AN EMPIRICAL INVESTIGATION OF THE RELEVANCE AND PREDICTIVE ABILITY OF THE SAS 99 FRAUD RISK FACTORS

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CHAPTER I

INTRODUCTION

Much attention has recently been focused on fraud committed by business executives and on the accounting firms that failed to detect and report financial statement fraud. This failure has resulted in a loss of public confidence in audited financial statements and created an environment where users of financial statements are questioning the procedures utilized to detect financial statement fraud.

Prior to the recent accounting scandals, the American Institute of Certified Public Accountants' (AICPA) Fraud Task Force directed the Accounting Standards Board (ASB) to consider revising *Statement of Auditing Standards (SAS) No. 82*, "Consideration of Fraud in a Financial Statement Audit." This was based on academic research, recommendations from the accounting profession, and recommendations provided by other financial reporting stakeholders. This process as well as other pressures resulted in the issuance of *SAS No. 99*, "Consideration of Fraud in a Financial Statement Audit" (which supersedes *SAS No. 82*). While the auditor's responsibility for detecting fraud remains unchanged, *SAS No. 99* is intended to focus auditing guidance and thus increase auditor effectiveness in detecting fraud.

SAS No. 99 describes a process wherein the auditor (1) gathers information needed to identify risks of material misstatement, (2) assesses these risks after taking into account an evaluation of the entity's programs and controls, and (3) responds to the results. Under *SAS No. 99*, the auditor must gather and consider much more information to assess fraud risks than in the past (Ramos 2003). This process involves gathering information and assessing firms' "fraud risk factors."

The theory behind the *SAS No. 99* fraud risk factors was developed by Donald R. Cressey in the late 1940s. Cressey surmised that three conditions are present when fraud occurs:

1. Pressure – management or other employees may have an incentive or be under pressure, which provides a motivation to commit fraud.
2. Opportunity – circumstances exist (i.e., the absence of controls, ineffective controls, or the ability of management to override controls) that provide an opportunity for fraud to be perpetrated.
3. Rationalization – those involved in a fraud rationalize a fraudulent act as being consistent with their personal code of ethics. Some individuals possess an attitude, a character and/or a set of ethical values that allow them to knowingly and intentionally commit a dishonest act (Ramos 2003).

Over the years, these three conditions of fraud have been referred to as the "fraud triangle."

The purpose of this study was to empirically examine the fraud risk factors adopted in *SAS No. 99*. Empirical explanation of the fraud risk factors is important since it sheds light on the validity of the AICPA's adoption of Cressey's fraud triangle theory in the detection of financial statement fraud. Further, a fraud prediction model was developed using the empirically valid fraud risk factors. It is important to note that this model is intended to provide users of publicly available information with a fraud prediction model. This model is not intended for those with proprietary information (i.e., auditors).

The first phase of testing involved identifying and testing proxies for pressure, opportunity, and rationalization. These proxies were examined for a sample of firms that have been convicted of fraud and compared with a sample of no-fraud firms. The second phase, in the same spirit as the bankruptcy prediction studies (initiated by Altman 1968), involved using the empirically relevant fraud risk factors identified in the first phase to develop a fraud prediction model.

The results of this study are of interest to academics, standard setters, and users of financial statement data. If Cressey's theory is correct, then the use of the *SAS No. 99* fraud risk factors may increase confidence in audited financial statements. A fraud prediction model is of interest to academics, standard setters, and users of financial statement data since it permits the use of publicly available data (unlike the proprietary data that auditors and other insiders may have access to) to assess the likelihood that a firm will be involved in the preparation of fraudulent financial statements (similar to Altman's Z-score [1968]).

The remainder of this dissertation is organized as follows. Chapter 2 discusses the relevant literature and empirical predictions. Chapter 3 introduces the sample selection and research design. Chapter 4 presents the empirical results and Chapter 5 offers concluding remarks and limitations of the study.

CHAPTER II

LITERATURE REVIEW

Definition of fraud

The primary definition of fraud used by practitioners comes from the Association of Certified Fraud Examiners (ACFE). The ACFE defines financial statement fraud in terms of managerial intent:

> Financial statement fraud is the *deliberate misrepresentation* of the financial condition of an enterprise accomplished through the *intentional misstatement* or *omission* of amounts or disclosures in the financial statements to *deceive* financial statement users. (ACFE 2003)

In this study, a fraud firm is a firm that has been identified by the Securities and Exchange Commission (SEC) as having issued financial statements that are in violation of Generally Accepted Accounting Principles (GAAP) or involved in an alleged violation of Rule 10(b)-5 of the 1934 Securities Exchange Act or Section 17(a) of the 1933 Securities Act. These provisions represent the primary antifraud provisions related to financial reporting. It is important to note that it was not until the issuance of *SAS No. 82* that an authoritative body defined fraud. *SAS No. 82* defined fraud on the basis of whether the underlying action that resulted in a misstatement of the financial statements was intentional or unintentional.

SAS No. 82 made it clear that in order to be considered fraud the following elements must be evident: a false representation of fact; knowledge that the representation was false; intent to induce another to act; justifiable reliance on the representation; and injury resulting from such reliance. *SAS No. 82* also points out two types of misstatements relevant to an auditor's responsibility:

1. Misstatements arising from fraudulent financial reporting, i.e., those involving intentional misstatements or omissions of amounts or disclosures in the financial statements.
2. Misappropriation of assets, i.e., situations involving the theft of an entity's assets, accompanied by financial statement misrepresentation.

SAS No. 99

In 2002, the AICPA issued *SAS No. 99.* Although *SAS No. 99* supersedes *SAS No. 82,* it does not change an auditor's responsibility to detect fraud. In fact, *SAS No. 99* provides new concepts, requirements, and guidance to assist auditors in fulfilling their current responsibility to detect fraud. *SAS No. 99* requires auditors to: 1) discuss the risks of material misstatement due to fraud among engagement personnel; 2) query management on its views of the risks of fraud in the entity and its knowledge of any known or suspected fraud; 3) broaden, beyond the factors provided in *SAS No. 82,* the range of information the auditor uses to assess the risks of material misstatement due to fraud; 4) consider management's programs and controls to address risks and determine whether such programs and controls will mitigate or exacerbate the identified risks; and 5) develop an appropriate response for each fraud risk identified (Montgomery et al. 2002).

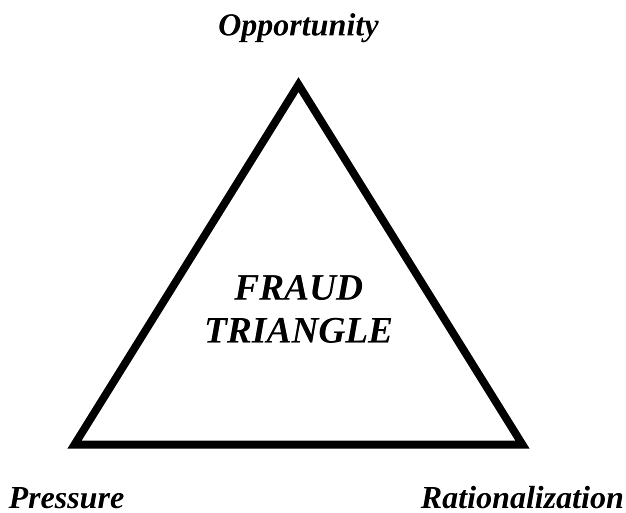
When considering fraud, *SAS No. 99* notes that "because fraud is usually concealed, material misstatements are difficult to detect. Nevertheless, the auditor may identify events or conditions that indicate *incentives/pressures* to perpetrate fraud, *opportunities* to carry out the fraud, or *attitudes/rationalizations* to justify a fraudulent action" (*SAS No. 99* para. 31). These events or conditions are referred to as fraud risk factors. *SAS No. 99* observes that the existence of such risk factors does not necessarily indicate the occurrence or existence of fraud; however, these factors are often present in the circumstances where fraud exists.

Fraud Risk Factors

The theory behind the fraud risk factors was first introduced by Donald R. Cressey in his work *Other People's Money: A Study in the Social Psychology of Embezzlement* (1953). Cressey interviewed approximately 200 individuals who had been incarcerated for embezzling funds. Through this process he determined that the frauds appeared to have three key common elements. First, the embezzler had the opportunity to perpetrate fraud. Second, there was a perceived non-shareable financial need (pressure). Third, the fraudster had the ability to rationalize the fraud. Figure 1 illustrates these three key common elements, which are better known as the "fraud triangle."

FIGURE 1

FRAUD TRIANGLE



It is important to note that Cressey argued that each element of the fraud triangle will exist in a given fraud, while *SAS No. 99* suggests that only one element of the fraud triangle needs to be present for a fraud to potentially occur. *SAS No. 99* provides examples of potential fraud risk factors that the auditor may discover. These risk factors are categorized into the three categories of the fraud triangle. Figure 2 provides a summary of the *SAS No. 99* fraud risk factors by category.

FIGURE 2

EXAMPLES OF FRAUD RISK FACTORS FROM SAS NO. 99 RELATING TO FINANCIAL STATEMENT MISSTATEMENTS[1]

Pressures	Opportunities	Rationalizations
1. Financial stability or profitability is threatened by economic, industry, or entity operating conditions: • High degree of competition or declining profit margins • High vulnerability to rapid changes (i.e., technology, obsolescence, or interest rates) • Declines in customer demand • Operating losses • Recurring negative cash flows from operations • Rapid growth or unusual profitability • New accounting, statutory, or regulatory requirements **2. Excessive pressure exists for management to meet requirements of third parties:** • Profitability/trend expectations • Need to obtain additional debt or equity financing • Marginal ability to meet exchange listing requirements or debt repayment or other debt covenant requirements • Likely poor financial results on significant pending transactions. **3. Management or directors' personal financial situation is:** • Significant financial interests in the entity • Significant performance based compensation • Personal guarantees of debts **4. There is excessive pressure on management or operating personnel to meet financial targets set up by directors or management.**	**1. Industry provides opportunities for** • Related-party transactions beyond ordinary • A strong financial presence or ability to dominate a certain industry sector that allows the entity to dictate terms or conditions to suppliers or customers • Accounts based on significant estimates • Significant, unusual, or highly complex transactions • Significant operations across international borders environments and cultures • Significant bank accounts in tax-haven jurisdictions **2. Ineffective monitoring of management allows** • Domination of management by a single person or small group • Ineffective board of directors or audit committee oversight **3. There is a complex or unstable organizational structure** • Difficulty in determining the organization or individuals that have control of company • Overly complex structure • High turnover of senior management, counsel, or board **4. Internal control deficient** • Inadequate monitoring of controls • High turnover rates or employment of ineffective accounting, internal audit, or information technology staff • Ineffective accounting and information systems.	**1. Attitudes/rationalizations by board members, management, or employees that allow them to engage in and/or justify fraudulent financial reporting** • Ineffective communication, implementation, support, or enforcement of ethics • Nonfinancial management's excessive participation in selection of accounting principles or the determining estimates • Known history of violations of securities laws or other laws • Excessive interest in maintaining or increasing stock price • Aggressive or unrealistic forecasts • Failure to correct known reportable conditions on a timely basis • Interest by management in employing inappropriate means to min. reported earnings for tax • Recurring attempts by management to justify marginal or inappropriate accounting on the basis of materiality • Strained relationship with current or predecessor auditor o Frequent disputes with the current or predecessor auditor o Unreasonable demands on the auditor, such as unreasonable time constraints o Restrictions on the auditor that inappropriately limit access o Domineering management behavior in dealing with the auditor

[1] From Statement on Auditing Standards No. 99, *Consideration of Fraud in a Financial Statement Audit*, Appendix: "Examples of Fraud Risk Factors." Copyright © 2002 by the American Institute of Certified Public Accountants, Inc., New York, New York

Other Relevant Research

Historically, fraud research either focused on the detection of fraud or explanation of the factors leading to fraud. Recently, earnings management research has begun to investigate fraud as an extension of earnings management. These studies seek to determine whether fraudulent income-increasing tactics are motivated by factors similar to those that are associated with income-increasing GAAP accounting method choices. The following research examines factors that may explain fraud and are important in identifying potential proxies for the *SAS No. 99* fraud risk factors.

Kinney and McDaniel (1989) authored an early study in this stream of research analyzing the characteristics of firms that reported corrections to previously issued interim financial statements. These corrections did not necessarily imply the existence of fraud, although virtually all situations involved corrected overstated (rather than understated) earnings. In fact, 14 percent of the firms were involved in lawsuits claiming that the financial statements from the corrected period had been fraudulently misstated. Kinney and McDaniel found that, consistent with earnings management motives, these firms are less profitable, have higher debt, and are slower growing than other firms in their industry.

