC 7372) has 90 firms. Dechow et al. (1996) and Beneish (1997) ranked the manufacturing industry, and the business and personal services industry in a similar way.

As shown in Table 2, the industry composition of the current research sample closely reflects the population from which the fraud firms are drawn (or the GAO list). These firms (in the current research sample) misrepresented their financial statements during the period 1998 to 2002. In the "Research Sample" column, the manufacturing industry ranks first with 30% or 9 firms, while the commodity production industry ranks second with 16% or 5 firms. The business and personal services industry, and the wholesale and retail trades both rank third with 13% or 4 firms each. The persistency of financial institutions drops to 10% or 3 firms due to insufficient financial information in Compustat.

In Table 3, the 840 firms reported in the GAO 2002 database are classified into nine groups in keeping with the GAO categories as follows: (1) revenue recognition; (2) restructuring, assets, or inventory; (3) cost or expense; (4) acquisitions and mergers; (5) securities related; (6) reclassification; (7) in-process research and development (IPR&D); (8) related-party transactions; (9) other. The restatements are classified on the basis of the issue that incited the restatement. The GAO assigned multiple[5] reasons for GAAP violations (for example, a sample firm may violate GAAP on multiple issues such as improper revenue recognition, cost or expense, or reclassification) using the most material violations. The first violation listed by the GAO was the most material violation and this classification is adopted in the current study. Of the 840 firms reported in the GAO database, 38% or 321 contravened GAAP by inappropriately recognizing revenue, 14% or 118 by misclassifying cost or expense

[5] Of the 840 firms reported by the GAO database for contravening GAAP, 155 firms cited multiple GAAP violations. For example, in the "Revenue recognition" category, 51 firms violated GAAP on numerous accounting issues such as improper revenue recognition, improper classification of accounting items, and improper recording of cost of goods sold. Other violations are: "Restructuring, assets, or inventory" category: 53 firms; "Cost or expense": 12 firms; "Related-party transaction":

charges, 13% or 113 by misrepresenting restructuring, assets or inventory charges, and 11% or 89 include other charges such as improper accounting for bad loans and loan write-offs (Table 3). A similar distribution is maintained throughout the research sample. This distribution is consistent with the evidence from the SEC, academic research, and the media (Levitt, SEC, 1998; Magrath & Weld, 2002; the GAO, 2002).

Table 3
Sample Description by Type of GAAP Violation, 1997 to 2002

	GAO Full Sample	%	GAO Adjusted Sample	%	Research Sample	%
Revenue recognition	321	38.21%	114	38.51%	11	36.67%
Restructuring, assets, or inventory	113	13.45%	44	14.86%	4	13.33%
Cost or expense	118	14.05%	40	13.51%	3	10.00%
Acquisitions and mergers	56	6.67%	17	5.74%	0	0.00%
Securities related	51	6.07%	12	4.05%	2	6.67%
Reclassification	32	3.81%	11	3.72%	2	6.67%
IPR& D	33	3.93%	15	5.07%	2	6.67%
Related-party transactions	27	3.21%	11	3.72%	2	6.67%
Other	89	10.60%	32	10.81%	4	13.33%
	840	100.00%	296	100.00%	30	100.00%

Note: "Other" includes improper accounting for bad loans, loan write-offs, and other unspecified irregularities

Earnings restatement should be an uncommon event but over the past 5 years, it has become a growing problem that investors are concerned with. In 2002, the GAO reported a dramatic increase in financial statement restatements. The current study finds a similar increase. Using 1997 as a base year, the number of firms which were required to restate their financial statements increased by 116% or from 92 to 199 firms between 1997 and 2001. The biggest single jump happened in 1999 with firms making restatements increasing from 95 to

10 firms; "Acquisitions and mergers": 9 firms; "securities related": 9 firms; "Reclassification": 5 firms; "IPR&D": 1 firm;

160. Two things may account for the increase in the number of firms that were identified as misrepresenting their financial statements. The first is that more firms are engaging in fraud. The second is that the SEC has become more vigilant and aggressive in identifying and sanctioning those firms that provide misleading financial statement information.

b. The Matched-pair Design

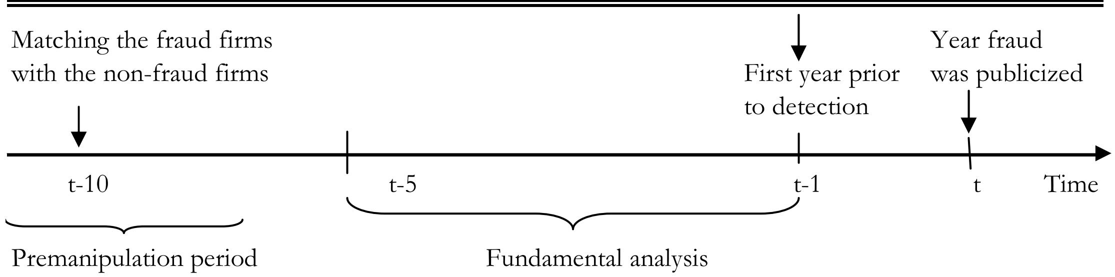
A matched-pair sample design is selected to compare the fraud firms and the non-fraud firms. This research design is chosen because (1) it makes it possible to simulate the strategy of an individual investor, who is comparing two unknown firms from the same industry (and is unlikely to compare all firms in the industry). This design also helps to (2) filter out the effects of the excluded variables that are not under observation in the current study. Another reason is that these variables are equally likely to appear in both the fraud firms and the non-fraud firms. For example, industry or size may be used as a predictor of fraud, and matching on them may nullify their potential effect. Matched-pair samples are typically used to estimate the population difference between two groups (Kohler, 2002). The matched-pair sample design is not the only acceptable approach but it is convenient and appropriate for the current research question. Since the research sample is small, adding variables for size and industry is problematic. Yet those variables are known to impact the various ratios.

The year in which the annual report of the fraud firm is restated for irregularities in prior years is designated as time t (Figure 1), and matching is done on the tenth year prior to

"Other": 5 firms.

this date, t-10 (see p. 18). The financial statement variables are measured on the basis of the last U.S. 10-K filing released prior to restatement, t-1.

Figure 1
Matching and Research Process Timeline



There are limitations associated with the type of matching technique reported in Table 4. Zmijewski (1984) associated the "oversampling" of distressed firms and sample selection bias with matching techniques that splits the data proportionately. In a study of bankrupt firms, he found that selection bias and the infrequent nature of bankruptcy produced biased estimated coefficients, resulting in inaccurate classification and prediction error rates. In addition, the design introduces nonrandom sampling because of the matching criteria described on p. 25. In a subsequent study, Platt and Platt (2002) supported Zmijewski's (1984) findings but found his empirical test to be weak. They agreed that a sample size closely reflecting the population would solve the problem. Consequently, it is possible that some bias may occur in the results of the current study because it splits the sample 50-50 between the fraud firms and the non-fraud firms.

d. Selection of the Non-fraud Firms

The selection of the non-fraud firms is contingent upon the classification of the fraud firms and the matched-pair design. The non-fraud firms are selected from the Compustat database and checked against the GAO 2002 list. These firms are not listed in the GAO database and they are not known to have been charged with accounting irregularities during the period under review. The U.S. 10-K filings of each non-fraud firm are also checked for fraudulent restatement and the firms that have restated due to financial misrepresentation are excluded from the research sample.

For each of the 30 fraud firms in the sample, a non-fraud firm that is GAAP compliant and with financial statements available in Compustat is identified based on the following criteria:

(1) Industry - The non-fraud firm is from the same four-digit SIC industry similar to that of the fraud firm.

(2) Sales and Total Assets - The non-fraud firm has sales and/or total assets similar to that of the fraud firm.

(3) The selected non-fraud firm has 10 years (see p.18) of available data which includes the restatement years of the fraud firm. For example, if a fraud firm restated in the year 2001, then data for matching should be available for the year 1991.

Table 4 reports the results of the t-test and the nonparametric Wilcoxon Mann-Whitney test for the means and medians which were calculated to determine whether significant differences exist between the samples. The descriptive statistics and the test of differences (t-test and Wilcoxon) show that the fraud firms and the non-fraud firms are homogenous based on total assets and sales at year $_{t-10}$ and size is not expected to be a factor.

Table 4
Descriptive Statistics Matching Fraud and Non-fraud Firms Ten Years Prior to Manipulation, 1988 to 1992

	Fraud Firms	Non-fraud Firms	Test of Differences
	Mean Median Standard Deviation	Mean Median Standard Deviation	t-test Wilcoxon p-value*
Sales	534.567	527.291	0.976
	139.841	129.021	0.929
	920.777	982.688	
	N = 30	N = 30	N=30
Total Assets	430.427	405.301	0.895
	162.621	114.664	0.836
	755.095	718.928	

Note: *p-value = two-tailed test

Data Collection

To test the fundamental signals, data for the fraud firms and the non-fraud firms are extracted from two sources. Detailed historical financial statements information for the non-fraud firms is extracted from the Compustat 2002 database, while the U.S. 10-K filings for the fraud firms are extracted from the SEC's database. Since Compustat restates financial statement numbers to reflect restatement adjustments, the original U.S. 10-K information filed with the SEC, which is the information that investors could easily access prior to the public announcement of financial statement misrepresentation, is used for the restatement years. The data available to investors prior to the publication of financial statement fraud are crucial to answering the research question posed by the current study.