DeChow, Sloan, and Sweeney (1996) examined 92 firms subject to Accounting and Auditing Enforcement Releases (AAERs) issued by the SEC, comparing them to a matched sample of firms not subject to an AAER. Specifically the study examined 1) the causes of earnings manipulations (i.e., debt hypothesis, bonus hypothesis, and political cost hypothesis), 2) governance characteristics related to opportunities to manipulate (i.e., Board of Directors and auditor characteristics), and 3) the consequences of manipulation (i.e., percent of shares shorted, dispersion of analysts' forecasts, stock price changes). They found that the desire to obtain low-cost financing is a primary motivation for the commission of fraud through earnings manipulation. Additionally, manipulating firms appear to have weaker governance systems and experience higher costs of capital once the fraud is revealed.

Beasley (1996) used logit analysis to test whether audit committees, board of director composition, and corporate governance affect the likelihood of financial statement fraud. Using a matched-pair approach, he found that the presence of an audit committee does not significantly affect the likelihood of financial statement fraud. He also found that the likelihood of financial statement fraud decreases as 1) outside director ownership in the firm and outside director tenure on the board increase and 2) as the number of outside directorships in other firms held by outside directors decreases.

Beneish (1997) presented a model to detect GAAP violation/earnings management among firms experiencing extreme financial performance, and compares the model's performance to discretionary accrual models. Beneish noted that total accruals divided by total assets, sales growth, and leverage were useful in identifying GAAP violators and aggressive accruers. He noted that these variables means for GAAP violators and non-GAAP violators are statistically different at the ten percent (10%) level. These variables are important since *SAS No. 99* identifies aggressive/unusual accounting behavior as a potential indicator of financial statement fraud.

Summers and Sweeney (1998) investigated the relationship between insider trading and fraud. They found that in the presence of fraud, insiders reduce their holdings of company stock through high levels of selling activity as measured by either the number of transactions, the number of shares sold, or the dollar amount of shares sold. Further, using a logit model, Summers and Sweeney showed firm-specific financial statement variables, such as growth, inventory, and ROA, differ from companies with fraud and companies without fraud.

Abbott *et al*. (2002) examined audit committee characteristics identified by the Blue Ribbon Committee (BRC) and evaluated the usefulness of these characteristics in identifying firms that have restated financial results with and without allegations of fraud. They found thatthe independence of the audit committee and whether the audit committee meets four times per year exhibit significance and a negative association with the occurrence of financial reporting fraud.

Dunn (2004) examined the issues of corporate governance and insider power in relation to fraud. He used logistic regression to examine the relationship between the top management team and board of directors' characteristics with the release of fraudulent financial statements. Dunn's results show that fraud is more likely to occur when there is a concentration of power in the hands of insiders.

The bankruptcy literature is important to the development of the fraud prediction model. Altman (1968) was the first among many (i.e., Altman *et al.*1977, Ohlson 1980, Platt and Platt 1991) to use ratio analysis models as part of analytical review procedures to assess the appropriateness of the "going concern" assumption. Through the use of financial ratios and the use of logistic and multiple discriminant analysis (MDA), bankruptcy prediction models were developed. This stream of research has been of interest to academics, and users and preparers of financial statements since it permits the use of publicly available information in the prediction of firm bankruptcy.

Altman (1968) and Altman *et al.*(1977) use d MDA to develop bankruptcy prediction formulas. These models classify data into discrete categories, and establish a boundary equation that maximizes discrimination between categories. Later bankruptcy research by Ohlson (1980) and Aziz *et al.*(1988 and 1989) favored logit regression over discriminant analysis. This preference resulted from logit regression requiring less restrictive statistical assumptions than MDA. Studies contrasting MDA and logit prediction models have found there to be no significant difference in accuracy between MDA and logit analysis (Cormier *et al.* 1995 and Allen and Chung 1998).

Following the bankruptcy literature, two studies (Person 1995 and Kaminski *et al.* 2004) sought to develop models based upon financial ratios to predict fraud. Person used a stepwise logistic approach and Kaminski *et al.*used MDA. Both models reported significant misclassification of fraud firms (between 58 and 98 percent). However, several financial ratio variables were shown to be useful in identifying and classifying fraud firms. These financial ratios include fixed assets divided by total assets, inventory divided by sales, inventory divided by current assets, sales divided by accounts receivable, and sales divided by total assets.

Empirical Predictions

Using the fraud triangle theory developed by Donald R. Cressey and adopted by the AICPA in *SAS No. 99*, this study first analyzed the relationship between the *SAS No. 99* fraud risk factors and financial statement fraud. Second, using the empirically valid fraud risk factors, this study developed a fraud prediction model. The following empirical predictions (EP) were examined to determine the usefulness of the fraud risk factors in explaining and predicting financial statement fraud.

EP1: The *SAS No. 99* fraud risk factors are useful in explaining financial statement fraud.

EP2: Using the significant fraud risk factors (identified in EP1) it is possible to develop a model for predicting financial statement fraud.

This study extends the research literature by empirically examining the role of pressure, opportunity, and rationalization in detecting and predicting fraud. The following chapter introduces the sample selection and research design.

CHAPTER III

SAMPLE SELECTION AND RESEARCH DESIGN

Sample Selection

The sample was limited to public companies since this study used information in financial statements and proxy statements filed with the SEC. Fraud firms were identified from the SEC Accounting and Auditing Enforcement Releases (AAERs). AAERs issued between January 1992 and December 2001 were examined for firms with alleged violation of Rule 10(b)-5 of the 1934 Securities Act or Section 17(a) of the 1933 Securities Act. A firm was included in the sample if its proxy and financial statement data filed with the SEC was available in the fraud year and the two years preceding the fraud. The proxy data was hand collected from the LexisNexis SEC Filings & Reports website and the 10K Wizard Database. The financial statement data was collected from the COMPUSTAT database. In most cases the actual fraud event was identified several years subsequent to the fraud. Therefore, the study does not look at firms beyond 2001 to allow for firms that may still be identified as fraud firms. Table 1 summarizes the identification of the fraud firms.

TABLE 1

SELECTION OF FRAUD FIRMS

Total Accounting and Auditing Enforcement Releases (AAERs) firms identified with violation of Rule 10(b)-5 of the 1934 Securities Act or Section 17(a) of the 1933 Securities Act	120
Criteria for exclusion:	
AAERs related to firms with no available proxy or financial statement data (e.g. small cap firms not required to file proxy statement information or immaterial subsidiary of larger corporation)	(27)
AAERs outside of the test period (fraud occurrence prior to 1992)	(5)
AAERs related to regulated industries	(2)
Total fraud firms included in sample	86

To create a comparison group (matched sample), no-fraud firms were identified that were similar to the fraud firms in size, industry, and time period. Each fraud firm was matched with a no-fraud firm based on the following requirements:

1. Firm Size. A no-fraud firm was considered similar to a fraud firm if its total assets, per COMPUSTAT, were within +/- 30 percent of the total assets for the fraud firm in the year preceding the fraud year. If no matches were found, a no-fraud firm was considered similar if total sales were within +/- 30 percent of the fraud firm in the year preceding the fraud year (Beasley 1996);
2. Industry. All firms in step 1 were reviewed to identify a no-fraud firm within the same four-digit SIC code as the fraud firm. The no-fraud firm selected was the one that had a total assets or total sales value closest to the fraud firm's total assets or total sales value. If no four-digit SIC code firm match was identified, the procedure was performed to identify a firm with the same three-digit SIC code. And if no three digit SIC code firm match was identified, the procedure was performed to identify a firm with the same two-digit SIC code;
3. Time Period. A no-fraud firm identified in steps 1 and 2 was included in the final sample if proxy and financial statement data were available for the time period used to collect data from the proxy and financial statements of the related firm.

The sample selection process identified 86 fraud firms individually matched with a no-fraud firm, creating a matched sample of 172 firms. Table 2 shows that the fraud and no-fraud firms do not differ significantly based on total assets and net sales.

TABLE 2

DESCRIPTIVE STATISTICS AND MATCHING OF FRAUD FIRMS AND NO-FRAUD FIRMS

	($ in hundreds of thousands)	
	Fraud Firms *Mean* *[Median]* *(Standard Deviation)*	*No-Fraud Firms* *Mean* *[Median]* *(Standard Deviation)*
Total Assets	1,420.10 [108.52] (4,414.39) *n=86*	797.91 [88.90] (2,892.58) *n=86*
Net Sales	1,627.76 [93.62] (5,537.39) *n=86*	1,049.42 [93.21] (4,137.71) *n=86*
Match Based On:		
4 Digit SIC Codes	23	
3 Digit SIC Codes	44	
2 Digit SIC Codes	19	
Total	86	

Note: Paired t-tests for means and Wilcoxon matched-pair sign-rank tests for medians were performed to determine whether fraud and no-fraud firms differ significantly based on Total Assets and Net Sales. No statistically significant differences exist at the 10 percent level.

Table 3 presents the various industries represented among the fraud firms. Approximately 19 percent of the firms are services-prepackaged software companies; 12 percent are computers, communication equipment and peripheral equipment companies; 8 percent are controlling, surgical, and photographic devices companies; and 7 percent are electrical equipment companies. The remaining firms represent such industries as wholesale goods, retail goods, health services, computer services, and apparel and other finished products of fabrics. Approximately 40 percent of the fraud firms in the sample represent "high-tech" firms. This may provide support for the idea that firms in certain industries have a greater likelihood of fraud.

TABLE 3

INDUSTRIES REPRESENTED AMONG THE FRAUD FIRMS

SIC Code	Industry Title	Number of Fraud Firms	Percent of Sample
1311	Crude Petroleum & Natural Gas	1	1.16%
1531	Operative Builders	1	1.16%
1600	Heavy Construction Other Than Building Construction – Contractors	1	1.16%
2000	Food and Kindred Products	1	1.16%
2250	Knitting Mills	1	1.16%
2300	Apparel & Other Finished Products of Fabrics	4	4.65%
2721	Periodicals: Publishing or Publishing & Printing	1	1.16%
2800	Chemicals & Allied Products	3	3.49%
3140	Footwear	1	1.16%
3400	Metal Products	3	3.49%
3500	Computers, Communication Equipment & Peripheral Equipment	10	11.63%
3600	Electrical Equipment	6	6.98%
3700	Truck & Bus Bodies, Transportation Equipment	2	2.33%
3800	Controlling, Surgical, & Photographic Devices	7	8.14%
5045	Wholesale-Computers & Peripheral Equipment & Software	2	2.33%
5060	Wholesale-Electrical Apparatus & Equipment, Wiring Supplies & Electronic Parts	2	2.33%
5122	Wholesale-Drugs, Proprietaries & Druggists' Sundries	1	1.16%
5172	Wholesale-Petroleum & Petroleum Products	1	1.16%
5331	Retail-Variety Stores	1	1.16%
5661	Retail-Shoe Stores	1	1.16%
5812	Retail-Eating Places	1	1.16%
5912	Retail-Drug Stores and Proprietary Stores & Miscellaneous Shopping Goods Stores	2	2.33%
5961	Retail-Catalog & Mail-Order Houses	3	3.49%
7359	Services-Equipment Rental & Leasing	1	1.16%
7370	Services-Computer Programming, Data Processing, etc.	4	4.65%
7372	Services-Prepackaged Software	16	18.60%
7373	Services-Computer Integrated Systems Design	2	2.33%
7389	Services-Business Services	1	1.16%
7990	Services-Miscellaneous Amusement and Recreation	2	2.33%
8000	Services-Health Services	4	4.65%
	TOTAL	**86**	**100.00%**

Table 4 displays the occurrence of fraud in the fraud sample by year. Approximately 16 percent of the frauds occurred in both 1997 and 1998, 15 percent in 1999, 10 percent in 1994, 9 percent in both 1992 and 1996, and 8 percent in 2000. The remaining years each represent less than 6 percent of the fraud sample. The last five years of the sample (1997-2001) represent 60 percent of the fraud sample.

TABLE 4

OCCURRENCE OF FRAUD BY YEAR

Year	Number of Fraud Firms	Percent of Sample
1992	8	9.30%
1993	5	5.81%
1994	9	10.47%
1995	4	4.65%
1996	8	9.30%
1997	14	16.28%
1998	14	16.28%
1999	13	15.12%
2000	7	8.14%
2001	4	4.65%
TOTAL	**86**	**100.00%**

Research Design

The *SAS No. 99* fraud risk factor categories are 1) Pressure, 2) Opportunity, and 3) Rationalization. Proxies for each of these categories are identified and discussed below. This study used a logit regression model to evaluate EP1, where

$$FRAUD = f(Pressure, Opportunity, Rationalization) \qquad [1]$$

Prior to discussing the design of the logit model, the proxies for pressure, opportunity, and rationalization must be introduced. The remainder of the research design section is organized as follows. The fraud risk factors proxies are categorized into pressure, opportunity, and rationalization. Following the categorization of the fraud risk factors, the logit regression analysis is introduced to examine EP1. The last research design section introduces the discriminant analysis model used to test EP2.