Description of Fundamental Signals

A set of fundamental signals or independent variables (used interchangeably) identified from prior research is used to model the relationship between earnings, operating cash flows, and accruals as indicators of financial statement misrepresentation. The fundamental signals are chosen because of their popularity in both the media and academic literature. Three years of data is used in the current study because it is difficult to identify a single period that maximizes the effect that fraud has on cash flows or earnings. Selecting only those years in which the accruals variable is at its highest in the analysis would imply that the presence of high accruals equate to fraud. Using periods longer than three years would mask the association between fraud and accruals or nullify the effect (Lee et al.). The investor, is also assume to analyze at least three years of data before making an investment decision.

The variables are averages of the three years preceding public disclosure of the financial statement misrepresentation. The averages are used to obtain accurate ratios because of the variations that occur in financial data from one statement period to the next. The ratio is computed for each of the three years under review and then averaged. The use of averages is in keeping with Poitras, Wilkins, and Kan (2002), who used three-year averages as opposed to individual year because the three-year averages produced more meaningful results. As the purpose of this exploratory research is to develop a model that individual investors could use to detect fraud firms, the three-year averages are particularly appropriate to the study because investors can calculate them fairly easily. In the case of a probit model, investors only have to calculate once for each firm as opposed to a firm-year observation which requires separate calculations for each year under review. The use of three-year averages is expected to generate meaningful information on the relationship between fraud and the accruals measure. The three-year averages include pre-manipulation data of 60% or 18 fraud firms that did not restate for the entire three consecutive years. According to Dechow and Skinner (2000) (Table 1), firms with fewer than three years restatement are likely to engage in aggressive earnings management, which is a precursor to earnings manipulation. Only 20% or six firms restated for more than three years. Because all the misstated years for the majority of the observations are included in the analysis, the likelihood of observing differences between the fraud and the non-fraud sample is maximized.

As described in Table 5, the fundamental signals developed below from prior research and the media are incorporated into a probit model in order to identify a set of financial variables that investors may use for fraud detection. The variables are reported on a firm's financial statement and they are easy to compute. This section discusses the fundamental signals and their predicted signs along with the descriptive and bivariate statistical tests that are performed prior to incorporating the financial variables into a probit model:

1. *Underlying Constructs*

Proxies for earnings, cash flows, and accruals are used in deriving several of the independent variables employed in subsequent testing. These key variables are defined as follows:

a. EBEI - earnings before extraordinary items (Compustat #123). This definition excludes non-recurring items, extraordinary items, and discontinued operations thereby making it a realistic measure of the level of cash flows and accruals (Sloan, 1996). EBEI is the best estimate for forecasting future earnings and its use in the current study is consistent with prior earnings management literature (Dechow et al., 1996; Collins & Hribrar, 2000; Phillips, Pincus, & Rego, 2003).

b. Cash Flows From Continuing Operations (CFCO) – the difference between cash flows from operating activities (CFO) (Compustat #308) minus cash flows from extraordinary items and discontinued operations (EIDO) (Compustat #124) included in CFO (CFO – EIDO). EIDO is removed from CFO to obtain a cash flow from continuing operations and it is the same concept used for EBEI, since neither extraordinary items nor discontinued operations are indicative of future cash flows. CFO is taken from the Statement of Cash Flows. It is in keeping with the direct method, SFAS 95 (FASB, 1987) that requires disclosure of cash from operations. Prior to SFAS 95, the balance sheet method was the only choice. Recently, Collins and Hribrar (2000) used both the direct and the balance sheet methods to calculate estimates of cash flow from operations. They then used each measure to determine total accruals, after which they tested each measure of total accruals in the modified Jones model. The results showed that the direct method provided a better estimate of total accruals and consequently discretionary accruals than the traditional balance sheet method.

c. Total Accruals (TotAcc) - the difference between earnings before extraordinary items and cash flows from continuing operations (EBEI – CFCO). In prior studies, total accruals are computed using the balance sheet method. This method is based on the changes in the working capital balance sheet accounts and the accrual components of revenues and expenses on the income statement. The current study makes use of the information required in the Statement of Cash Flows because it is found to be superior to the traditional method. The direct method of calculating total accruals is as follows:

$$TotAcc_t = EBEI_t - CFCO_t$$

2. Independent Variables

a. Accruals

Accruals, which comprise a discretionary and a nondiscretionary component, consist of revenues and expenses not represented by cash flows and the discretionary component is commonly used in earnings management to meet managers' objectives (Dechow et al., 1995, 1996; Myers & Skinners, 1999; Payne & Robb, 2000; Abarbanell & Lehavy, 2000). As discretionary accruals are susceptible to managerial manipulation, this component is measured to detect financial statement misrepresentation. Unlike normal accruals which reverse, accruals that are fraudulent have the tendency to perpetuate until they are discovered.

Discretionary accruals are also associated with measurement errors and problems of data requirements. These errors occur because discretionary accruals, which are unobservable, are usually estimated. Many studies have used the Jones models (1991 & 1995) to estimate discretionary accruals. They employed a long time series regression of total accruals on information for each firm or a cross-sectional regression within specific industries. This method makes the Jones models complex. Because the current study is designed to make it possible for ordinary investors to estimate accruals fairly easily, it is not necessary to estimate discretionary accruals or to segregate total accruals into its different components. This approach facilitates the research question and ensures accessibility of data that can be easily calculated by the ordinary investor. The proxies developed for accruals are TAcc, daeAcc, and CPIT and they are operationalized as follows:

i. Total Accruals (TAcc) - Beneish (1997, 1999) found that fraud is correlated with total accruals which proxy for discretionary accruals. The fraud firms' accruals are expected to be more positive or less negative than those of the non-fraud firms because managers can use their discretionary judgment to inflate earnings. Recording fictitious sales will also affect earnings and other current asset accounts. TAcc is computed as the three-year average of TotAcc scaled by lagged total assets (TA) to minimize the effect of firm size and it is operationalized as follows:

$$TAcc = \frac{1}{3}\sum_{t-1}^{t-3} \frac{TotAcc_t}{TA_{t-1}}$$

where TA = total assets (Compustat #6) at year t-1

ii. Total Accruals (daeAcc) - daeAcc is, arguably, a better approximation of discretionary accruals than total accruals since it excludes depreciation and amortization (DAE). On average, total accruals are negative largely because of DAE. Depreciation is a cost allocation and does not represent a source or use of future cash from operations. While some portion of depreciation may be discretionary, disclosure standards make its use less likely in financial statement misrepresentation. As an alternative to TAcc and analogous to Lee et al., DAE is added back to EBEI to model and compare the relationship between earnings and operating cash flows as another measure of accruals. The operating performance of a firm may be discerned from this signal. The second measure of accruals (daeAcc[6]), is computed as TotAcc plus DAE, as shown in the formula below:

$$Accr_t = (TotAcc_t + DAE_t)$$

[6] Lee et al. used the balance sheet approach to calculate daeAcc while the current study uses the direct approach.

where DAE = depreciation and amortization (Compustat #14) at time t. The three-year average of daeAcc scaled by lagged TA is operationalized as follows:

$$\text{daeAcc} = \frac{1}{3}\sum_{t-1}^{t-3} \frac{\text{Accr}_t}{\text{TA}_{t-1}}$$

iii. Current Portion of Income Tax (CPIT) - is an exploratory examination in which current income tax rates are used as a proxy for discretionary accruals. Firms are unlikely to manage earnings using accruals that will increase the amount of tax payable. On the other hand, firms may use accruals to increase taxes payable when loss carry-forward would otherwise be lost; this action leads to lower current tax expenses. In addition, the computation of income tax provides managers with less discretion because it is less susceptible to manipulation. Therefore, when cash flows are declining, managers may prefer to use accruals adjustments such as lower valuation allowances that do not affect the tax return. Since income tax regulation allows less reporting discretion and relies more on realized cash flows, lower income tax rates signal greater use of accruals in computing financial statement income. Lower income tax rates are expected for the fraud firms relative to the non-fraud firms.

Unlike Phillips, Pincus, and Rego (2003), who used deferred tax expense to proxy for discretionary accruals, and Dhaliwal, Gleason, and Mills (2002), who used changes in tax expense to proxy for missed earnings target, the current model uses the proportion of CPIT to pretax income as a proxy for earnings management. CPIT is a component of total taxes reported in a firm's U.S. 10-K filings with the SEC; it may also be computed as the difference between total taxes and deferred taxes. This third measure of accruals is calculated as a three-year average of CPIT divided by the absolute value of PTI to smooth out differences in incentive to manage earnings either upward (downward) and it is operationalized as follows:

$$CPIT = \frac{1}{3}\sum_{t-1}^{t-3} \frac{CPIT_t}{\left|PTI_t\right|}$$

where CPIT = current portion of income tax at year t

PTI = pretax income (Compustat #17) at time t

b. Income Smoothing

The income smoothing literature provides two relatively new proxies for income smoothing (ESm1, ESm2). They are tested as indicators of financial statement misrepresentation. The measures may help investors to detect whether accruals are being used to smooth volatility in income in order to conceal poor firm performance. Because these income smoothing measures are used as exploratory measures in the current study, they may function differently from the results of Leuz, Nanda, and Wysocki (2003). The measures are computed as time series analysis with five years of data (starting at year t-1 to t-5) that are easily accessible to investors and can be computed using an Excel spreadsheet:

i. ESm1 - if firms engage in financial misrepresentation in order to mask declining performance, the standard deviation of earnings is expected to be small relative to the standard deviation of cash flows which cannot be easily smoothed artificially. ESm1 is calculated to measure the extent to which components of accruals are used to smooth reported earnings. Because earnings smoothing reduces variability in a firm's earnings stream, managers may employ earnings smoothing to signal the amount of future earnings that investors can anticipate or to camouflage deteriorating financial performance. If managers are controlling earnings volatility, then the value of this measure is expected to be lower for the fraud firms. Similar to Leuz et al. (2003), the measure is calculated as the standard deviation of EBEI divided by the standard deviation of CFCO (both EBEI and CFCO are scaled by lagged TA) and it is operationalized as a three-year average as follows:

$$ESm1 = \frac{1}{3}\sum_{t-1}^{t-3} \frac{\sigma\, EBEI_t}{\sigma\, CFCO_t}$$

where, σ = standard deviation

ii. ESm2 – Leuz et al. stated that cash flows and earnings are negatively correlated even without income manipulation. If cash is slow coming in, AR and payables will both increase. If fraud is undertaken to mask failing performance any short-fall in cash must be off-set by income-increasing accruals if earnings are to be maintained or to imply growth. Consequently, changes in CFCO and changes in TAcc are expected to be negatively correlated. This measure is expected to reveal the extent to which managers misrepresent their financial performance by inflating reported earnings. Highly negative correlation between changes in cash flows and changes in accruals would suggest more aggressive smoothing (Leuz et al.). ESm2 is expected to be lower for the fraud firms. It is calculated as the Spearman Rho correlation coefficient of the three-year average of changes in CFCO and changes in TAcc (both CFCO and TAcc are scaled by lagged TA) and it is operationalized as follows:

$$ESm2 = 1/3 \sum_{t-1}^{t-3} \rho(\Delta CFCO_t, \Delta TAcc_t)$$

where ρ = Spearman Rho correlations

Δ = change

c. Free Cash Flow

Free Cash Flow (Free-C) is designed to capture a firm's ability to fund on-going property plant and equipment (PP&E) needs from current operations. A fraud firm that capitalizes major repair expenses can improve cash from operations but PP&E would increase. Consequently, this measure is expected to capture the impact of the fraudulent behavior on cash. Even if some firms fail to capitalize expenditures in PP&E, those firms that resort to misrepresentation may be less likely to generate enough cash from operations to fund on-going capital equipment needs. In this case, a signal indicating higher Free-C is expected to reduce the probability of fraud. On the other hand, as the requirement for external financing increases with highly negative Free-C, these firms may be motivated to misrepresent their financial statement information (Dechow et al, 1996). Because they are financially strapped, if the firms are not actively replacing operating assets or selling assets to fund current operations during the misstatement period, then the results for Free-C may not be strong. While Dechow et al. (1996) measured average capital expenditure (CAPX) prior to manipulation, in the current study the measurement of CAPX includes the manipulation years.

CAPX is defined as investment in PP&E reported under investing activities on the statement of cash flows. Average CAPX is used since CAPX is lumpy across time. Free-C is expected to be lower for the fraud firms relative to the non-fraud firms but the result may differ from that of Dechow et al. (1996). The measure is computed as the difference between CFCO and average CAPX over three years scaled by lagged current assets[7] (CA) and it is operationalized as follows:

$$\text{Free-C} = \frac{1}{3}\sum_{t-1}^{t-3} \frac{\text{CFCO} - \left(\frac{1}{3}\sum_{t-1}^{t-3}\text{CAPX}\right)}{\text{CA}_{t-1}}$$

where PP&E = net property, plant and equipment

CAPX = capital expenditure (Compustat #128)

CA = current assets (Compustat #4)

d. Change Variables

This section examines change variables in relation to revenue fraud and other specific measures that the media and academics believe that firms use to violate GAAP. The measures are expected to convey crucial information about a firm's fundamentals and may be useful early warning signals about a firm's performance. Change variables are incorporated in the current study because of the assumption that fraud exacerbates. They are applied in accordance with Beneish (1997, 1999). The assumption is that because fraud exacerbates the change variables of the fraud firms will be higher on average than those of the non-fraud firms; otherwise there may be no difference. When the fraudulent activity is a nonrecurring event or does not evolve overtime or if it is corrected in the next year, then the ratio itself may be higher but the change may be lower. These variables are components of accruals and are used to capture recurring financial statement fraud:

i. Days Sales in Receivables Index (DSRI) - significant imbalances between changes in accounts receivable relative to sales are usually associated with fraudulently activities. Academics and the media have cited revenue inflation as the most prevalent reason for restatement (Dechow et al., 1996; Beneish 1997; Palmrose, & Scholz, 2000; Palmrose, Richardson, & Scholz, 2001; Magrath & Weld, 2002). The GAO also reported that 38% or 321 firms in its study (Table 3) falsified revenue, while 33% or 306 firms reported by the Financial Executive Institute (FEI) falsified revenue during

[7] In keeping with Dechow et al. (1996), Free-C is scaled by CA to control for differences in the magnitude of CA which represents the readily available funds to the firm such as short-term investments or cash.

the period 1977 to 2000. Because revenue is frequently overstated by manipulating sales, examining its relationship to accounts receivable (AR) is crucial to the current study. Since AR is directly affected by revenue, one way to examine this relationship is to determine whether changes in AR are in line with changes in sales (Compustat # 12), as shown in the formula below. Because accruals for fraudulent sales are not accompanied by increased cash flows in the future (as accruals perpetuate until discovered in these cases), AR relative to sales accelerates. For example, unscrupulous managers may book nonexistent sales to inflate revenue so that earnings targets can be met. Loebbecke, Eining, and Willingham (1989) reported that 14% of the fraud firms in their sample used AR account to misstate their financial statement. A material increase in the ratio indicates that a firm's AR may be overstated (Beneish 1997, 1999). On the other hand, substantial increases in AR relative to sales may be attributed to the firm’s difficulties in collecting its AR. The firms may also have adopted a more liberal credit policy.

DSRI is expected to be positive and significantly higher for the fraud firms than for the non-fraud firms. The results may, however, differ from those of Beneish (1997, 1999), whose computation is derived from the first year of misrepresentation. While Beneish (1997, 1999) captured distortion in DSRI using a single year of misrepresentation, over a three-year period this distortion may not be captured if the fraud does not perpetuate or if it is a single event of insignificant magnitude. The three-year average of change in the ratio of AR to sales at year t to the corresponding change in the ratio AR to sales at year t-1 and it is operationalized as follows:

$$DSRI = \frac{1}{3}\sum_{t-1}^{t-3} \frac{AR_t \,/\, Sales_t}{AR_{t-1} \,/\, Sales_{t-1}}$$

where AR = accounts receivable (Compustat # 2) at time t.

ii. Inventory (INV) - inventory is another common method used to misrepresent earnings. For example, managers may book nonexistent INV or deliberately overvalue inventory thereby magnifying fraud because accruals do not reverse in these situations. According to Loebbecke et al. (1989), INV accounted for 22% of the fraud firms in their sample. In order to determine whether inventory and sales are out-of balance, their relationship is examined in the current study. The ratio is expected to be positive and significantly higher for the fraud firms than for the non-fraud firms if fraud perpetuates, and it is of significant magnitude over the three-year period. This computation is a three-year average of the ratio changes in INV to sales at year t to the corresponding ratio changes in INV to sales in year t-1 and it is operationalized as follows:

$$INV = \frac{1}{3}\sum_{t-1}^{t-3} \frac{INV_t \,/\, Sales_t}{INV_{t-1} \,/\, Sales_{t-1}} - 1$$

where INV = inventory (Compustat #3) at time t.

iii. Sales Growth Index (SGI) - when stock price reduces significantly because market expectations are not met, high growth firms are more inclined to violate GAAP in order to dissipate the impression that their growth is deteriorating (Abarbanell & Lehavy, 2000; Payne & Robb, 2000; Bartova et al., 2002). Though rapid growth is not necessarily due to fraudulent activities, it is a strong motivation for fraud because it pressures managers to maintain their financial position "in a market that is unforgiving of companies that miss their estimates" (Levitt, 1998, p. 3). In their 1989 study, Loebbecke et al. found that high growth firms accounted for 29% of their sample of fraud firms. Beneish (1997, 1999) also found that high growth is positively related to manipulation. Similarly, findings of high sales growth in the current study would be appropriately construed as an indicator of fraud. If a fraud firm is attempting to maintain a certain level of sales growth, then continuous recording of the fraudulent sales will cause the change ratio to become larger each year the fraud exacerbates. On the other hand, if the fraud is a one-time event then the change ratio will not become disproportionately larger each year; instead it may become lower. The results of the current study would, however, be different from those of Loebbecke et al. as well as from those of Beneish (1997, 1999) because the fraud samples of these researchers contain a large number of start-up firms that frequently exhibit high growth, while the current study sampled only mature firms. The sales growth ratio is predicted to be higher and positive for the fraud firms relative to the non-fraud firms if the rapid growth results from fraud. Averaged sales growth over the three-year period covered by the current study is measured as sales in year t divided by sales at t-1 and it is operationalized as follows:

$$SGI = \frac{1}{3}\sum_{t-1}^{t-3} \frac{Sales_t}{Sales_{t-1}}$$

ii. Asset Quality Index (AQI) – in keeping with Beneish (1997, 1999), this construct measures changes in the risk of asset realization. A high ratio of intangible assets to total assets suggests an asset structure of high realization risk (Siegel, 1991). AQI calculates that portion of total assets from which future benefits are more uncertain. If significant changes in capitalized intangibles are attributed to capitalization rather than expenses, then it may mean that net income is being deprived of proper charges (Siegel, 1991). Consequently, higher values are expected to increase the probability that a firm has engaged in income manipulation. Firms that capitalize deferred charges such as advertising will have a higher AQI than firms that invest in tangible assets. According to Beneish (1999), AQI will be higher than one as a firm increasingly defers cost. Beneish (1999) also noted that since manipulators rarely engage in acquisition increases, the increase in the index is not likely to be due to goodwill arising from mergers. Therefore, if a firm fraudulently capitalizes deferred charges over time to inflate revenue, then the AQI of the fraud firms is expected to be higher relative to the AQI of the non-fraud firms. The index is computed as the change in the ratio CA plus net PP&E over TA at year t to the corresponding ratio CA plus PP&E (Compustat #8) over TA at year t-1 and it is operationalized as follows:

$$AQI = \frac{1}{3}\sum_{t-1}^{t-3} \frac{1-(CA_t + PP\&E_t)/TA_t}{1-(CA_{t-1} + PP\&E_{t-1})/TA_{t-1}}$$

iii. Leverage (LEV) - the debt[8]-to-asset ratio change variable measures the amount of debt that a firm employs to finance its projects and programs. This ratio depicts the financial structure as reflected by a measure of LEV. A relatively large amount of debt in a firm's capital structure reduces its ability to finance new projects and progressive programs relative to the firms with lower debt-to-asset ratios. This suggests that the propensity to violate GAAP increases with a high debt ratio. LEV is expected to be higher for fraud firms that expanded their use of accounts payable in order to finance continuing operations. Consequently, higher changes in LEV are expected to be an indicator of manipulation. Therefore, the leverage