Fraud Risk Factor Proxies

Pressures

Cressey argued that non-shareable pressure was perhaps the most important element of the fraud triangle. In his interviews the embezzlers cited personal needs that engaging in fraud could potentially meet (Cressey 1953). *SAS No. 99* cites the following four pressures that may lead an individual to engage in fraud:

1. Financial stability or profitability of the firm is threatened by economic, industry, or entity operating conditions.
2. External pressure exists for management to meet the requirements or expectations of third parties.
3. Management or directors' personal financial situation is threatened.
4. There is excessive pressure on management or operating personnel to meet financial targets set up by directors or management.

Proxy variables representing each of the four *SAS No. 99* fraud risk factor categories of pressure were developed and tested. Figure 3 summarizes the fraud risk factor proxies for pressure.

FIGURE 3

FRAUD RISK FACTOR PROXIES FOR PRESSURE

Fraud Risk Factors	**SAS No. 99 Categories**	**Proxies**	**Definition of proxies**
Pressures	Financial Stability	*COMPMARG*	(-HHI/GP%) when GP% is greater than zero and (-GP%/HHI) when GP% is less than or equal to zero.
		NICFOTA	$\frac{\text{Operating income – Cash flow from operations}}{\text{Total assets}}$
		SGROW	Change in Sales – Industry Average Change in Sales
		SGROWA	|Change in Sales – Industry Average Change in Sales|
		AGROW	The average percentage change in total assets for the two years ending before the year of fraud.
		AGROWA	The absolute value of the average percentage change in total assets for the two years to the fraud year.
		FATA	Fixed Assets / Total Assets
		SALAR	Sales / Accounts Receivable
		SALTA	Sales / Total Assets
		INVSAL	Inventory / Sales
		INVCA	Inventory / Current Assets
	External Pressure	*FINANCE*	$\frac{\text{Cash from operations}_t - \text{Average capital expenditures}_{t-3 \text{ to } t-1}}{\text{Current Assets}_{t-1}}$
		FREEC	Net cash flow from operating activities - cash dividends - capital expenditures
		LEVERAGE	Total Debt / Total Assets
		LEV	((Long Term Debt$_t$ + Current Liabilities$_t$) / (Total Assets$_t$)} / {(Long Term Debt$_{t-1}$ + Current Liabilities$_{t-1}$) / (Total assets$_{t-1}$)}
	Personal Financial Need	*OWNERSHIP*	The cumulative percentage of ownership in the firm held by insiders.
		5%OWN	The percentage of shares held by management who hold greater than 5% of the outstanding shares.
	Financial Targets	*ROA*	Return on assets

Pressure: Financial Stability Variables

SAS No. 99 suggests that when financial stability or profitability is threatened by economic, industry, or entity operating conditions, a firm faces pressure to commit financial statement fraud. The proxies for financial stability include *COMPMARG, NICFOTA, SGROW, SGROWA, AGROW, AGROWA, FATA, SALAR, SALTA, INVSAL,* and *INVCA*. These proxies are discussed below.

COMPMARG – measures the financial stability pressure a firm faces when a high degree of competition or market saturation is accompanied by a declining gross profit percentage. *COMPMARG* is composed of two elements: degree of market competition and gross profit percentage. When a firm is operating in a market with a high degree of competition (larger number of firms) and a declining gross profit percentage, it is predicted that such a firm would have greater pressure than a firm with a low degree of competition and a declining gross profit percentage. Furthermore, a firm with a high degree of competition and an increasing gross profit percentage would have more pressure than a firm with a low degree of competition and an increasing gross profit percentage. Figure 4 illustrates the predicted pressure.

FIGURE 4

PREDICTED PRESSURE RESULTING FROM COMBINATIONS OF DEGREE OF COMPETITION AND GROSS PROFIT PERCENTAGE

Degree of Competition	Low	High	Low	High
Gross Profit %	Increasing	Increasing	Declining	Declining
Predicted Pressure	Least ⟷			Greatest

Degree of competition is the first element computed in the measure of *COMPMARG*. This element is computed using the Herfindahl-Hirschman Index (HHI). HHI is a commonly accepted measure of market concentration. Since 1982 the U.S. Department of Justice has used this index to assess market concentration or competition within a market. It is calculated by squaring the market share of each firm competing in the market and then summing the resulting numbers. For example, for a market consisting of four firms with shares of 30, 30, 20, and 20 percent, the HHI is 2600 ($30^2 + 30^2 + 20^2 + 20^2 = 2600$) (USDOJ 2000).

In this study, HHI was calculated for each firm individually. This was done by identifying all firms found in COMPUSTAT with the same four-digit SIC code. Then the market share was calculated as the percentage of sales held by each firm in that four-digit SIC code category. One inherent limitation of the above HHI calculation involved the exclusion of non-COMPUSTAT (private companies) from the market share calculation.

The second element, gross profit percentage (GP%), measures the change in gross profit percentage. Albrecht (2002) has argued that when a revenue-related financial statement fraud is being perpetrated, a company's gross profit percentage may decrease dramatically. He argued that this dramatic decrease may be a result of financial statement fraud. GP% is computed as the ratio of gross profit to sales in year t less the ratio of gross profit to sales in year $t - 1$, where t is the year prior to the fraud occurrence.

COMPMARG is computed as follows: 1) when GP% is increasing (greater than zero) *COMPMARG* is computed as -1 multiplied by HHI divided by GP% (-HHI/GP%) and 2) when GP% is decreasing (less than or equal to zero) *COMPMARG* is computed as

-1 multiplied by GP% divided by HHI (-GP%/HHI). When GP% is less than zero, *COMPMARG* yields the concentration per unit of gross profit decline. The larger the *COMPMARG* number the greater the pressure would be expected. For example, as competition increases (HHI gets smaller) and the gross profit decline increases, there is increasing pressure on a firm. Thus, a firm with an HHI value of 500 and a 5 percent decrease in GP% should have greater pressure than a firm with an HHI value of 10,000 and a 5 percent decrease in GP% (i.e., -(-5/10,000) = 0.0005, which is smaller than -(-5/100) = 0.05). In this case the firm with the lower HHI value has a larger pressure score.

When GP% is greater than zero, this measure yields the gross profit decline per unit of concentration. Once again, the larger the *COMPMARG* number the greater the pressure would be expected. For example, as competition decreases (HHI increases) and the gross profit margin increases, there is decreasing pressure on a firm. Thus, a firm with an HHI value of 10,000 and a 5 percent increase in GP% should have less pressure than a firm with an HHI value of 100 and a 5 percent decrease in GP% (i.e., -10,000/5 = -2,000, which is smaller than -100/5 = -20). In this case the firm with the lower HHI value has a larger pressure score. Figure 5 illustrates how the pressure score *COMPMARG* is computed. *COMPMARG* was measured as follows.

COMPMARG = (-HHI/GP%) when GP% is greater than zero and
(-GP%/HHI) when GP% is less than or equal to zero.

FIGURE 5

MEASUREMENT OF PRESSURE SCORE

Competition	Low	Low	High	High	Low	Low	High	High
HHI	10000	10000	100	100	10000	10000	100	100
GP%	5	20	5	20	-5	-20	-5	-20
COMPMARG	-2000	-500	-20	-5	0.0005	0.002	0.05	0.2
Pressure	Least	←→						Greatest

NICFOTA – *SAS No. 99* suggests an indicator of financial stability may be represented by recurring negative cash flows from operations or an inability to generate cash flows from operations while reporting earnings and earnings growth. *NICFOTA* is measured as follows:

$$NICFOTA = \frac{\text{Operating income} - \text{Cash flow from operations}}{\text{Total assets}}$$

Where the numerator is the difference between reported net income and cash flow from operations. The denominator is total assets and is used to standardize the numerator. Over time, this ratio should hover around zero, with some positive years and some negative years. Progressive deterioration in this ratio (measured by increasingly longer positive numbers) can often spell trouble and hint that financial statement fraud is occurring (since reported net income is increasing while cash flows are decreasing) (Albrecht 2002).

SGROW, SGROWA, AGROW, and *AGROWA* – Rapid growth or unusual profitability, especially compared to that of other companies in the same industry, might indicate financial instability. Since one of the most significant “red flag” fraud indicators is the presence of rapid company growth, growth proxies for differences in firm growth between fraud and no-fraud firms. Loebbecke *et al*. (1989) and Bell *et al*. (1991) stated that if the company has been experiencing rapid growth, management may be motivated to misstate the financial statements during a downturn to give the appearance of stable growth. Also, if a firm experiences growth that is less than the industry average, management may have pressure to engage in financial statement fraud. Either scenario for growth, whether above or below industry averages, may be an indicator of fraud.

Two methods used for calculating growth are put forth in the literature, sales growth (Beasley [1996] and Summers and Sweeney [1998]) and asset growth (Beneish [1997] and Beasley *et al*. [2000]). For each of these types of growth, the growth variable and absolute value of growth may provide insight into a firm's stability. The *SGROW* proxy is computed as the change in sales less the industry average change in sales. The *SGROWA* proxy is computed as the absolute value of the change in sales less the industry average change in sales. The *AGROW* proxy is computed as the change in assets less the industry average change in assets. The *AGROWA* proxy is computed as the absolute value of the change in assets less the industry average change in assets.

SGROW = Change in Sales – Industry Average Change in Sales

SGROWA = |Change in Sales – Industry Average Change in Sales|

AGROW = Change in Assets – Industry Average Change in Assets

AGROWA = |Change in Assets – Industry Average Change in Assets|

<u>*FATA*, *SALAR*, *SALTA*, *INVSAL*, and *INVCA*</u> – Albrecht (2002) and Wells (1997) have argued for the inclusion of financial ratios in the detection of fraud. They argued that certain ratios computed from the income statement and balance sheet differ among fraud and no-fraud firms. Kaminski *et al*. (2004) and Persons (1995) found that the following variables were useful in detecting fraud:

FATA – Fixed assets divided by total assets

SALAR – Sales divided by accounts receivables

SALTA – Sales divided by total assets

INVSAL – Inventory divided by sales

INVCA – Inventory divided by current assets

Interestingly, both studies argued that the use of financial ratios should be based on theory and coupled with demonstrated empirical evidence for their usefulness. They also noted that an acceptable theoretical foundation for the selection of ratios for decision making does not exist. This study argues that ratios are an important measure of the pressure management feels related to the firm's financial stability. Therefore, the financial ratio proxies *FATA*, *SALAR*, *SALTA*, *INVSAL*, and *INVCA* were included in the study.

Pressure: External Pressure

Proxies for external pressure include *FINANCE*, *FREEC*, *LEVERAGE*, and *LEV*. External pressure exists for management to meet the requirements or expectations of third parties due to the following:

FINANCE and *FREEC* – Need to obtain additional debt or equity financing to stay competitive, including financing of major research and development or capital expenditures. This external pressure is measured as follows.

Dechow *et al*. (1996) argued that the demand for external financing depends not only on how much cash is generated from operating and investment activities but also on the funds already available within the firm. They assumed that current assets are readily convertible into cash and represent the funds available to the firm. They also suggested that the average capital expenditures during the three years prior to financial statement manipulation are a measure of the desired investment level during the financial statement manipulation period. Dechow *et al*. (1996) used both of these variables to measure the firms' *ex ante* demand for financing in the first year of manipulation, *t*, where:

$$FINANCE_t = \frac{\text{Cash from operations}_t - \text{Average capital expenditures}_{t\text{-}3 \text{ to } t\text{-}1}}{\text{Current Assets}_{t\text{-}1}}$$

When *FINANCE* is negative, the absolute value of the ratio (1/*FINANCE*) provides an indication of the number of years that the firm can continue to internally fund its current level of activity. Dechow *et al*. (1996) noted that when the *FINANCE* variable is equal to –0.5, absent external financing, a firm will consume all of its available assets within two years. As *FINANCE* becomes more negative, the pressure to engage in financial statement manipulation is more likely. They also noted that if a firm has enough internal funds to last several years, then managers are unlikely to engage in manipulation immediately.

An alternative approach to calculating *FINANCE* discussed by Dechow *et al.* (1996) is to calculate *FREEC* as net cash flow from operating activities *less* cash dividends *less* capital expenditures. While this approach was not used by Dechow *et al.* (1996), it may provide useful insight into the detection of fraud. Therefore, the study included *FREEC* in addition to *FINANCE*.

$$FREEC = \text{Net cash flow from operating activities} - \text{cash dividends} - \text{capital expenditures}$$

<u>*LEVERAGE* and *LEV*</u> – Marginal ability to meet exchange listing requirements or debt repayment or other debt covenant requirements. *LEVERAGE* may be positively or negatively associated with discretionary accruals (Vermeer 2003). Press and Weintrop

(1990) found that closeness to the violation of debt covenants is associated with discretionary accrual choices. DeAngelo *et al*. (1994) noted that troubled companies have large negative accruals because contractual renegotiations provide incentives to reduce earnings. DeFond and Jiambalvo (1994) found that high-leveraged firms have incentives to make income increasing discretionary accruals. To control for the possibility of positive or negative effects of high leverage, this study includes two different measures of leverage found in the literature. The first measure, *LEVERAGE,* follows DeAngelo *et al*. (1994) and DeFond and Jiambalvo (1994), and the second measure, *LEV,* follows Beneish (1997). The leverage measures are calculated as follows:

$$LEVERAGE = \text{Total Debt} / \text{Total Assets}$$

$$LEV = ((\text{Long Term Debt}_t + \text{Current Liabilities}_t) / (\text{Total Assets}_t)\} / \{(\text{Long Term Debt}_{t-1} + \text{Current Liabilities}_{t-1}) / (\text{Total Assets}_{t-1})\}$$

Pressure: Personal Financial Need

Individuals may face significant pressure to engage in financial statement fraud when they face a personal financial need. *OWNERSHIP* and *5%OWN* are used to proxy for the personal financial need pressure.

OWNERSHIP and *5%OWN* – Findings from Beasley (1996), COSO (1999), and Dunn (2004) indicate that managements' personal financial situation is threatened by the entity's financial performance arising from executives having significant financial interests in the entity. *OWNERSHIP* and *5%OWN* were measured as follows:

OWNERSHIP = the cumulative percentage of ownership in the firm held by insiders. Shares owned by management divided by the common shares outstanding. This yields the percent of common shares outstanding that are owned by management.

5%OWN = the cumulative percentage of ownership in the firm held by management who hold 5 percent of the outstanding shares or more divided by the common shares outstanding. This yields the percent of common shares outstanding owned by 5 percent management owners.

Pressure: Financial Targets

The last pressure category presented in *SAS No. 99* relates to financial targets. Loebbecke *et al*. (1989) found that profit relative to industry was inadequate for 35 percent of the companies with fraud in their sample. Summers and Sweeney (1998) used return on assets (*ROA)* as a measure of financial performance to control for performance differences between fraud and no-fraud firms in their sample. They found that *ROA* is significantly different among fraud and no-fraud firms. Therefore, this study used *ROA* to differentiate performance among fraud and no-fraud firms. *ROA* was calculated as follows:

ROA = Net Income before extraordinary items $_{t1}$ divided by Total Assets $_{t}$

Opportunity

Cressey has argued that without the opportunity to engage in fraud, one cannot commit fraud. According to the fraud triangle, pressure alone is not sufficient. According to Cressey's theory, all three elements must be present for fraud to occur. Pressure creates the motive for the crime to be committed, but the employee must also perceive that the opportunity to commit the crime without being caught exists (Cressey 1953). *SAS No. 99* cites the following four opportunities that may allow an individual to engage in fraud:

1. The nature of the industry or the entity's operations provides opportunities to engage in fraudulent financial reporting.

2. There is ineffective monitoring of management.
3. There is a complex or unstable organizational structure.
4. Internal control components are deficient.

Proxy variables representing each of the four *SAS No. 99* fraud risk factor categories of opportunity were developed and tested below. Figure 6 summarizes the fraud risk factor proxies for opportunity.

FIGURE 6

FRAUD RISK FACTOR PROXIES FOR OPPORTUNITY

Fraud Risk Factors	**SAS No. 99 Categories**	**Proxies**	**Definition of proxies**
Opportunity	Nature of Industry	*RECEIVABLE*	$(Receivables_t/Sales_t - Receivables_{t-1}/Sales_{t-1})$
		INVENTORY	$(Inventory_t/Sales_t - Inventory_{t-1}/Sales_{t-1})$
		FOROPS	Foreign Sales / Total Sales
	Ineffective Monitoring	*BOUT*	The number of board members who are outside members.
		BOUTP	The percentage of board members who are outside members.
		BIN	The number of board members who are inside members.
		BINP	The percentage of board members who are inside members.
		BSIZE	The number of directors on the board.
		AUDCOMM	A dummy variable where 1 = mention of oversight by an internal audit committee and 0 = no mention of oversight.
		AUDCSIZE	The size of the audit committee.
		NOEXPERT	Indicator variable with the value of 1 if audit committee includes no directors with financial expertise.
		AUDINDEPP	The percentage of audit committee members who are independent of the company.
		AUDINDNUM	Number of independent members on the audit committee.
		MINMEET	Indicator variable with the value of 1 if audit committee meets at least four times annually during the period prior to the fraud; 0 otherwise.
		AUDMEET	The number of audit committee meetings held.
		INTAUD	Indicator variable with the value of 1 if company indicates it has an internal audit function which reports to the audit; 0 otherwise.
		BLOCK	Institutional shareholders who own greater than 5 percent of the outstanding common stock.
	Organizational Structure	*TOTALTURN*	The number of executives leaving the company in the two years prior to fraud.
		CEOTURN	Indicator variable with a value of 1 if the CEO left the company in the two years prior to fraud; 0 otherwise.
		CEOCHAIR	Indicator variable with a value of 1 if the chairperson of the board holds the managerial positions of CEO or president; 0 otherwise.

Opportunity: Nature of Industries

The nature of the industry or the entity's operations may provide opportunities to engage in fraudulent financial reporting. *RECEIVABLE, INVENTORY*, and *FOROPS* are measures of this type of opportunity.

RECEIVABLE and *INVENTORY* – Certain assets, liabilities, revenues, or expenses are based on significant estimates that involve subjective judgments or uncertainties that are difficult to corroborate. Summers and Sweeney (1998) noted that receivables and inventory accounts involve subjective judgment in estimating uncollectible accounts and obsolete inventory. They suggested that since subjective judgment is involved in determining the value of these accounts, management may use these accounts as tools for financial statement manipulation.

This argument is supported by Loebbecke *et al*. (1989), who found that the accounts receivable and inventory account were involved in a significant number of frauds in their sample. Summers and Sweeney (1998) tested both receivables and inventory accounts and found that only inventory accounts differed between fraud and no-fraud companies. However, this study measured both receivables and inventory.

Following Summers and Sweeney (1998), the proxy for estimates related to accounts receivables is the ratio of changes in receivables to sales. This measure was computed as the ratio of receivables to sales in year *t* less the ratio of receivables to sales in year *t* – 1, where *t* is the year prior to the fraud occurrence.

$$RECEIVABLE = (\text{Receivable}_t/\text{Sales}_t - \text{Receivable}_{t\text{-}1}/\text{Sales}_{t\text{-}1})$$

Again, following Summers and Sweeney (1998), the proxy for inventory estimates is the ratio of changes in inventory to sales. This measure was computed as the ratio of inventory to sales in year *t* less the ratio of inventory to sales in year *t* – 1, where *t* is the year prior to the fraud occurrence.

$$INVENTORY = (\text{Inventory}_t/\text{Sales}_t - \text{Inventory}_{t\text{-}1}/\text{Sales}_{t\text{-}1})$$

FOROPS – *SAS No. 99* suggests that when significant operations are located or conducted across international borders in jurisdictions where differing business environments and cultures exist, the opportunity to commit fraud may be more prevalent. Albrecht (2002) further argued that rules and regulations for how companies conduct business differ from one country to the next (i.e., government regulation, financial reporting requirements, laws, etc.), thus allowing for greater opportunity to engage in financial statement fraud. *FOROPS* proxies for pressure resulting from foreign operations:

FOROPS = Percent of sales which are foreign. This is calculated as total foreign sales divided by total sales.

Opportunity: Ineffective Monitoring

Ineffective monitoring of management may result from ineffective board of directors or audit committee oversight over the financial reporting process and internal control. This study uses*BOUT, BOUTP, BIN, BINP, BSIZE, ADCOMM, AUDSIZE, NOEXPERT, MINMEET, AUDMEETS, INTAUD, AUDINDNUM, AUDINDEPP,* and *BLOCK* as proxies for ineffective monitoring.

BOUT, BOUTP, BIN, BINP and *BSIZE* – Beasley *et al*. (2000) found that board characteristics between fraud and no-fraud firms have one significant difference. This difference is that the percentage of board members who are outside members is much lower for fraud companies than for no-fraud companies. This finding is consistent with Beasley (1996) and Dechow *et al*. (1996). Dunn (2004) has made the same argument, but examined board inside members instead of board outside members. His results are also consistent with Beasley (1996). Therefore, this study used the following proxy combinations of board composition:

BOUT = The number of board members who are outside members.

BOUTP = Percentage of board members who are outside members.

BIN = The number of board members who are inside members.

BINP = Percentage of board members who are inside members.

BSIZE = The total number of board members (inside + outside members)

AUDCOMM and *AUDCSIZE* – Beasley *et al*. (2000) found that the existence of an internal audit committee was less common among fraud companies than no-fraud companies. The existence of an internal audit committee was based on whether proxy disclosures regarding audit-committee activities mentioned oversight of an internal audit function. This study used the following measure to proxy for ineffective monitoring.

AUDCOMM = Indicator variable with the value of 1 if mention of oversight by an internal audit committee; and 0 otherwise.

AUDCSIZE = The number of board members who are on the audit committee

Also relating to ineffective monitoring, Beasley (1996) found that board size and director tenure are also significantly different in fraud and no-fraud companies. Dechow *et al*. (1996) found that CEO and board chair positions held by the same person are correlated with fraud. However, Beasley *et al*. (2000) reported results that contradict Beasley (1996) and Dechow *et al*. (1996) regarding these two measures. These proxies were included in the study, even though there is some conflicting evidence in the literature.

<u>*NOEXPERT*, *AUDINDEPP*, *MINMEET*, and *AUDMEET*</u> – The Blue Ribbon Committee on Improving the Effectiveness of Corporate Audit Committees (BRC) made several recommendations in 1999. These recommendations were examined by Abbott *et al*. (2002). They found that the BRC recommendations, *NOEXPERT, MINMEET*, and *AUDINDEPP*, are significant in identifying fraud firms. *NOEXPERT* attempts to operationalize the BRC recommendation that at least one member of the audit committee possess financial expertise, through past employment experience in accounting or finance, requisite professional certification in accounting, or any other comparable experience of background which results in the individual's financial sophistication, including being or having been a CEO or other senior officer with financial oversight. *NOEXPERT* was coded as follows:

> NOEXPERT = Indicator variable with the value of1 if the audit committee does not include at least one director who is (or has been) a CPA, investment banker or venture capitalist, served as CFO or controller, or has held a senior management position (CEO, President, COO, VP, etc.) with financial responsibilities; and 0 otherwise.

AUDINDEPP is found to be significant in identifying fraud firms by Abbott and Parker (2000), Abbott *et al*. (2002), Beasley *et* al. (2000), and Robinson (2002). *AUDINDEPP* represents the percentage of the audit committee members who are independent of the firm. An independent director is defined in this study as one who is not: a current employee of the firm, former officer or employee of the firm or related entity, a relative of management, professional advisor to the firm, officers of significant suppliers or customers of the firm, interlocking directors, and/or one who has no significant transactions. This definition of independence follows Robinson (2002) and is a stricter definition of independence than the other cited studies. In addition to the percentage of independent audit committee members, the actual number of committee members may provide some insight into the importance of the audit committee's size. *AUDINDEPP* and *AUDINDNUM* were calculated as follows:

> *AUDINDEPP* = The percentage of audit committee members who are independent of the company.
>
> *AUDINDNUM* = Number of independent members on the audit committee.

MINMEET – Identified in Abbott *et al*. (2002) as a dichotomous variable, *MINMEET* relates to the number of meetings held by the audit committee. The BRC suggests that the audit committee should meet four times per year at a minimum. Therefore, following Abbott *et al*. (2002) this study coded *MINMEET* as follows:

> *MINMEET* = Indicator variable with the value of1 if the audi t committee met at least four times during the first fraud year; and 0 otherwise.

<u>*AUDMEET*</u> attempts to measure whether the actual number of audit committee meetings is useful in identifying firms with fraudulent financial statements. *AUDMEET* was calculated as follows:

> *AUDMEET* = The number of audit committee meetings held.

<u>*INTAUD*</u> – Measures whether the audit committee has oversight over the internal audit function of the firm. Defond and Jiambalvo (1991), Beasley (1996), and Bell and Carcello (2000) have investigated whether the role of internal monitoring mechanisms mitigate risk of financial misstatement. To test the audit committee's oversight (monitoring) of the firm, the study calculated *INTAUD* as follows:

> *INTAUD* = Indicator variable with the value of 1 if the company indicates it has an internal audit function which reports to the audit committee; and 0 otherwise.

<u>*BLOCK*</u> – Loebbecke and Willingham (1988) found that week controls and internal decentralization are positively associated with the risk of financial misstatements. Abbott *et al*. (2002) followed this research and used *BLOCK*, which they intended to control for the impact of internal control. *BLOCK* is the proportion of stock controlled by unaffiliated 5 percent owners (it excludes the individuals identified in the *5%OWN* variable). Following Abbott *et al*. (2002) this study calculated *BLOCK* as follows:

> *BLOCK* = Institutional shareholders who own greater than 5 percent of the outstanding common stock divided by total shares outstanding. This variable excludes 5 percent insider shareholders.