[8] Total debt is both long- and short-term debt obligations. This ratio can be calculated in two ways. (1) It can be calculated as total debt (current liabilities plus long term debt) divided by total assets. This signifies the use of significant amount of short-term debt on a regular basis (for permanent finance). (2) It can be calculated as total debt (total debt or long-term debt) to signify the use of small amount of short-term debt, or the use of short-term debt on a seasonal basis by some companies.

ratio should be higher for the fraud firms than for the non-fraud firms. Dechow et al. (1996) and Beneish (1997, 1999) used this measure in the first year of the misstatement and the previous premanipulation year, while the current study uses three years of misstatement preceding the fraud discovery. This computation is a three-year average of the ratio change in CL plus LTD over TA at year t to the corresponding ratio change in CL plus LTD over TA at year t-1 and it is operationalized as follows:

$$LEV = 1/3 \sum_{t-1}^{t-3} \frac{(LTD_t + CL_t)/TA_t}{(LTD_{t-1} + CL_{t-1})/TA_{t-1}}$$

where CL = current liabilities (Compustat #5);

LTD = long term debt (LTD) (Compustat #9)

Table 5 delineates the computation of the fundamental signals that are adopted in the current study. It also provides the definitions of the constructs and their acronyms, the predicted signs for each variable and the authors who had used them.

TABLE 5
Fundamental Signals

Construct	Acronym	Computation	Predicted Sign	Applied By
Total Accruals	TAcc daeAcc	1. $TAcc = \frac{1}{3}\sum_{t-1}^{t-3} \frac{TotAcc_t}{TA_{t-1}}$ 2. $daeAcc = \frac{1}{3}\sum_{t-1}^{t-3} \frac{Accr_t}{TA_{t-1}}$	+ +	Collins and Hribrar, 2000 Lee et al., 1999
Current Tax Rate	CPIT	$CPIT = \frac{1}{3}\sum_{t-1}^{t-3} \frac{CPIT_t}{\lvert PTI_t \rvert}$	-	Exploratory
Income Smoothing	ESm1 ESm2	1. $ESm1 = \frac{1}{3}\sum_{t-1}^{t-3} \frac{\sigma\, EBEI_t}{\sigma\, CFCO_t}$ 2. $ESm2 = \frac{1}{3}\sum_{t-1}^{t-3} \rho(\Delta CFCO_t, \Delta TAcc_t)$	- -	Leuz et al., 2003
Free Cash Flow	Free-C	$Free\text{-}C = \frac{1}{3}\sum_{t-1}^{t-3} \frac{CFCO - (\frac{1}{3}\sum_{t-1}^{t-3} CAPX)}{CA_{t-1}}$	-	Dechow et al., 1996
Change Variables:				
Days Sales in Accounts Receivable	DSRI	$DSRI = \frac{1}{3}\sum_{t-1}^{t-3} \frac{AR_t / Sales_t}{AR_{t-1} / Sales_{t-1}}$	+	Beneish, 1997, 1999
Days in Inventory	INV	$INV = \frac{1}{3}\sum_{t-1}^{t-3} \frac{INV_t / Sales_t}{INV_{t-1} / Sales_{t-1}} - 1$	+	Beneish, 1997, 1999
Sales Growth Index	SGI	$SGI = \frac{1}{3}\sum_{t-1}^{t-3} \frac{Sales_t}{Sales_{t-1}}$	+	Beneish, 1997, 1999
Asset Quality Index	AQI	$AQI = \frac{1}{3}\sum_{t-1}^{t-3} \frac{1-(CA_t + PP\&E_t)/TA_t}{1-(CA_{t-1} + PP\&E_{t-1})/TA_{t-1}}$	+	Beneish, 1997, 1999
Leverage	LEV	$LEV = \frac{1}{3}\sum_{t-1}^{t-3} \frac{(LTD_t + CL_t)/TA_t}{(LTD_{t-1} + CL_{t-1})/TA_{t-1}}$	+	Beneish, 1997, 1999

Note: The variables are averages of the three years prior to public discovery of the manipulation. ρ=Spearman Rho correlation; ∈= change

Statistical Analysis

Descriptive statistics are computed for each sample firm to determine whether the means and medians of the independent variables for the fraud firms and the non-fraud firms are different (Table 5). Next, the t-test and the Wilcoxon Mann-Whitney test are used to assess differences in the means and medians of the two groups, respectively. The statistics determine whether the distributions are consistent with the samples being drawn from the same population. The p-value represents the probability of rejecting the null hypothesis that no difference exists between the samples when the null is in fact true. Subsequently, a correlation matrix for continuous variables is examined to identify variables that are highly correlated.

The probit regression model is then used to distinguish the fraud firms from the non-fraud firms. The equation for the model is described below where F, the dichotomous dummy dependent variable, represents one for the probability of fraud and zero otherwise. The constant (intercept) or parameter (slope coefficient) to be estimated on the explanatory (independent) variables is β_0 or β_1, respectively. X is the matrix of the explanatory variables, and the subscript i represents the firm being analyzed. The slope coefficient (β_1) indicates the effect of a unit change in X on the function of the probability of F and ε represents the error term:

$$F_i = \beta_0 + \beta_1 X_i + \varepsilon$$

The probit model is appropriate for the nonmetric dichotomous dependent variable fraud. As a nonlinear model, probit makes it possible to estimate models with dichotomous dependent variables. A dichotomous dependent variable violates the assumptions of normality, resulting in misleading OLS[9] estimates (Hair, Anderson, Tatham, & Black, 1998; Freund & Wilson, 2003). OLS is, therefore, not optimal for the current study. Another problem of OLS is that the estimated value of the dependent variable can occur outside the range of 0 and 1. The cumulative normal distribution attributes of probit constrain the predicted value of the dependent variable within the range 0, 1. Probit and logit are similar, except that logit uses the cumulative logistic function while probit uses the cumulative normal distribution. The left hand side of probit (in this case F) can be considered as a Z score.[10] Therefore, a unit change in X yields a β unit change in the cumulative normal probability (or Z score) that F falls into a specific category. Although logit has more diagnostic tools than probit for analyzing data, both the logit and the probit regression reach the same statistical conclusion and using either of them is a matter of personal preference.

The effectiveness of the probit regression model is tested with a cross-validation sample. The test is computed by using one part of the data to build a model (the estimation sample) in order to estimate the coefficients. The result of the estimation sample is then applied to the other part of the data (validation or holdout sample) to predict the dependent variable values for the rest of the sample. The single cross-validation method is not the only approach used for cross-validation; it is used in the current study because of its popularity and

[9] OLS means Ordinary Least Squares. It is the technique used to calculate the regression equation that minimizes the sum of the squares of the error terms. In other words, it is the difference between the observed values and the predicted values for the dependent variable (Wright, 1998).

[10] A Z score is a statistical measure of the distance a data point is from the population mean. It is calculated as: $Z=x-\Phi/\sigma$

convenience. As high multicollinearity[11] makes sample-to-sample regression coefficients unstable, the cross-validation is performed because it helps to determine the stability of the coefficients across different test models as well as the model's predictive accuracy.

According to Steckel and Vanhonacker (1993), who developed a formal test for the cross-validation of regression models using the simple random-splitting framework, splitting the data into halves is suboptimal in small samples. They recommended that more observations should be used for the estimation sample than for the validation or holdout sample and that for moderate samples ($20 \leq <100$), one-quarter to one-third validation provides a higher power. On the basis of this recommendation, the total sample of 60 firms is split into two in the current study. One subsample consisting of 40 firms (20 matched pairs) is used to estimate the model while the second subsample consisting of 20 firms (10 matched pairs) is used to estimate the model's predictive accuracy. The coefficients from the estimation sample are used to test the sensitivity of the probit model across different test models. The holdout sample tests the classificatory power of the model to determine its effectiveness as an indicator of the probability of fraud.

[11] Multicollinearity is defined as the extent to which any variable effect can be accounted for by other variables in the analysis (Hair et al.). It may cause the predictor variables to display high correlations among themselves. This condition distorts the value of the estimated regression coefficients, inflates the standard error of beta, and thus makes it more difficult to determine which predictor variable is having an effect. Multicollinearity may also be attributed to a small sample size; its occurrence in variables may compromise the robustness of a model (Leahy, 2000).

V. EMPIRICAL RESULTS

This section reports the statistical results of a sample of the fraud firms and the non-fraud firms that have not misrepresented their financial statements. First, it reports the descriptive statistics and comparisons of the sample along with the correlation matrix. Second, it discusses the stepwise selection procedure of the final regression model. Third, it discusses the results of the probit regression modeling the probability that a firm has misrepresented its financial statement. Fourth, it analyzes the results of the probit model as a classificatory tool that ordinary investors could use to discriminate risky fraud firms from less risky non-fraud firms.