Opportunity: Organizational Structure

Complex or unstable organizational structure may be evidenced by high turnover of senior management, counsel, or board members. Loebbecke *et al*. (1989) noted that in 75 percent of the fraud cases they examined, operating and financial decisions were dominated by a single person. They argued that this factor creates an environment allowing management to commit financial statement fraud. Beasley (1996) controlled for the CEO's power to control the company and board of directors based on tenure, surmising that length of time strengthens the CEO's position of power. This study used the *TOTALTURN* proxy to measure the influence of the management, where executive turnover may indicate less ability for management to engage in financial statement fraud. Additionally, the study used a variable measuring whether CEO turnover alone was related to financial statement fraud. *TOTALTURN* and *CEOTURN* were calculated as follows:

> *TOTALTURN* = the number of executives that left the firm in the two years prior to fraud.

> *CEOTURN* **=** Indicator variable with a value of 1 if the CEO left the

company in the two years prior to fraud; and 0 otherwise.

CEOCHAIR – Loebbecke *et al*. (1989), Flatt (1996), Beasley *et al*. (1999), Abbott *et al*. (2002), and Dunn (2004) described the structural power of the firm in varying forms. The major tenant of each of these studies is that as the CEO accumulates titles, the CEO is in a position to dominant or control decision. The belief is that as the CEO accumulates more titles, he will increase his opportunity to commit fraud. *CEOCHAIR* attempts to capture the increased opportunity to commit fraud through obtaining titles.

CEOCHAIR = Indicator variable with a value of 1 if the chairperson of the board holds the managerial positions of CEO or president; and 0 otherwise.

Rationalization

The final element in the fraud triangle is rationalization. Cressey pointed out that rationalization is a necessary component of the crime before it takes place. He argued that it is part of the motivation (like pressure) for the crime. Cressey found that individuals generally rationalized their crimes by viewing them as: 1) essentially non-criminal, 2) justified, or 3) part of a general irresponsibility for which they were not completely accountable. Notably, an individual's rationale is very difficult to observe. It is not until the individual reveals his/her rationale that it becomes clear (Cressey 1953). *SAS No. 99* recognizes the difficulty of identifying an individual's rationale and states the following:

> Risk factors reflective of attitudes/rationalizations by board members, management, or employees that allow them to engage in and/or justify fraudulent financial reporting, may not be susceptible to observation by the auditor. Nevertheless, the auditor who becomes aware of the existence of such information should consider it in identifying the risks of material misstatement arising from fraudulent financial reporting. (*SAS No. 99* Appendix)

While rationalization is not easily identifiable, the relationship between management and the current or predecessor auditor may be informative. A strained auditor/management relationship may reveal disputed accounting choices that were rationalized by management. *AUDCHANG*, *AUDREPORT*, and *TATA* are used to proxy for rationalization. These proxies are summarized in Figure 7.

FIGURE 7

FRAUD RISK FACTOR PROXIES FOR RATIONALIZATION

Fraud Risk Factors	**SAS No. 99 Categories**	**Proxies**	**Definition of proxies**
Rationalization	Rationalization	*AUDCHANG*	A dummy variable for change in auditor where 1 = change in auditor in the 2 years prior to fraud occurrence and 0 = no change in auditor.
		AUDREPORT	A dummy variable for an audit where 1 = an unqualified opinion and 0 = an unqualified opinion with additional language.
		TATA	Total accruals/total assets, where total accruals are calculated as the change in current assets, minus the change in cash, minus changes in current liabilities, plus the change in short-term debt, minus depreciation and amortization expense, minus deferred tax on earnings, plus equity in earnings.

<u>*AUDCHANG*</u> – Studies by Stice (1991) and St. Pierre and Anderson (1984) indicate that while a change in auditor may occur for legitimate reasons, the risk of audit failure and subsequent litigation is higher during an initial engagement than in subsequent years. Loebbecke *et al*. (1989) found that a significant number of frauds in their sample were perpetrated in the first two years of an auditor's tenure. Summers and Sweeney (1998) have argued that a change in auditor has no significant relationship to financial statement fraud. Summers and Sweeney's argument is not supported by *SAS No. 99* or

Albrecht (2002), who suggested a change in auditor is associated with financial statement fraud. Therefore, this study included the following proxy:

AUDCHANG = a dummy variable for change in auditor where 1 = change in auditor in the 2 years prior to fraud occurrence and 0 = no change in auditor.

AUDREPORT – Francis and Krishnan (1999) found that auditors are less likely to issue a standard unqualified opinion for firms with high discretionary accruals. Discretionary accruals should be negatively associated with a standard unqualified opinion because auditors are less likely to issue a standard unqualified opinion for firms with high discretionary accruals (Vermeer 2003). To control for the possible effects discretionary accruals have on the type of audit report, this study proposes to include a dummy variable that measures whether or not a firm received a standard unqualified opinion. The following measure was used to proxy for this type of rationalization:

AUDREPORT = a dummy variable for an audit where 1 = an unqualified opinion and 0 = an unqualified opinion with additional language.

TATA – Beneish (1997), Francis and Krishnan (1999), and Vermeer (2003) argued that accruals are representative of management's decision making and provide insight into their financial reporting rationalizations. Beneish further argued that incentives to violate GAAP or commit fraud may increase, if managers who have previously made income-increasing accruals either attempt to avoid accrual reversals or run out of ways to increase earnings. To capture this potential rationalization that managers may face, this study uses *TATA*. *TATA* was calculated following Beneish's accrual calculation:

TATA = Total accruals divided by total assets, where total accruals are calculated as the change in current assets, minus the change in cash, minus changes in current liabilities, plus the change in short-term debt, minus depreciation and amortization expense, minus deferred tax on earnings, plus equity in earnings.

Empirical design

Logit Regression

Since the dependent variable (*FRAUD*) is dichotomous, logit regression analysis was used to examine EP1 (Beasley 1996 and Stone and Rasp 1991). The estimation was based on a matched sample where 50 percent of the firms have experienced financial statement fraud and 50 percent of the firms have not experienced financial statement fraud. The firms were matched based on size, industry, and time period (Beasley 1996).

The following logit cross-sectional regression model was used to test EP1. This equation examines the empirically predicted relationship between the *SAS No. 99* fraud risk factors and the occurrence of financial statement fraud described in EP1. The equation below expands equation 1 to include proxies for pressure, opportunity, and rationalization.

$$\begin{aligned} FRAUD_i = \alpha &+ \beta_1 COMPMARG_i + \beta_2 NICFOTA_i + \beta_3 SGROW_i + \beta_4 SGROWA_i \\ &+ \beta_5 AGROW_i + \beta_6 AGROWA_i + \beta_7 FATA_i + \beta_8 SALAR_i + \beta_9 SALTA_i \\ &+ \beta_{10} INVSAL_i + \beta_{11} INVCA_i + \beta_{12} FINANCE_i + \beta_{13} FREEC_i \\ &+ \beta_{14} LEVERAGE_i + \beta_{15} LEV_i + \beta_{16} OWNERSHIP_i + \beta_{17} 5\%OWN_i \\ &+ \beta_{18} ROA_i + \beta_{19} RECEIVABLE_i + \beta_{20} INVENTORY_i + \beta_{21} FOROPS_i \\ &+ \beta_{22} BOUT_i + \beta_{23} BOUTP_i + \beta_{24} BIN_i + \beta_{25} BINP_i + \beta_{26} BSIZE_i \\ &+ \beta_{27} AUDCOMM_i + \beta_{28} AUDCSIZE_i + \beta_{29} NOEXPERT_i \\ &+ \beta_{30} AUDINDEPP_i + \beta_{31} AUDINDNUM_i + \beta_{32} MINMEET_i \\ &+ \beta_{33} AUDMEET_i + \beta_{34} INTAUD_i + \beta_{35} BLOCK_i + \beta_{36} TOTALTURN_i \\ &+ \beta_{37} CEOTURN_i + \beta_{38} CEOCHAIR_i + \beta_{39} AUDCHANG_i \\ &+ \beta_{40} AUDREPORT_i + \beta_{41} TATA_i + \varepsilon_i \end{aligned} \qquad [2]$$

Predicting Fraud – Logit and Multiple Discriminant Analysis (MDA)

To test EP2, predicting whether a firm is a fraud/no-fraud firm, this study used MDA. MDA is a multivariate technique that can be used to build rules that can classify firms into the appropriate population. MDA is similar to regression analysis except that the dependent variable is categorical (i.e., fraud = 1, no fraud = 0). MDA allows the model to predict class membership of an individual firm based on a set of predictor variables (Johnson 1998). In this study the predictor variables are the significant fraud risk factors identified by the logit analysis testing of EP1. The model used to test EP2 is as follows:

$$FRAUD = f(Significant\ Fraud\ Risk\ Factors) \qquad [3]$$

where

Significant Fraud Risk Factors = the fraud risk factors identified as significantly related to the identification of fraud in equation 2.

Numerous bankruptcy prediction studies have used discriminant analysis to identify firms likely to fall into bankruptcy. Altman (1968) and Altman *et al.* (1977) used MDA to develop bankruptcy prediction formulas. Use of MDA allowed them to establish an equation that maximizes discrimination between categories. However, MDA is flawed in that it requires the unlikely assumption that independent variables for both sets of firms have identical, normal distributions (Mossman *et al*. 1998). To combat this problem, subsequent research examining bankruptcy used logistic regression instead of MDA (see Ohlson 1980 and Aziz *et al*. 1988, 1989). Logit regression requires less restrictive statistical assumptions and offers better empirical discrimination (Zavgren 1983).

On the other hand, several studies have shown that MDA is robust in bankruptcy prediction and that there is no significant difference in accuracy between MDA models and logit analyses (see Collins and Green 1982, Cormier *et al*. 1995, and Allen and Chung 1998). Kuruppu *et al*. (2003) argued that the MDA models have greater accuracy in predicting when compared with a logit model developed from the same data. Therefore, this study used MDA to predict financial statement fraud. The developed model is referred to as the "fraud prediction model."

The discriminant function that maximally discriminates between the sample groups can be derived from either stepwise or simultaneous estimation (Hair *et al*. 1995, and George and Mallery 2001). The stepwise procedure is often used in preference to simultaneous estimation because, in practice, the stepwise discriminant procedure performs better than when all the variables are simultaneously entered in to the discriminant function (George and Mallory 2001, and Kuruppu *et al*. 2003).

Validation of Fraud Prediction Model

Validation of the developed model can be performed by one of two methods (Kuruppu *et al*. 2003). The first method applies the developed model to a new sample (hold out sample) of companies not used to derive the model. The second approach is called the Lachenbruch procedure (Jones 1987, Hair*et al*. 1995, and Kuruppu *et al*. 2003). The Lachenbruch procedure (also known as jackknife or cross-validation) develops a model from $n - 1$ observations, and applies it to the observation not used in developing the model. This is repeated until all the firms in the sample are used to assess the model's accuracy. Most importantly, the Lachenbruch method provides an unbiased estimate of the misclassification rate (Hair *et al*. 1995). Since the entire sample can be used to cross-validate the results, this method is considered particularly useful for studies with small sample sizes (Kuruppu *et al*. 2003). Due to the small sample size, this study used the Lachenbruch method to validate the fraud prediction model.

Kuruppu *et al*. (2003) also noted that an important step following the validation of the model is determining the accuracy of the model. The model validation by the Lachenbruch method provides an almost unbiased estimation of the misclassification rate.

CHAPTER IV

RESULTS AND SENSITIVITY TESTS

The purpose of this study was to empirically examine the fraud risk factors adopted in *SAS No. 99* and to develop a fraud prediction model. The examination begins with an empirical analysis of the relationships between fraud risk factors. Followed by empirical examination the fraud triangle risk factors adopted in *SAS No. 99*. The analysis concludes with the development of a fraud prediction model.

Correlations and Multicollinearity

Table 5 contains the correlation coefficients for the independent variables used in the original logit model. These coefficients were examined to determine whether multicollinearity exists in the model. The greater the correlation between variables, the higher the variance will be, due to multicollinearity. If variables are perfectly correlated, the result is an infinite variance and it is not possible to separate the individual effects of the components (Greene 2000). Further, Kennedy (1998) has suggested that correlation coefficients greater than 0.80 may indicate considerable collinearity.

The highest correlation coefficients obtained relate to the growth variables. *AGROW* and *AGROWA* are correlated at 0.99 and *SGROW* and *SGROWA* are correlated at 0.92. These high correlations are to be expected since *AGROWA* is the absolute value of *AGROW* and *SGROWA* is the absolute value of *SGROW*. The coefficient for *BOUT* and *BSIZE* is 0.84. This indicates that the number of outside directors increases as the board size increases. The coefficient for *AUDINDNUM* and *AUDCSIZE* is 0.8. This large coefficient is not surprising since *AUDINDNUM* is a subset of *AUDCSIZE*.

AUDMEETS and *MINMEETS* have a correlation coefficient of 0.79. This correlation may be explained in that *MINMEETS* is a dummy variable for number of audit committee meets equal to or greater than 4, while *AUDMEETS* is the number of audit committee meetings. *AUDINDNUM* and *AUDINDEPP* have a correlation coefficient of 0.77, since *AUDINDNUM* represents the number of independent audit committee members and *AUDINDEPP* represents the percentage of audit committee members who are independent, this high correlation is to be expected. There are no other correlation coefficients greater than 0.75, with the vast majority of the remaining coefficients having values less than 0.5.