Data Description

Table 6 reports the descriptive statistics of the independent variables for both the fraud firms and the non-fraud firms. Because of extreme values, the sample is winsorized to minimize their effect thereby obtaining more robust computation of the statistics. Researchers popularly use winsorization to substitute extreme values with less extreme values and it is used in the current study for the same reason. The extreme observations are trimmed by setting them to equal the limit, thereby reducing their weight without removing them from the sample. The limit, in the current study, is set equal to the mean plus (minus) three standard deviations (Summers & Sweeney, 1998). Winsorization is especially useful in a small sample, where extreme values may mask the relationship between the dependent variable and the independent variable. The results of the winsorized data are reported in Tables 6 to 11, and those of the non-winsorized data are located in Appendix A.

Table 6
Descriptive and Comparative Statistics for the Fraud and the Non-fraud Firms Using Winsorized Data

		Fraud Firms N = 30			Non-Fraud Firms N = 30				Test of Differences in	
Construct Acronym	Predicted Sign	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median	Mean Difference	Mean p-value	Median p-value
TAcc	+	-0.040	0.112	-0.047	-0.052	0.058	-0.056	0.013	0.295	0.384
daeAcc	+	0.015	0.102	0.010	0.000	0.060	0.000	0.016	0.237	0.197
ESm1	-	1.314	1.147	0.932	1.245	1.182	0.823	0.069	0.410	0.348
ESm2	-	-0.609	0.302	-0.697	-0.517	0.600	-0.837	-0.092	0.229	0.163
CPIT	-	0.365	0.445	0.327	0.325	0.315	0.328	0.040	0.344	0.370
Free-C	-	0.036	0.146	0.044	0.003	0.188	0.066	0.033	0.227	0.427
DSRI	+	1.038	0.207	1.013	1.012	0.123	1.030	0.026	0.279	0.415
INV	+	0.025	0.187	0.015	0.006	0.112	-0.010	0.019	0.316	0.027
SGI	+	1.178	0.233	1.099	1.146	0.159	1.115	0.032	0.267	0.459
AQI	+	0.029	0.067	0.018	0.004	0.055	0.008	0.025	0.059	0.061
LEV	+	1.135	0.279	1.039	1.056	0.186	1.032	0.079	0.101	0.253

Note: t-tests are used to assess differences in the means and Wilcoxon W test are used to assess differences in the medians. pvalue= one-tailed. See Table 5 for the definitions of the construct acronyms.

The reported p-value is one-tailed because the direction of the difference between the groups is predicted. As shown in Table 6, the change variables AQI (mean=0.059; median=0.061) and LEV (mean=0.101; median=0.253) show significant differences between the fraud firms and the non-fraud firms. The result is consistent with the findings of Beneish (1997, 1999). This suggests that these change variables may be used as probable early warning signals of fraud. For the change variable INV, the median (0.027) is significant but the mean (=0.316) is insignificant. AQI and LEV may provide some economic benefit to investors, but contrary to prior earnings management research the remainder of the variables are inferentially similar.

Correlation Matrix

Table 7 reports the Pearson correlation matrix for the variables of the combined sample. The table shows the variables that are co-linear and may be excluded from the final regression model. As expected, the matrix reveals correlation among many of the variables at the $p<.05$ significance level. The variables TAcc, daeAcc, and CPIT are designed to proxy for accruals. Most of the variables are correlated with TAcc and daeAcc. For example, TAcc is highly and significantly correlated with daeAcc (.919) suggesting that both variables have the same influence on the dependent variable and will be insubstantial in the same model. TAcc is, however, somewhat less strongly correlated with CPIT (.311) and the change variables SGI (.346) and AQI (.348). There is a negative correlation between TAcc, ESm1 (-.353), and Free-C (-.323). The only variables that do not correlate with TAcc are ESm2 and the change variables DSRI, INV, and LEV.

Except for ESm1, the same variables that are correlated with TAcc are also correlated with daeAcc. The matrix also shows intercorrelations among some of the variables. This means that they may not be combined in the final model because they are proxying for the same construct. As they are measuring the same phenomenon, these variables may not help in discriminating between the fraud firms and the non-fraud firms.

Table 7
Pearson Correlation for the Fraud and Non-fraud Samples Using Winsorized Data

	Construct Acronym										
	TAcc	DaeAcc	ESm1	ESm2	CPIT	Free-C	DSRI	INV	SGI	AQI	LEV
TAcc	1										
daeAcc	.919(**)	1									
ESm1	-.353(**)	-0.196	1								
ESm2	-0.169	-0.148	.406(**)	1							
CPIT	.311(*)	.381(**)	0.041	-0.080	1						
Free-C	-.323(*)	-.268(*)	-0.081	-.281(*)	0.073	1					
DSRI	0.230	0.191	-0.118	-0.096	.305(*)	-0.112	1				
INV	-0.221	-0.206	0.164	0.127	-0.173	0.026	0.135	1			
SGI	.346(**)	.391(**)	0.035	-0.147	-0.051	-0.100	0.090	0.026	1		
AQI	.348(**)	.362(**)	-0.013	-0.117	-0.002	-0.115	-0.068	-0.031	-0.241	1	
LEV	0.004	-0.119	-0.108	-0.111	-0.211	-0.229	-0.039	-0.195	0.209	0.1	1

Note: * and **correlation is significant, p=0.05 and 0.01 respectively. See the definitions of the construct acronyms in Table 5.

Selecting the Final Regression Model

Backward-stepwise Elimination Procedure

In searching for a good-fit submodel for the data, the probit backward-stepwise procedure is used in order to refine the selection of variables that strongly influence the dependent variable. This procedure is possible because the computer has an algorithm that works to figure out what combination of variables will give the highest probability of not rejecting the null when it is true. Of the several submodels estimated by this procedure, Step 6 (appendix B) contained the criteria for the best-fitting model and it was used to test the probit regression. This model contains five variables: daeAcc, Free-C, INV, AQI, and LEV. It meets the selection criteria that (1) the estimated coefficient for each variable is significant, and (2) the model's predictive accuracy is improved as a result of including the variable. This approach focuses on the explanatory power of the variables and it helps to reduce the effects of multicollinearity. Table 8 reports the results of the model and the results of the backward-stepwise regression are located in Appendix B.

Variables Eliminated

The ineffective variables are dropped from the model. Of the three accrual proxies, daeAcc is the most effective predictor of financial fraud, and it is consistent with the findings of Lee et al. TAcc and CPIT are less effective and they proxy the same construct as daeAcc. ESm1 and ESm2 are correlated with total accruals and their impact indicates that the fraud firms are not using fraudulent activities to smoothing earnings.

Of the change variables, only two variables DSRI and SGI, are eliminated. The insignificant result of DSRI is disappointing because revenue inflation is a popular citation for restatement in the media and academic literature. Not surprisingly, the results of SGI also differ from those of Beneish (1997, 1999). The disparity between the results of Beneish (1997, 1999) and those of the current study is probably due to the difference in misstatement periods. While Beneish used the first year prior to misstatement and the first misstatement year, the first three years prior to public disclosure of the fraud is used in the current study. The impact from differences in the samples is another factor in that the sample of Beneish (1997, 1999) contained a large number of start-up firms while the current study sampled only mature firms.

Probit Regression Results

This section reports the probit regression results (Table 8). Although logistic regression is also performed, its results are not reported in the current study because they are similar to the results reported in the probit regression. The analysis reports a probit model with marginally statistically significant results (p=0.073) that support the hypothesis in the alternative form. The model consists of a single accrual proxy, daeAcc and the variables Free-C, AQI, and LEV. This model provides evidence concerning the usefulness of Lee et al. daeAcc vis-à-vis other accrual proxies in detecting earnings management. The dichotomous dependent variable (which measures the actual probability of fraud) of the probit model is that a firm is either a fraud firm or a non-fraud firm. In the probit regression, the independent variables are assigned a value of one for the fraud-discovered firms and zero otherwise.

The Probit Model

This section reports the result of the probit model with daeAcc as the single measure of accruals (Table 8). The model is represented as follows:

Dependent Variable_i[12] $= \beta_o + \beta_1\text{daeAcc}_i + \beta_2\text{Free-C}_i + \beta_3\text{INV}_i + \beta_4\text{AQI}_i + \beta_5\text{LEV}_i + \varepsilon_i$ or

$\text{Fraud}=1.990 + 5.219(\text{daeAcc}) + 1.513(\text{Free-C}) + 1.785(\text{INV}) + 6.041(\text{AQI}) + 1.645(\text{LEV}) + \varepsilon_i$

This parsimonious model appears to capture the maximum information about financial statement misrepresentation, and it is potentially likely to benefit investors in their investment decision-making. The overall goodness-of-fit of the model as measured by the log

[12] Investors wishing to convert the predicted probit into probability values may do so in Excel using the following formula: $\text{NORMSDIST}(\beta_o + \beta_1\text{daeAcc}_i + \beta_2\text{Free-C}_i + \beta_3\text{INV}_i + \beta_4\text{AQI}_i + \beta_5\text{LEV}_i)$

likelihood chi-square statistic is 10.078, and it is significant at p=0.073, rejecting the null hypothesis that the coefficients for all the independent variables are all zero. The model's psuedo-R^2 is 21%. Unlike OLS models which have real R^2, in logistic and probit regression models, the Pseudo R^2 is a descriptive measure of fit. There is no exact analog of the R^2 of OLS regression for models such as probit and logit that use maximum likelihood estimators. The reason is that in these models, the Psuedo R^2 does not have a sampling distribution that allows it to be tested (Hosmer & Lemeshow, 2000).