When correlations are high, one of the variables is removed from the logit regressions. This is done to prevent multicollinearity. In addition to reviewing the correlation coefficients, the study also regressed each independent variable on the remaining variables. This was done to test for significance among independent variables. The results from the regressions were similar to those identified in the correlation test and did not reveal any significant relationships other than those identified in the correlation analysis. Therefore, the independent variable regressions are not presented here.

TABLE 5

CORRELATION MATRIX

		1	2	3	4	5	6	7	8	9	10	11
1	*FRAUD*	1.000	-0.091	0.022	0.066	0.050	0.070	0.080	-0.021	0.050	-0.095	0.113
2	*COMPMARG*		1.000	-0.040	0.009	0.028	-0.037	-0.036	0.047	0.017	0.026	0.022
3	*NICFOTA*			1.000	0.009	0.031	0.011	0.023	-0.067	0.022	-0.097	-0.054
4	*SGROW*				1.000	0.920	-0.019	-0.021	0.050	0.030	0.065	0.006
5	*SGROWA*					1.000	-0.015	-0.017	-0.023	0.007	0.041	-0.013
6	*AGROW*						1.000	0.993	0.189	-0.005	-0.012	-0.044
7	*AGROWA*							1.000	0.193	-0.007	-0.018	-0.047
8	*FATA*								1.000	0.132	-0.042	0.035
9	*SALAR*									1.000	0.000	-0.028
10	*SALTA*										1.000	-0.180
11	*INVSAL*											1.000
12	*INVCA*											
13	*FINANCE*											
14	*FREEC*											
15	*LEVERAGE*											
16	*LEV*											
17	*OWNERSHIP*											
18	*5%Own*											
19	*ROA*											
20	*RECEIVABLE*											
21	*INVENTORY*											
22	*FOROPS*											
23	*BOUT*											
24	*BOUTP*											
25	*BIN*											
26	*BINP*											
27	*BSIZE*											
28	*AUDCOMM*											
29	*AUDCSIZE*											
30	*NOEXPERT*											
31	*AUDINDEPP*											
32	*AUDINDNUM*											
33	*MINMEET*											
34	*AUDMEET*											
35	*INTAUD*											
36	*BLOCK*											
37	*TOTALTURN*											
38	*CEOTURN*											
39	*CEOCHAIR*											
40	*AUDCHANG*											
41	*AUDREPORT*											
42	*TATA*											

TABLE 5 (CONTINUED)

CORRELATION MATRIX

	12	13	14	15	16	17	18	19	20	21	22
1 *FRAUD*	-0.035	-0.064	-0.087	0.017	-0.004	-0.072	0.227	-0.067	-0.086	0.091	0.089
2 *COMPMARG*	-0.030	-0.034	0.394	-0.089	-0.009	0.077	0.089	-0.044	0.016	0.011	-0.130
3 *NICFOTA*	0.046	0.221	-0.052	0.023	-0.098	0.000	-0.032	0.644	0.044	-0.025	0.154
4 *SGROW*	-0.028	-0.049	-0.070	-0.027	-0.033	0.164	0.142	-0.031	0.008	-0.057	-0.013
5 *SGROWA*	-0.130	-0.033	0.043	-0.105	-0.029	0.172	0.145	-0.014	0.075	-0.047	0.007
6 *AGROW*	-0.014	0.079	0.262	0.017	-0.019	-0.130	0.003	0.047	-0.015	-0.006	-0.002
7 *AGROWA*	-0.020	0.082	0.261	0.014	-0.016	-0.138	0.004	0.056	-0.016	-0.007	-0.003
8 *FATA*	0.121	-0.132	0.061	0.254	-0.048	-0.033	0.037	0.032	-0.095	0.054	0.032
9 *SALAR*	0.017	0.019	-0.014	0.094	-0.038	-0.034	0.038	0.030	-0.022	-0.117	-0.008
10 *SALTA*	0.194	0.123	0.002	-0.022	-0.011	0.256	0.099	0.071	-0.107	-0.131	-0.019
11 *INVSAL*	0.244	-0.732	-0.035	0.061	-0.055	-0.049	-0.040	-0.494	0.028	0.667	-0.004
12 *INVCA*	1.000	-0.098	-0.142	0.140	-0.006	0.017	-0.172	-0.039	-0.110	0.018	0.005
13 *FINANCE*		1.000	0.196	-0.044	0.019	0.079	0.070	0.725	0.008	-0.552	0.045
14 *FREEC*			1.000	-0.096	-0.015	0.028	0.034	0.057	-0.010	-0.012	0.069
15 *LEVERAGE*				1.000	-0.063	0.119	0.035	-0.056	0.001	-0.051	0.106
16 *LEV*					1.000	-0.113	-0.113	-0.045	-0.033	-0.026	-0.191
17 *OWNERSHIP*						1.000	0.556	0.044	-0.074	-0.068	-0.092
18 *5%Own*							1.000	0.048	0.015	-0.066	-0.049
19 *ROA*								1.000	-0.040	-0.258	0.108
20 *RECEIVABLE*									1.000	0.065	0.006
21 *INVENTORY*										1.000	0.000
22 *FOROPS*											1.000
23 *BOUT*											
24 *BOUTP*											
25 *BIN*											
26 *BINP*											
27 *BSIZE*											
28 *AUDCOMM*											
29 *AUDCSIZE*											
30 *NOEXPERT*											
31 *AUDINDEPP*											
32 *AUDINDNUM*											
33 *MINMEET*											
34 *AUDMEET*											
35 *INTAUD*											
36 *BLOCK*											
37 *TOTALTURN*											
38 *CEOTURN*											
39 *CEOCHAIR*											
40 *AUDCHANG*											
41 *AUDREPORT*											
42 *TATA*											

TABLE 5 (CONTINUED)

CORRELATION MATRIX

	23	24	25	26	27	28	29	30	31	32	33
1 *FRAUD*	-0.090	-0.115	-0.013	0.115	-0.094	-0.214	-0.086	-0.094	-0.286	-0.210	0.016
2 *COMPMARG*	-0.204	-0.056	-0.050	0.056	-0.223	0.009	-0.264	-0.080	0.004	-0.243	0.047
3 *NICFOTA*	0.062	0.025	0.087	-0.025	0.107	0.169	0.083	0.117	0.050	0.024	0.111
4 *SGROW*	-0.121	-0.139	-0.026	0.139	-0.130	-0.284	-0.158	-0.088	-0.197	-0.136	-0.092
5 *SGROWA*	-0.159	-0.141	-0.015	0.141	-0.160	-0.260	-0.194	-0.067	-0.168	-0.151	-0.004
6 *AGROW*	0.207	0.083	0.014	-0.083	0.207	0.049	0.225	0.131	0.073	0.230	0.228
7 *AGROWA*	0.224	0.083	0.025	-0.083	0.228	0.053	0.226	0.142	0.081	0.235	0.257
8 *FATA*	0.219	0.091	0.048	-0.091	0.236	0.112	0.224	0.071	0.084	0.183	0.193
9 *SALAR*	0.036	0.094	-0.081	-0.094	-0.010	0.033	0.022	-0.044	-0.021	-0.018	-0.043
10 *SALTA*	-0.001	-0.023	0.006	0.023	0.002	-0.080	0.027	0.100	0.018	0.077	-0.030
11 *INVSAL*	-0.106	-0.098	0.039	0.098	-0.080	-0.018	-0.081	-0.070	0.006	-0.064	-0.085
12 *INVCA*	0.204	0.156	-0.055	-0.156	0.166	0.003	0.102	0.096	-0.062	0.025	-0.040
13 *FINANCE*	0.227	0.251	-0.133	-0.251	0.144	0.167	0.180	0.119	0.138	0.172	0.032
14 *FREEC*	-0.037	0.045	-0.098	-0.045	-0.089	0.014	-0.137	0.042	0.030	-0.114	0.195
15 *LEVERAGE*	0.130	0.066	0.029	-0.066	0.141	0.011	0.095	0.033	0.096	0.134	-0.021
16 *LEV*	-0.020	0.015	-0.063	-0.015	-0.054	-0.031	-0.013	-0.096	-0.029	-0.017	-0.023
17 *OWNERSHIP*	-0.143	-0.113	0.023	0.113	-0.125	-0.041	-0.136	0.017	0.075	-0.034	-0.179
18 *5%Own*	-0.177	-0.161	0.000	0.161	-0.170	-0.009	-0.065	-0.004	0.033	-0.020	-0.078
19 *ROA*	0.124	0.088	0.046	-0.088	0.144	0.207	0.172	0.140	0.167	0.164	0.105
20 *RECEIVABLE*	-0.068	-0.162	0.261	0.162	0.078	0.022	-0.002	-0.083	0.042	0.021	-0.051
21 *INVENTORY*	-0.090	-0.204	0.173	0.204	0.008	-0.022	-0.082	-0.115	0.046	-0.025	-0.017
22 *FOROPS*	0.119	0.141	-0.037	-0.141	0.094	0.023	0.063	-0.011	-0.010	0.025	0.154
23 *BOUT*	1.000	0.701	-0.211	-0.701	0.843	0.316	0.511	0.301	0.291	0.473	0.250
24 *BOUTP*		1.000	-0.706	-1.000	0.284	0.338	0.386	0.212	0.326	0.363	0.146
25 *BIN*			1.000	0.706	0.348	0.013	-0.058	-0.017	-0.119	-0.107	-0.051
26 *BINP*				1.000	-0.284	-0.338	-0.386	-0.212	-0.326	-0.363	-0.146
27 *BSIZE*					1.000	0.310	0.458	0.280	0.213	0.395	0.211
28 *AUDCOMM*						1.000	0.540	0.233	0.604	0.473	0.108
29 *AUDCSIZE*							1.000	0.284	0.432	0.802	0.166
30 *NOEXPERT*								1.000	0.307	0.359	0.065
31 *AUDINDEPP*									1.000	0.774	0.152
32 *AUDINDNUM*										1.000	0.200
33 *MINMEET*											1.000
34 *AUDMEET*											
35 *INTAUD*											
36 *BLOCK*											
37 *TOTALTURN*											
38 *CEOTURN*											
39 *CEOCHAIR*											
40 *AUDCHANG*											
41 *AUDREPORT*											
42 *TATA*											

TABLE 5 (CONTINUED)

CORRELATION MATRIX

		34	35	36	37	38	39	40	41	42
1	*FRAUD*	-0.050	-0.013	0.038	-0.009	0.029	0.122	0.038	0.079	-0.075
2	*COMPMARG*	-0.033	-0.121	0.026	0.044	0.071	-0.056	0.002	0.044	-0.013
3	*NICFOTA*	0.086	0.055	0.089	-0.121	-0.198	0.061	-0.100	-0.045	0.658
4	*SGROW*	-0.130	-0.041	0.176	0.127	0.117	-0.124	0.239	-0.043	-0.027
5	*SGROWA*	-0.049	-0.077	0.120	0.192	0.185	-0.139	0.231	-0.038	-0.010
6	*AGROW*	0.267	0.192	-0.001	-0.099	-0.054	0.124	-0.062	0.065	0.016
7	*AGROWA*	0.284	0.193	-0.001	-0.095	-0.039	0.114	-0.067	0.084	0.017
8	*FATA*	0.268	0.153	0.079	-0.132	-0.004	0.166	-0.100	0.162	0.010
9	*SALAR*	0.004	-0.044	-0.009	0.033	-0.048	-0.126	0.256	-0.050	0.004
10	*SALTA*	-0.015	0.149	-0.026	-0.015	0.127	0.067	0.150	0.062	-0.218
11	*INVSAL*	-0.102	0.043	-0.080	0.000	0.033	0.070	-0.075	0.043	0.020
12	*INVCA*	0.016	0.139	0.048	-0.163	-0.059	0.144	-0.055	-0.056	0.027
13	*FINANCE*	0.071	0.006	0.161	-0.017	-0.070	-0.052	-0.004	0.047	0.243
14	*FREEC*	0.111	-0.023	0.031	0.046	0.069	0.007	-0.008	0.057	0.002
15	*LEVERAGE*	-0.022	0.089	0.167	0.108	0.105	0.100	0.057	0.044	0.046
16	*LEV*	-0.108	-0.081	0.014	-0.030	-0.107	-0.059	-0.077	0.170	0.035
17	*OWNERSHIP*	-0.136	-0.138	-0.005	0.080	0.047	-0.065	0.273	-0.074	-0.022
18	*5%Own*	-0.112	-0.138	0.013	0.113	0.086	-0.114	0.132	0.061	-0.085
19	*ROA*	0.160	0.101	0.141	-0.135	-0.210	0.039	-0.025	-0.004	0.505
20	*RECEIVABLE*	-0.055	-0.046	0.025	-0.068	-0.054	0.049	-0.031	-0.047	0.038
21	*INVENTORY*	-0.015	0.113	-0.053	-0.017	-0.013	0.121	-0.159	-0.036	0.033
22	*FOROPS*	0.165	0.051	0.112	0.066	0.040	0.166	0.056	0.039	0.003
23	*BOUT*	0.344	0.351	0.171	0.029	0.062	0.039	-0.110	0.086	0.129
24	*BOUTP*	0.242	0.147	0.150	0.040	0.108	-0.163	-0.031	0.105	0.139
25	*BIN*	-0.053	0.002	-0.032	-0.046	-0.112	0.215	-0.077	-0.082	0.013
26	*BINP*	-0.242	-0.147	-0.150	-0.040	-0.108	0.163	0.031	-0.105	-0.139
27	*BSIZE*	0.301	0.338	0.146	0.002	-0.002	0.156	-0.148	0.038	0.131
28	*AUDCOMM*	0.292	0.151	0.087	-0.082	-0.109	-0.092	-0.221	0.023	0.296
29	*AUDCSIZE*	0.364	0.272	0.080	-0.115	-0.078	0.067	-0.170	0.057	0.187
30	*NOEXPERT*	0.228	0.243	-0.021	0.038	0.088	0.013	0.002	0.059	0.067
31	*AUDINDEPP*	0.304	0.236	-0.046	-0.032	-0.065	-0.017	-0.096	0.010	0.178
32	*AUDINDNUM*	0.381	0.327	-0.032	-0.074	-0.049	0.030	-0.111	0.057	0.142
33	*MINMEET*	0.787	0.143	-0.028	0.084	0.085	0.129	-0.141	0.055	0.033
34	*AUDMEET*	1.000	0.217	-0.050	0.073	0.073	0.132	-0.164	0.015	0.089
35	*INTAUD*		1.000	0.058	-0.076	-0.084	0.225	-0.022	-0.046	0.046
36	*BLOCK*			1.000	0.064	0.085	-0.026	-0.066	0.212	0.083
37	*TOTALTURN*				1.000	0.555	-0.095	0.010	0.061	-0.056
38	*CEOTURN*					1.000	-0.157	-0.074	0.181	-0.160
39	*CEOCHAIR*						1.000	-0.069	0.007	-0.052
40	*AUDCHANG*							1.000	-0.128	-0.226
41	*AUDREPORT*								1.000	0.039
42	*TATA*									1.000

Empirical Results

The first empirical prediction (EP1) addresses the usefulness of the *SAS No. 99* fraud risk factors in identifying financial statement fraud. Usefulness in this study is defined as a significant difference among fraud risk factors between fraud and no-fraud firms or as individual fraud risk factors found to be significant in explaining fraud. The study employs two methods to identify the significant fraud risk factors, univariate analysis and logistical regression.

Table 6 presents univariate descriptive statistics for each independent variable for the sample of fraud firms and their related match firm. The mean and standard deviation for each independent variable are presented along with statistical comparison between means and medians for each independent variable between fraud and no-fraud firms. Differences in means are evaluated using *t*-tests, while differences in medians are evaluated using Wilcoxon rank-sum tests (Dunn 2004). There are significant differences between means at the 1 percent level for the variables *AUDINDEPP*, *5%OWN*, *AUDCOMM*, and *AUDINDNUM*. There are no other significant differences among means less than the 10 percent level. Significant differences among medians are found at the 1 percent level (*AUDINDEPP*, *5%OWN*, *AUDCOMM*, *FREEC* and *AUDINDNUM*), the 5 percent level (*BOUT, BOUTP*, *BINP*, *BSIZE*, *AGROW*, *AGROWA*, *SALTA*, *SALAR,* and *NICFOTA*), and the 10 percent level (*CEOCHAIR*, *SGROW,* and *FINANCE,*).

The significant differences among means(medians) identified one(nine) pressure and four(eight) opportunity risk factors. It is interesting that no rationalization risk factors were identified as being significantly different. This supports *SAS No. 99's* assertion that rationalization is difficult to identify and observer. This may also be an indicator that additional or better rationalization risk factors need to be identified. This study does not identify any further fraud risk factors for rationalization. These initial results may indicate that at least some of the pressure and opportunity fraud risk factors may be useful in identifying fraud firms. However, further analysis is needed to determine whether the univariate results are useful.

TABLE 6

WILCOXON SIGN-RANK TEST

Variable	NO-FRAUD FIRMS Mean	NO-FRAUD FIRMS Std Dev	FRAUD FIRMS Mean	FRAUD FIRMS Std Dev	t-statistic *T* Value	t-statistic Pr > |*t*|		Wilcoxon t Approximation Z	Wilcoxon t Approximation Pr > |Z|	
COMPMARG	-433.70	930.15	-1552.00	8651.20	1.190	0.236		0.075	0.470	
NICFOTA	-0.04	0.15	-0.03	0.28	-0.290	0.772		-1.824	0.034	**
SGROW	-39.17	362.12	81.87	1250.00	-0.860	0.391		-1.429	0.077	*
SGROWA	170.83	321.17	259.61	1225.20	-0.650	0.517		0.458	0.324	
AGROW	155.30	663.76	333.56	1679.90	-0.920	0.362		-1.814	0.035	**
AGROWA	161.83	662.18	364.63	1673.30	-1.050	0.298		-1.823	0.034	**
FATA	0.18	0.17	0.18	0.16	0.270	0.788		0.250	0.402	
SALAR	11.78	25.99	20.02	113.07	-0.660	0.511		2.075	0.019	**
SALTA	1.42	1.49	1.19	0.88	1.250	0.214		1.983	0.024	**
INVSAL	0.17	0.31	0.35	1.08	-1.480	0.141		-0.331	0.371	
INVCA	0.26	0.24	0.24	0.23	0.460	0.649		0.558	0.288	
FINANCE	-0.10	0.51	-0.18	0.67	0.840	0.402		1.524	0.064	*
FREEC	15.89	170.69	-9.16	112.47	1.140	0.258		3.236	0.001	***
LEVERAGE	0.20	0.25	0.21	0.22	-0.220	0.826		-0.785	0.216	
LEV	1.40	2.62	1.38	2.21	0.050	0.961		0.026	0.490	
OWNERSHIP	0.23	0.20	0.20	0.19	0.950	0.345		1.069	0.143	
5%OWN	0.21	0.21	0.32	0.23	-3.040	0.003	***	-3.173	0.001	***
ROA	-4.25	34.23	-9.40	42.61	0.870	0.383		0.522	0.301	
RECEIVABLE	0.14	0.99	0.02	0.11	1.130	0.261		-0.097	0.462	
INVENTORY	-0.04	0.62	0.10	0.81	-1.190	0.236		0.480	0.316	
FOROPS	-0.02	0.37	0.04	0.18	-1.170	0.245		0.664	0.254	
BOUT	5.09	1.93	4.66	2.76	1.180	0.239		1.952	0.026	**
BOUTP	0.69	0.18	0.64	0.19	1.510	0.132		1.717	0.043	**
BIN	2.27	1.52	2.23	1.21	0.170	0.868		-0.527	0.299	
BINP	0.31	0.18	0.36	0.19	-1.510	0.132		-1.717	0.043	**
BSIZE	7.36	1.89	6.90	2.96	1.230	0.222		2.149	0.016	**
AUDCOMM	0.99	0.11	0.88	0.32	2.850	0.005	***	2.793	0.003	***
AUDCSIZE	2.84	0.99	2.64	1.29	1.130	0.262		1.173	0.121	
NOEXPERT	0.49	0.50	0.40	0.49	1.230	0.222		1.223	0.111	
AUDINDEPP	0.88	0.25	0.68	0.39	3.880	0.000	***	3.719	<0.001	***
AUDINDNUM	2.57	1.06	2.04	1.42	2.800	0.006	***	2.983	0.001	***
MINMEET	0.14	0.35	0.15	0.36	-0.220	0.830		-0.213	0.416	
AUDMEET	2.04	1.81	1.86	1.70	0.650	0.515		0.646	0.259	
INTAUD	0.26	0.44	0.24	0.43	0.180	0.861		0.174	0.431	
BLOCK	0.24	0.23	0.26	0.23	-0.490	0.625		-0.551	0.291	
TOTALTURN	1.14	1.39	1.12	1.29	0.110	0.910		-0.061	0.476	
CEOTURN	0.19	0.39	0.21	0.41	-0.380	0.704		-0.380	0.352	
CEOCHAIR	0.59	0.49	0.71	0.46	-1.600	0.111		-1.593	0.056	*
AUDCHANG	0.09	0.29	0.12	0.32	-0.500	0.621		-0.494	0.311	
AUDREPORT	0.19	0.39	0.26	0.49	-1.030	0.304		-0.814	0.208	
TATA	-3.57	22.69	-93.85	851.02	0.980	0.328		-0.801	0.212	

*$p<0.10$; **$p<0.05$; ***$p<0.01$.

Tables 7 through 10 present the logit regression results. Table 7 presents the logit results for all fraud risk factors, excluding those that are correlated at greater than 80 percent. This model has a pseudo-R^2 of 34.64 percent. The pseudo R-square is similar to the R-square that is found in ordinary least squares regression analysis. The larger the pseudo R-square the better the independent variables explain the dependent variable. In this study, the larger the pseudo R-square the better the fraud risk factors are in explaining fraud. The pseudo R-square value in this model is similar or slightly larger than other studies in this area (Robinson 2002). The model has a Wald chi-square value of 34.938 and a likelihood ratio of 73.1335, both of which are significant at the 1 percent level. The Wald chi-square and likelihood ratio were used to measure the fit of the model. In general, the likelihood-ratio test and the Wald test give approximately the same value when the sample size is large. In small to moderate samples, such as this study, it is recommended that the likelihood ratio test be used (Greene 2000).

Six variables were found to be significant in this model. They were *5%OWN* and *OWNERSHIP* at the 1 percent level, *ROA* and *FREEC* at the 5 percent level, and *NICFOTA* and *FINANCE* at the 10 percent level. Each of the significant variables is a pressure variable, indicating that pressure may be the most significant fraud risk factor category.

TABLE 7

LOGIT REGRESSION: ALL VARIABLES

$$FRAUD_i = \alpha + \beta_1 COMPMARG_i + \beta_2 NICFOTA_i + \beta_3 SGROW_i + \beta_4 AGROWA_i + \beta_5 FATA_i + \beta_6 SALAR_i + \beta_7 SALTA_i + \beta_8 INVSAL_i + \beta_9 INVCA_i + \beta_{10} FINANCE_i + \beta_{11} FREEC_i + \beta_{12} LEVERAGE_i + \beta_{13} LEV_i + \beta_{14} OWNERSHIP_i + \beta_{15} 5\%OWN_i + \beta_{16} ROA_i + \beta_{17} RECEIVABLE_i + \beta_{18} INVENTORY_i + \beta_{19} FOROPS_i + \beta_{20} BOUT_i + \beta_{21} BOUTP_i + \beta_{22} BIN_i + \beta_{23} AUDCOMM_i + \beta_{24} NOEXPERT_i + \beta_{25} AUDINDEPP_i + \beta_{26} AUDINDNUM_i + \beta_{27} MINMEET_i + \beta_{28} AUDMEET_i + \beta_{29} INTAUD_i + \beta_{30} BLOCK_i + \beta_{31} TOTALTURN_i + \beta_{32} CEOTURN_i + \beta_{33} CEOCHAIR_i + \beta_{34} AUDCHANG_i + \beta_{35} AUDREPORT_i + \beta_{36} TATA_i + \varepsilon_i$$

Variable	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	
Intercept	5.6959	2.8384	4.0269	0.0448	**
COMPMARG	-0.0001	0.0002	0.6552	0.4183	
NICFOTA	4.2857	2.3953	3.2012	0.0736	*
SGROW	0.0000	0.0006	0.0017	0.9673	
AGROWA	0.0004	0.0004	0.8083	0.3686	
FATA	-0.1902	1.7403	0.0120	0.9129	
SALAR	0.0037	0.0091	0.1674	0.6825	
SALTA	-0.1821	0.2632	0.4788	0.4890	
INVSAL	0.9153	0.7947	1.3266	0.2494	
INVCA	-1.2972	1.1248	1.3299	0.2488	
FINANCE	3.1049	1.6685	3.4628	0.0628	*
FREEC	-0.0045	0.0020	5.0632	0.0244	**
LEVERAGE	-0.0890	0.9816	0.0082	0.9278	
LEV	0.0495	0.0830	0.3561	0.5507	
OWNERSHIP	-4.6756	1.6624	7.9107	0.0049	***
5%OWN	5.9666	1.4201	17.6523	<0.0001	***
ROA	-0.0424	0.0220	3.7113	0.0540	**
RECEIVABLE	-2.4294	1.6639	2.1318	0.1443	
INVENTORY	0.8566	0.9768	0.7691	0.3805	
FOROPS	1.2357	1.0797	1.3099	0.2524	
BOUT	0.0411	0.1746	0.0554	0.8140	
BOUTP	-4.3854	3.7645	1.3571	0.2440	
BIN	-0.4480	0.3614	1.5367	0.2151	
AUDCOMM	-1.5377	1.4761	1.0852	0.2975	
NOEXPERT	0.1180	0.4518	0.0682	0.7940	
AUDINDEPP	-1.1349	1.1265	1.0150	0.3137	
AUDINDNUM	-0.3308	0.2994	1.2213	0.2691	
MINMEET	-0.0614	0.9097	0.0046	0.9462	
AUDMEET	0.2073	0.1981	1.0955	0.2953	
INTAUD	0.5394	0.5535	0.9497	0.3298	
BLOCK	0.3886	0.9954	0.1524	0.6963	
TOTALTURN	-0.2578	0.1815	2.0184	0.1554	
CEOTURN	0.3655	0.6530	0.3134	0.5756	
CEOCHAIR	0.6280	0.4601	1.8627	0.1723	
AUDCHANG	0.7236	0.7970	0.8242	0.3639	
AUDREPORT	0.3373	0.4786	0.4966	0.4810	
TATA	-0.0004	0.0018	0.0436	0.8346	