The interpretation of the estimated probit coefficient is in the metrics of the standard normal scoring (Z score). It can be interpreted directly or converted to probabilities using the standard normal distribution table. A high Z score implies higher probability of fraud and vice versa. The sign of the coefficient indicates the direction of the effect. The positive coefficient indicates that as the ratio increases, the probability of fraud increases while the other variables are held constant. In the probit model, the coefficient of daeAcc is positive (5.219) and it is highly significant at p=0.018 (one tailed). The interpretation of the estimated coefficient suggests that for the fraud firms, one unit increase in daeAcc results in a 5.219 increase along the "fraud" spectrum. This result is consistent with the findings of Lee et al. Throughout the backward-stepwise iterations, the change variables INV (p=0.073), AQI (p=0.031), and LEV (p=0.030) show significant differences between the fraud firms and the non-fraud firms, indicating their usefulness as early detectors of fraud. For the fraud firms, these differences suggest that a unit increase in INV increases the probability of fraud as shown by the positive coefficient (1.785). The indication is that fraud may be associated with a high ratio of inventory relative to sales from one period to the next or with large and growing amounts of inventory that is out-of balance with sales. Similarly, for every unit increase in AQI, the probability of fraud increases. This means that firms engaged in income manipulation are more likely to capitalize normal expenses in this setting than those that are not. Also, the positive coefficients suggest that as LEV increases the propensity to violate GAAP increases with high debt ratio. Free-C (p=0.098) has an unexpectedly positive coefficient. This result is surprising and inexplicable. Perhaps the inclusion of components such as principal repayments on debt should have been incorporated into the calculation of this measure as firms need cash to cover principal that becomes due for payment.

Table 8
Probit Regression Results Using Winsorized Data

		The Probit Model	
Construct Acronym	Predicted Sign	Coefficient	P-value
Intercept	n/a	-1.990	0.043*
daeAcc	+	5.219	0.018
Free-C	-	1.513	0.098
INV	+	1.785	0.073
AQI	+	6.041	0.031
LEV	+	1.645	0.030
Log Likelihood			73.101
X^2 *Statistic*			10.078
p-value			0.073*
Pseudo-R^2			21%

Note: *p-value = two-tailed test. See Table 5 for the definitions of the construct acronyms

Classification Result of the Model

This section reports the classification result and the classification accuracy of the model (Table 9). The number of observations that are correctly classified as fraud and non-fraud are reported in the "Number Classified Correctly" column of the table. The corresponding number of fraud firms misclassified as non-fraud firms and the number of non-fraud firms misclassified as fraud firms are reported in the "Number Classified Incorrect" column. The corresponding number correctly classified as fraud firms vis-à-vis non-fraud firms is reported in the "Percentage Classified Correctly" column. The purpose of the model is to provide a framework for rational-investment decision making in a market of imperfect information. The model uses the probabilities derived from the computed value of the probit regression reported in Table 8 to segregate the fraud firms from the non-fraud firms. Table 9 shows two results. First, at a cutoff value of 0.5, the model correctly classifies 67% of the total firms in the population. The firms with predicted probability above 0.5 are classified as fraud firms and those below 0.5 are classified as non-fraud firms. Although a cutoff value of 0.5 is a popular threshold in this type of research, this threshold is arbitrary and not necessarily ideal as is the case in the current study, where an investor's decision is based on a pairwise comparison. Pairwise, that is comparing a fraud firm to its matched non-fraud firm, the model correctly classifies 80% of the fraud firms in the population. Pairwise uses the converted Z score or the predicted probability to rate the firms. Since a high Z score means a higher probability of fraud, an investor, who is comparing two firms from the same industry, may use the lower probability score of the model and improve the chances of avoiding a fraud firm by at least 30%. On the other hand, an investor who relies on simple heuristics has only a 50-50 chance of distinguishing a fraud firm from a non-fraud firm. While this is a simple rule of thumb it controls for industry difference in ratios and the variables included in the model are frequently used as indicators of financial performance. The predictive accuracy of the model is subsequently assessed on a validation sample, and it is described below in the "Validation Sample Result" section.

Table 9
Probit Model Actual Classification Result Using Winsorized Data

	Total Number of Firms	Number Classified Correctly	Number Classified Incorrectly	Percentage Classified Correctly	Percentage Classified Incorrectly	Fraud Pairwise % Correct	Fraud Pairwise % Incorrect
Fraud	30	18	12	60	40	80%	20%
Non-fraud	30	22	8	73	27		
Total	60	40	20	67	33		

***Estimation and Validation* Sample Results**

This section reports the sensitivity of estimated coefficients to the estimation sample and the ability of the model to correctly classify firms in the holdout sample. To test for robustness across different samples, the estimation model is rerun 10 times with 10 random samples of 20 fraud firms and their matched-non-fraud firms (a total of 40 firms) using random numbers generated in Excel. Likewise, the holdout sample with 10 fraud firms and their matched-non-fraud firms (a total of 20 firms) is rerun 10 times simultaneously with the estimation sample. The holdout sample is discussed in more detail in the next section under "Validation Sample Result."

Estimation Sample Result

Table 10 reports the results of the descriptive statistics and sensitivity of the estimation sample. The statistics reported in the table consist of the mean, standard deviation, and median of the estimated coefficient for each variable. Although the results are robust, there are some variations in the magnitude of some of the estimated coefficient means and medians (daeAcc, mean=5.894; median=5.256). The sensitivity of the results reported in the matrix indicates how often each coefficient is significant throughout the ten iterations and how often the predicted sign of each remains correct. For example, the variable daeAcc is significant throughout 60% (p=0.05) of the iterations and its predicted sign is 100% correct in all the iterations. Except, for Free-C, the predicted signs of the variables remain consistent throughout the iterations. The statistical significance of the variables throughout the iterations, however, was much higher at the 10% significance level than at the 5% significance level. Despite the variations, the result supports the findings reported in Table 8 which demarcate between fraudulent and non-fraudulent financial reporting.

Table 10
Descriptive Statistics and Sensitivity of Results for the Estimation Sample Using Winsorized Data

Construct Acronym	Mean	Standard Deviation	Median	Predicted Sign	Significant at 10 Percent Level	Significant at 5 Percent Level	Significant at 2.5 Percent Level
Intercept	-1.767	1.060	-1.499	n/a	40%*	20%*	10%*
daeAcc	5.894	2.603	5.256	100%	80%	60%	50%
INV	1.313	0.860	1.060	100%	30%	10%	0%
Free-C	1.555	0.432	1.557	0%	20%	0%	0%
AQI	6.735	2.532	6.458	100%	60%	60%	30%
LEV	1.443	0.973	1.155	100%	40%	30%	10%

Note: *indicates two-tailed test.

Validation Sample Result

This section reports the classification results of the probit validation model (Table 11). The coefficient estimates in each of the estimation probit model are used to calculate the probability of fraud for the 20 holdout samples (10 matched-pairs) excluded from the estimation sample. The estimated probabilities from the 20 holdout samples, consisting of both the fraud firms and the non-fraud firms, are used to test the model's predictive ability. Table 11 reports two results. First, at a cutoff value of 0.5, the model correctly classifies 62% of the total firms in the population. Second, pairwise, the model correctly classifies 73% of the fraud firms in the population. The model may decrease the probability of investing in a fraud firm to 27% from 50%.

Table 11
Probit Model Predicted Classification Result Using Winsorized Data

	Fraud N=10	Non-fraud N=10	Fraud
	Percent Classified Correctly	Correctly	% Pairwise Correct
	<.5	>.5	
Sample 1	60%	40%	60%
Sample 2	60%	50%	80%
Sample 3	80%	70%	60%
Sample 4	30%	70%	80%
Sample 5	60%	40%	70%
Sample 6	80%	60%	80%
Sample 7	40%	90%	80%
Sample 8	70%	80%	80%
Sample 9	50%	80%	70%
Sample 10	60%	70%	70%
Total	59%	65%	73%
Overall	62%		73%

VI. CONCLUSION

The current study examines the issue of whether by carefully analyzing financial reports and other publicly available information, investors could determine that firms are fraudulently reporting their financial position and performance. A matched-pair design is used in the analysis to simulate the investment strategy of an individual investor, who is comparing two unknown firms from the same industry (and is unlikely to compare all firms in the industry). The analysis reports a model that is marginally statistically significant at p=0.073. These results support the hypothesis in the alternative form that diligent investors could improve their chances of detecting fraudulent accounting by using fundamental financial statement analysis. The model indicates that taken together, the variables daeAcc, Free-C, INV, AQI, and LEV provide an increased ability to separate fraud firms from non-fraud firms. The results indicate that daeAcc is consistent with the probability that the fraud firms may have used accruals to fraudulent manage earnings relative to the non-fraud firms. The fraud firms demonstrate larger and growing amounts of inventory relative to sales than the non-fraud firms. They also show higher probability of misclassifying normal expenses as indicated by changes in the asset quality index and higher debts than the non-fraud firms. However, of the five variables, only AQI and LEV have independent discriminatory power. As a classificatory tool, the model correctly classifies 73% of the observations. This means that an investor, who is comparing two unknown firms from the same industry, may use the lower Z score of the model and improve the chances of avoiding a fraud firm by at least 23%.

This final model contains important information that may benefit ordinary investors in making investment decisions relating to fraud firms and non-fraud firms. This model is potentially useful because if an investor uses it to make investment decision the market may function more efficiently. Because this model has not correctly classified all fraud firms in the population, it means that some fraud firms may be able to hide their misconduct. Investors should not entirely rely on the model but consider it in conjunction with other factors connected with fraud risk such as the work of Dechow et al. (1996) which indicates that governance issues are also important indicators of fraud. Despite the exploratory nature of the current study and the fact that the results must be considered within its limitations, the financial ratios show that an individual investor, who uses this model may be able to uncover financial statement misrepresentation. The findings of the current study provide justification for further investigation in order to ascertain whether a larger sample would provide a more robust model for detecting financial statement misrepresentation.

Contributions

This examination of the role and responsibility of investors in getting the truth of corporate earnings would help to fill some of the gaps in the relevant literature. Although the study is based on a small sample, it has produced results that are consistent with those of Lee et al. and Beneish (1997, 1999), who used much larger samples. The matched-pair design is fairly informative and may have been more effective over a larger sample. The results of the current study provide new insights into the understanding of the problem of abusive earnings management. Since the result is not unequivocally conclusive, it provides justification for further investigation in order to ascertain whether a larger sample would provide a more robust model for detecting financial statement misrepresentation.

Limitations of the Study

As with any exploratory study, there are limitations with the current investigation. First, the study is restricted to a relatively small sample of fraud firms located in the U.S. only. Second, the study sampled only mature firms and firms whose fraudulent cases were publicly disclosed thereby making it difficult to determine their representativeness relative to all firms that may be involved in earnings manipulation. Third, the probit model is restricted to a population that is split 50-50. These constraints mean that the research results cannot be generalized back to the sample population.

Suggestions for Future Research

Developing models that naïve investors could use to detect earnings management is inadequately researched. Future research should focus on how to develop robust models for investors. This investigation should attempt to expand the current study by selecting large samples of firms from multiple geographies. This sort of sample could yield superior results. Future research on earnings management should also focus on the relative return that naïve investors could obtain from using a model than relying solely on analysts' forecast.

APPENDIX A

Table 6A
Descriptive Statistics and Comparison of Means for the Fraud and Non-fraud Samples Using Non-winsorized Data

		N = 30 Fraud Firms			N = 30 Non-fraud Firms					
Construct Acronym	Predicted Sign	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median	Mean Difference	t-test p-value	Wilcox W p-value
TAcc	+	-0.031	0.139	-0.047	-0.052	0.058	-0.056	0.021	0.449	0.779
daeAcc	+	0.019	0.128	0.004	0.004	0.057	-0.002	0.015	0.566	0.813
ESm1	-	1.319	1.164	0.932	1.254	1.209	0.823	0.066	0.831	0.701
ESm2	-	-0.609	0.302	-0.697	-0.513	0.611	-0.837	-0.096	0.443	0.322
CPIT	-	0.454	0.900	0.327	0.325	0.315	0.328	0.129	0.462	0.745
Free-C	-	0.036	0.146	0.044	0.001	0.193	0.066	0.035	0.437	0.859
DSRI	+	1.046	0.232	1.013	1.012	0.123	1.030	0.034	0.479	0.836
INV	+	0.037	0.226	0.015	0.006	0.112	-0.010	0.030	0.511	0.052
SGI	+	1.190	0.270	1.099	1.146	0.159	1.115	0.044	0.441	0.906
AQI	+	0.027	0.073	0.017	0.003	0.059	0.007	0.025	0.157	0.121
LEV	+	1.153	0.341	1.039	1.056	0.186	1.032	0.097	0.176	0.506

Note: t-tests are used to assess differences in the means and Wilcoxon W test are used to assess differences in the medians. p-value= one-tailed. See Table 5 for the definitions of the construct acronyms.

Table 7A
Spearman Rho Correlation Matrix for the Combined Fraud and Non-fraud Sample Using Non-winsorized Data

	Construct Acronym										
	TAcc	daeAcc	ESm1	ESm2	CPIT	Free-C	DSRI	INV	SGI	AQI	LEV
TAcc	1										
daeAcc	.903(**)	1									
ESm1	-.428(**)	-.310(*)	1								
ESm2	-0.224	-0.112	.601(**)	1							
CPIT	0.164	0.169	-0.051	-0.17	1						
Free-C	-.348(**)	-.361(**)	-0.067	-0.062	.272(*)	1					
DSRI	0.184	0.108	-0.089	-0.171	0.182	-0.121	1				
INV	0.062	0.043	0.052	0.149	0.079	-0.114	0.117	1			
SGI	.364(**)	.408(**)	-0.047	-0.071	0.003	-0.079	0.155	-0.195	1		
AQI	-0.162	-0.116	0.084	.272(*)	0.004	0.155	0.115	0.054	0.132	1	
LEV	0.032	-0.025	0.046	-0.018	-0.241	0.237	-0.120	-0.11	.282(*)	.294(*)	1

Note: * and **correlation is significant at the p = 0.05 and p = 0.01 (2-tailed) respectively.
See Table 5 for the definitions of the constructs and their acronyms.

Appendix B

Table 8A
Backward-stepwise Elimination Result

		Intercept	Tacc	daeAcc	ESm1	ESm2	CPIT	DSRI	INV	SGI	Free-C	LEV	AQI	Log Likelihood	X^2 Statistic	p-value
Step 0	Coefficient	-2.128	-0.543	8.884	0.257	-0.311	-0.371	0.703	1.890	-1.410	2.020	2.187	7.455			
	p-value	0.325	0.466	0.099	0.103	0.250	0.268	0.319	0.075	0.126	0.097	0.024	0.020	70.464	12.713	0.313
Step 1	Coefficient	-2.063		8.380	0.263	-0.315	-0.369	0.673	1.895	-1.401	2.036	2.161	7.499			
	p-value	0.311		0.012	0.078	0.246	0.269	0.323	0.074	0.127	0.093	0.021	0.019	70.472	12.708	0.241
Step 2	Coefficient	-1.402		8.116	0.243	-0.346	-0.258		1.974	-1.257	1.777	2.010	7.658			
	p-value	0.324		0.012	0.087	0.223	0.316		0.063	0.142	0.100	0.020	0.017	70.676	12.502	0.187
Step 3	Coefficient	-1.626		7.331	0.222	-0.315			2.019	-1.083	1.671	2.002	7.193			
	p-value	0.226		0.010	0.100	0.240			0.059	0.168	0.109	0.020	0.019	70.904	12.274	0.139
Step 4	Coefficient	-1.594		7.476	0.180				1.989	-1.023	1.981	2.123	6.719			
	p-value	0.233		0.008	0.135				0.059	0.176	0.060	0.015	0.023	71.394	11.784	0.108
Step 5	Coefficient	-2.375		5.871	0.151				1.817		1.765	1.814	6.109			
	p-value	0.029		0.012	0.173				0.076		0.074	0.024	0.029	72.252	10.926	0.091
Step 6	Coefficient	-1.990		5.219					1.785		1.513	1.645	6.041			
	p-value	0.043		0.018					0.073		0.098	0.030	0.031	73.101	10.077	0.073
Step 7	Coefficient	-1.573		4.360					1.594			1.287	6.708			
	p-value	0.081		0.031					0.094			0.054	0.017	74.771	8.407	0.078
Step 8	Coefficient	-1.245		3.625								1.030	6.058			
	p-value	0.148		0.055								0.092	0.026	76.558	6.620	0.085
Step 9	Coefficient	-0.124		3.207									6.307			
	p-value	0.479		0.076									0.022	78.377	4.800	0.091
Step 10	Coefficient	-0.069											4.395			
	p-value	0.684											0.061	80.574	2.604	0.107
Step 11	Coefficient	0.000														
	p-value	1.000														

REFERENCES

Abarbanell, J. S., & Bushee, B. J. (1997). Fundamental analysis, future earnings, and stock prices. Journal of Accounting Research, 35(1), 1-24.

Abarbanell, J. S., & Bushee, B. J. (1998). Abnormal returns to a fundamental analysis strategy. The Accounting Review, 73(1), 19-45.

Abarbanell, J. S., & Lehavy, R. (2000). Can stock recommendations predict earnings management and analysts' earnings forecast errors? Unpublished manuscript, University of North Carolina, NC.

Altman, Edward I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 23(4), 589-609.

Bartova, E., Givolyb, D., & Haync, C. (2002). The rewards to meet or beat earnings expectations. Journal of Accounting and Economics, 33, 173-204.

Beasley, M. S. (1996). An empirical analysis of the relation between the board of director composition and financial statement fraud. The Accounting Review, 71(4), 443-465.

Beaver, W. H. (1966). Financial ratios as predictors of failure. Journal of Accounting Research, 4(Suppl. 3), 71-111.

Beaver, W. H. (1968). Market prices, financial ratios, and the prediction of failure. Journal of Accounting Research, 179-192.

Beneish, M. D. (1997). Detecting GAAP violation: Implications for assessing earnings management among firms with extreme financial performance. Journal of Accounting & Public Policy, 16(3), 271-309.

Beneish, M. D. (1999). The detection of earnings manipulation. Financial Analysts Journal, 55(5), 24-36.

Beneish, M. D., & Vargus, M. E. (2002). Insider trading, earnings quality, and accrual mispricing. The Accounting Review, 77(4), 755-791.

Bing, S. (2002, February, 18). Lessons from the Abyss. Fortune, 145(4), 49-50.

Boritz, J. E. (1991). *The going concern assumption.* Toronto: Canadian Institute of Chartered Accountants.

Boritz, J. E., & Kennedy, D. B. (1995). Effectiveness of neural network types of prediction of business failure. Expert Systems With Applications, 9(4), 503-512.

Brown, P. (2001). Capital markets-based research in accounting: An introduction. Retrieved February 8, 2002 from Lancaster University, School of Management website http://www.lums2.lancs.ac.uk/ACFIN/Staff/PB_Monograph1.pdf.

Cleary, W. S., & Jones, C. P. (2000). *Investments Analysis and Management* (Canadian ed.). Etobicoke, Ontario: Wiley, J., & Sons.

Collins, D. W., & Hribrar, P. (2000). Errors in estimating accruals: Implications for empirical research. Retrieved July 29, 2003 from http//.icf.som.yale.edu /pdf/ 20rev.pdf.

Cote, J. (2000). Analyst credibility: The investor's perspective. Journal of Managerial Issues, 12(3), 352-362.

Dechow, P. M., & Skinner, D. J. (2000). Earnings management: Reconciling the view of accounting academics, practitioners, and regulators. Accounting Horizons, 14(2), 235-250.

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. Accounting Review, 70(2), 193-225.

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

Dhaliwal, D., Gleason, C.A., & Mills, L.F. (2002). Last Chance Earnings Management: Using the tax expense to achieve earnings targets. Retrieved March 13, 2003 from http://ctsi.anu.edu.au/workshop.mills.paper/taxearnMay2002.pdf.

Donaldson, L. (2002). Damned by our own theories: contradictions between theories and management education. Academy of Management Learning & Education, 1, 96-106.

Dowen, R. J., & Bauman, W. S. (1995). Finanical statements, investment analyst forecasts and abnormal returns. Journal of Business Finance and Accounting, 22(3), 431-448.

Dreman, D. (1996, May 6). Ben Graham was Right--Again. Forbes, 157 (9). Retrieved March 11, 2002 from http://www.investorhome.com/anomaly.htm.

Fairfield, P. M., & Whisenant, J. S. (2001). Using fundamental analysis to assess earnings quality: Evidence from the Center for Financial Research and Analysis. Journal of Accounting, Auditing & Finance, 16(4), 273-299.

Fama, E.F. (1970). Efficient capital markets: a review of theory and empirical work. Journal of Finance, 25(2), 383-417.

Financial Executive Research Foundation Inc. (2001). Quantitative measures of the quality of financial reporting. Retrieved April 7, 2002 from http://www.fei.org /download/ QualFinRep-6-13-2k1.ppt.

Freund, R. J., & Wilson, W. J. (2003). *Statistical methods* (2nd ed.). San Diego: Academic Press.

GA0-03-395R. (2002). Financial Statement Restatements: Trends, market impacts, regulatory responses, and remaining challenges. United States General Accounting Office. Retreived April 10, 2003 from http://www.gao..gov.

Greig, A. C. (1992). Fundamental analysis and subsequent stock returns. Journal of Accounting and Economics, 15, 413-442.

Hair, J. F. Jr., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th ed.). Upper Saddle River, NJ: Prentice Hall.

Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. Accounting Horizons, 13(4), 365-383.

Hemraj, M. (2003). The detection of financial irregularities in US corporations. Company Lawyer, 23(9), 288-291.

Hill, N. T., & Perry, S. E. (1996). Evaluating firms in financial distress: An event history analysis. Journal of Applied Business Research, 12(3), 60-75.

Holthausen, R. W., & Larcker, D. F. (1992). The prediction of stock returns using financial statement information. Journal of Accounting and Economics, 15, 373-411.

Hosmer, D.W., & Lemeshow,S. (2000). *Applied logistic regression* (2nd ed.). New York:Wiley.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3, 305-360.

Khan, J. (2002, February 18). Dirty Numbers: Off Balance Sheet--And Out Of Control. Fortune, 145(4), 84.

Kohler, H. (2002). *Statistics for business and economics*. Toronto, On: Nelson Thomson Learning.

Leahy, K. (2000). Multicollinearity: When the solution is the problem. Retrieve January 13, 2004 from http://www.dmreview.com/whitepaper/WID427.pdf.

Lee, T. A.., Ingram, R. W., & Howard, T. P. (1999). The difference between earnings and operating cash flow as an indicator of financial reporting fraud. Contemporary Accounting Research 16(4), 749-786.

Leuz, C., Nanda, D., & Wysocki, P. D. (2003). Earnings management and investor protection: an international comparison. Journal of Financial Economics, 69(3), 505-527.

Lev, B., & Thiagarajan, S. R. (1993). Fundamental information analysis. Journal of Accounting Research, 31(2), 190-215.

Levitt, A. (1998, September). The numbers game. U. S. Securities and Exchange Commission. Retrieved December 28, 2002 from http://www.sec.gov/news/speech/speecharchive /1998 /spch220.txt

Loebbeke, J. K., Eining, M. M., & Willingham, J. J. (1989). Auditor's experience with material irregularities: Frequency, nature, and detectability. Auditing: A Journal of Practice & Theory, 9, 1-28.

Madura, J. (2004). What every investor need to know about accounting fraud (1st ed.). New York: McGraw-Hill.

Magrath, L., & Weld, L. G. (2002). Abusive earnings management and early warning signs. The CPA Journal, 72(8), 50-54.

Moriarty, G. B., & Livingston, P. B. (2001, June 7). Quantitative measures of the quality of financial reporting. Financial Executive. Retrieved January 16, 2001 from http://www.fei.org./download/QualiFinRep-6-13-2ki.ppt.

Myers, L. A., & Skinner, D. J. (1999). Earnings momentum and earnings management. Unpublished manuscript, University of Michigan Business School.

National Association of Certified Fraud Examiners. (1993). Cooking the books: What every accountants should know about fraud. No. 92-5401. Self-study work book: 12.

Nocera, J. (2002 June 9). System Failure. FORTUNE. Retrieved February 20, 2002 from http://www.fortune.com/fortune/investing/articles/0, 15114,370318,00.html

Nutt, S. R., Easterwood, J. C., & Easterwood, C. M. (1999). New evidence on serial correlation in analyst forecast errors. Financial Management, 28(4), 106-117.

Ohlson, J. (1980). Financial ratio and the probabilistic prediction of bankruptcy. Journal of Accounting Research, 18(1), 109-131.

Ou, J. A. (1990). The information content of nonearnings accounting numbers as earnings predictors. Journal of Accounting Research, 28(1), 144-163.

Ou, J. A., & Penman, S. H. (1989). Financial statement analysis and the prediction of stock returns. Journal of Accounting & Economics, 11(4), 295-329.

Palmrose, Z. V., Richardson, V. J., & Scholz, S. (2001). Determinants of market reactions to restatement announcements. Retrieved Febuary 9, 2002 from http://www. business .ku.edu/home/gbittlingmayer/corpcontrol/schedule/scholz.pdf.

Palmrose, Z. V., & Scholz, S. (2000). Restated financial statements and auditor litigation. Retrieved February 9, 2002 from http://accounting.rutgers.edu/raw/ aaa/audit/ midyear/01midyear /papers/Scholz.pdf.

Payne, J. L., Robb, & S. W.G. (2000). Earnings management: The effect of ex ante earnings expectations. Journal of Accounting, Auditing & Finance, 15(4), 371-392.

Platt, H. D., & Platt, M. B., & Pedersen J. G. (1994). Bankruptcy discrimination with real variables. Journal of Business Finance and Accounting, 21(4), 491-510.

Platt, H. D., & Platt, M. B. (2002). Predicting corporate financial distress: Reflections on choice-based sample bias. Journal of Economics and Finance, 26(2), 184-199.

Phillips, J., Pincus, M., & Rego, S. O. (2003). Earnings Management: New evidence based on deferred tax expense. The Accounting Review, 78(2), 491-521.

Piotroski, J. D. 2000. Value investing: The use of historical financial statement information to separate winners from losers. Journal of Accounting Research, 39(Suppl.), 1-41.

Plummer, E., & Mest, D. P. (2001). Evidence of earnings management components. Journal of Accounting, Auditing & Finance, 16(4), 301-323.

Poitras, G., Wilkins, T., & Kwan, Y. S. (2002). The timing of assets sales: Evidence of earnings management? Journal of Business Finance & Accounting, 29(7, 8), 903-934.

Sauer, R. C. (2002). Financial statement fraud: The boundaries of liability under the federal securities laws. The Business Lawyer, 57, 955-997.

Scott, W.R. (2001). Financial Accounting Theory (Canadian ed.). Scarborough, Ontario: Prentice-Hall.

Serwer, A. (2002, February 18). Dirty rotten numbers. Fortune, 145(4), 75-84.

Siegel, J. G. (1991). *How to analyze businesses, financial statements, and the quality of earnings* (2nd ed.) Englewood Cliffs, NJ: Prentice Hall.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review, 71(3), 289-315.

Sridharan, U. V., Dickes, L., & Caines, W. R. (2002). The social impact of business failure: Enron. Mid-American Journal of Business, 17(2), 11-21.

Steckel, J. H. & Vanhonacker, W. R. (1993). Cross-validating regression models in marketing research. Marketing Science, 12(4), 415-427.

Stiner, F. M. Jr. (2002, August 17). Bankruptcy of an accounting firm: Causes and consequences of the Laventhol & Horwath failure. Paper presented at the Annual Meeting of the American Accounting Association, San Antonio, Texas.

Stober, T. L. (1992). Summary financial statement measures and analysts' forecasts of earnings. Journal of Accounting and Economics, 15, 347-372.

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

Turner, L. (2001). The state of financial accounting today: an unfinished chapter. Retrieved February 22, 2002 from http://www.sec.gov/news/speech/ spch496.htm.

Wright, D. B. (1998). *Understanding statistics: An introduction for the social sciences*. Thousand Oaks, CA: Sage Pulications.

Zmijewski, M. E. (19984). Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting Research, 22(Suppl.), 59-82.