TABLE 7 (CONTINUED)

Pseudo-R2	0.3464	
Liklihood ratio	73.1335	***
Wald Chi-Square	34.9380	

**p* <0.10; ***p* <0.05; ****p* <0.01.

Table 8 examines whether the fraud risk factors found to be significantly different among fraud and no-fraud firms under the Wilcoxon test were useful in identifying fraud. This model has a Pseudo R-square of 20.96 percent and a likelihood ratio of 75.5502, which was significant at the 1 percent level. The logit regression identifies three fraud risk factors (two pressure and one opportunity variable) with significance less than 10 percent. These include *5%OWN* at the 1 percent level and *FREEC* and *AUDINDEPP2* at the 10 percent level. These results indicate that only a few of the variables identified as significantly different among fraud and no-fraud firms using the Wilcoxon test were useful. See Table 8 below.

TABLE 8

LOGIT REGRESSION: WILCOXON 10% SIGNIFICANT VARIABLES

$$FRAUD_i = \beta_0 + \beta_1 NICFOTA + \beta_2 AGROW + \beta_3 AGROWA + \beta_4 SALAR + \beta_5 SALTA + \beta_6 FREEC + \beta_7 5\%OWN + \beta_8 BOUT + \beta_9 BOUTP + \beta_{10} BSIZE + \beta_{11} AUDCOMM + \beta_{12} AUDINDEPP + \beta_{13} AUDINDNUM + \varepsilon$$

Variable	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	4.4709	2.4810	3.2474	0.0715 *
NICFOTA	0.7383	0.8814	0.7017	0.4022
AGROW	-0.0061	0.0065	0.8724	0.3503
AGROWA	0.0066	0.0066	1.0134	0.3141
SALAR	0.0009	0.0024	0.1553	0.6935
SALTA	-0.2827	0.2145	1.7376	0.1874
FREEC	-0.0025	0.0014	3.0809	0.0792 *
5%OWN	0.0258	0.0085	9.2692	0.0023 ***
BOUT	0.4365	0.4827	0.8177	0.3659
BOUTP	-2.6281	3.5085	0.5611	0.4538
BSIZE	-0.3974	0.3295	1.4549	0.2277
AUDCOMM	-1.0091	1.3178	0.5863	0.4439
AUDINDEPP	-1.5871	0.9385	2.8597	0.0908 *
AUDINDNUM	-0.1079	0.2460	0.1925	0.6608
Pseudo-R^2	0.2096			
Likelihood ratio	75.5502 ***			
Wald chi-square	26.0350 **			

*p <0.10; **p <0.05; ***p <0.01.

The next step in the study was to examine the fraud risk factors relationship to fraud using a variation of logit regression called stepwise logit regression. Stepwise regression is a technique for choosing which variables to include in a regression model. This technique consists of two components: forward selection and backward selection. The model goes through an iteration process where forward stepwise is used initially to select the first variable, the variable with the greatest statistical significance to be introduced into the model. The first step is followed by backward stepwise to remove variables from the model that are statistically insignificant. The process at each forward step adds the most statistically significant term (the one with the highest Wald chi-statistic or lowest p-value). The stepwise process alternates between forward selection and backward selection until no more variables can be added or removed at a prespecified significance level. This study uses a significance level of 10 percent.

An important assumption behind this method is that some iput variables in a logit regression do not have an important explanatory effect on the response. If this assumption is true, then it is a convenient simplification to keep only the statistically significant terms in the model. One common problem that may exist in logit regression analysis is multicollinearity of the input variables. The input variables may be as correlated with each other as they are with the response. If this is the case, the presence of one input variable in the model may mask the effect of another input. This may result in the stepwise regression including different variables than the normal logit regression, depending on the choice of starting model and inclusion strategy.

Table 9 presents the stepwise logit regression for all included fraud risk factors. This model has an R-square of 20.86 percent and likelihood ratio of 40.2321 that was significant at the 1 percent level. Four variables (two pressure and two opportunity) were found to be significant using this approach. 5*%OWN*, *OWNERSHIP,* and *AUDINDEPP* were significant at the 1 percent level and *CEOCHAIR* was significant at the 5 percent level.

TABLE 9

STEPWISE LOGIT REGRESSION: ALL VARIABLES

$$FRAUD_i = \alpha + \beta_1 COMPMARG_i + \beta_2 NICFOTA_i + \beta_3 SGROW_i + \beta_4 AGROWA_i + \beta_5 FATA_i + \beta_6 SALAR_i + \beta_7 SALTA_i + \beta_8 INVSAL_i + \beta_9 INVCA_i + \beta_{10} FINANCE_i + \beta_{11} FREEC_i + \beta_{12} LEVERAGE_i + \beta_{13} LEV_i + \beta_{14} OWNERSHIP_i + \beta_{15} 5\%OWN_i + \beta_{16} ROA_i + \beta_{17} RECEIVABLE_i + \beta_{18} INVENTORY_i + \beta_{19} FOROPS_i + \beta_{20} BOUT_i + \beta_{21} BOUTP_i + \beta_{22} BIN_i + \beta_{23} AUDCOMM_i + \beta_{24} NOEXPERT_i + \beta_{25} AUDINDEPP_i + \beta_{26} AUDINDNUM_i + \beta_{27} MINMEET_i + \beta_{28} AUDMEET_i + \beta_{29} INTAUD_i + \beta_{30} BLOCK_i + \beta_{31} TOTALTURN_i + \beta_{32} CEOTURN_i + \beta_{33} CEOCHAIR_i + \beta_{34} AUDCHANG_i + \beta_{35} AUDREPORT_i + \beta_{36} TATA_i + \varepsilon_i$$

Summary of Stepwise Selection:

Step	Entered	Removed	Wald Chi-Square	
1	*AUDINDEPP*		14.0199	***
2	*5%OWN*		10.36	***
3	*OWNERSHIP*		9.8319	***
4	*CEOCHAIR*		4.0874	***
5	*RECEIVABLE*		2.6646	
6		*RECEIVABLE*	--	

Summary of Stepwise Logit Model:

Variable	Estimate		Standard Error	Wald Chi-Square	Pr > ChiSq	
Intercept	0.7602		0.5677	1.7932	0.1805	
OWNERSHIP	-0.0381		0.0125	9.2076	0.0024	***
5%OWN	0.0465		0.011	17.7829	<0.0001	***
AUDINDEPP	-2.0962		0.5731	13.3791	0.0003	***
CEOCHAIR	0.7403		0.3694	4.0158	0.0451	**
Pseudo-R^2	0.2086					
Likelihood ratio	40.2321	***				
Wald chi-square	28.4858	***				

*p <0.10; **p <0.05; ***p <0.01.

Table 10 reports whether the fraud risk factors found to be significantly different among fraud and no-fraud firms under the Wilcoxon test were useful in predicting fraud. The stepwise logistic regression approach was used in this model. This model has a Pseudo R-square of 13.71 percent and a likelihood ratio of 25.3695, which was significant at the 1 percent level. Using this approach, two variables (1 pressure and 1 opportunity) were found to be significant in predicting fraud, 5*%OWN* and *AUDINDEPP*. Both variables were significant at the 1 percent level.

TABLE 10

STEPWISE LOGIT REGRESSION: WILCOXON 10% SIGNIFICANT VARIABLES

$$FRAUD_i = \beta_0 + \beta_1 NICFOTA + \beta_2 AGROW + \beta_3 AGROWA + \beta_4 SALAR + \beta_5 SALTA + \beta_6 FREEC + \beta_7 5\%OWN + \beta_8 BOUT + \beta_9 BOUTP + \beta_{10} BSIZE + \beta_{11} AUDCOMM + \beta_{12} AUDINDEPP + \beta_{13} AUDINDNUM + \varepsilon$$

Summary of Stepwise Selection:

Step	Entered	Removed	Wald Chi-Square
1	*AUDINDEPP*		14.0199 ***
2	*5%OWN*		10.36 ***
3	*SALTA*		2.2651
4		*SALTA*	--

Summary of Stepwise Logit Model:

Variable	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	0.9808	0.4915	3.9821	0.046 **
5%OWN	0.0239	0.0077	9.6344	0.0019 ***
AUDINDEPP	-2.0311	0.5477	13.7501	0.0002 ***

Pseudo-R^2	0.1371
Likelihood ratio	25.3695 ***
Wald chi-square	20.7083 ***

*p <0.10; **p <0.05; ***p <0.01.

Table 11 reports the significant fraud risk factors identified through the univariate and logit techniques. Of the significant fraud risk factors under the various logit approaches, only *5%OWN* was found to be significant in each of the four models. *AUDINDEPP* was significant in the last three logit models. *FREEC* was found to be significant in the first and second logit models, and *OWNERSHIP* was found to be significant in the first and third models. The following four variables (*CEOCHAIR, NICFOTA, FINANCE,* and *ROA*) were found to be significant in only one logit model. No other variables were found to be significant in the logit regression analysis.

These initial results indicate that the pressure and opportunity fraud risk factors are more useful or are stronger indicators of fraud than the rationalization variables. This may be an actuality or may be due to inadequate identification of rationalization fraud risk factors. Whichever the case, there remains a need to continue to try and identify fraud risk factors in all categories that may be useful in differentiating between fraud and no-fraud firms. Furthermore, from the identified fraud risk factors, the pressure fraud risk factors were found to be significantly different among the models more often than the opportunity fraud risk factors. This may indicate that pressure is the strongest indicator of fraud. The Table 11 results are found below.

TABLE 11

SUMMARY OF SIGNIFICANT VARIABLES

Significant Variable	Wilcoxon	Model 1	Model 2	Model 3	Model 4	# of Models Significant
NICFOTA	Yes	Yes	No	No	No	2
SGROW	Yes	No	No	No	No	1
AGROW	Yes	No	No	No	No	1
AGROWA	Yes	No	No	No	No	1
SALAR	Yes	No	No	No	No	1
SALTA	Yes	No	No	No	No	1
FINANCE	Yes	Yes	No	No	No	2
FREEC	Yes	Yes	Yes	No	No	3
OWNERSHIP	No	Yes	No	Yes	No	2
5%Own	Yes	Yes	Yes	Yes	Yes	5
ROA	No	Yes	No	No	No	1
BOUT	Yes	No	No	No	No	1
BOUTP	Yes	No	No	No	No	1
BINP	Yes	No	No	No	No	1
BSIZE	Yes	No	No	No	No	1
AUDCOMM	Yes	No	No	No	No	1
AUDINDEPP	Yes	No	Yes	Yes	Yes	4
AUDINDNUM	Yes	No	No	No	No	1
CEOCHAIR	Yes	No	No	Yes	No	2

Model 1 = Logit with all variables (TABLE 7)
Model 2 = Logit with only significant Wilcoxon variables (TABLE 8)
Model 3 = Stepwise logit all variables (TABLE 9)
Model 4 = Stepwise logit only significant Wilcoxon variables (TABLE 10)

Discriminant Analysis

The second empirical prediction (EP2) used the significant fraud risk factors identified in EP1 to develop a model for predicting financial statement fraud. The study used discriminant analysis to test the usefulness of the significant fraud risk factors in predicting financial statement fraud. There are three discriminant analysis methods that could be used to perform this test. The resubstitution method uses the same data both to define and to evaluate the classification criterion. Since the resubstitution method tests the model with the data used to create the model, it is generally considered to have greater bias than other methods. The second method, cross-validation, which is also known as the Lachenbruch or jackknifing method, removes the first observation from the data set and finds a discriminant rule using the remaining observations. The model predicts the classification of the removed observation, and then repeats the process for each observation. The resulting number of different classifications can be used to find a nearly unbiased estimate of the discriminant rule's accuracy (Neter et al. 1996). According to Neter et al. (1996), if given a choice between these two methods, cross-validation should be used since it generally provides results that are less biased. The best method is to use a hold-out or split sample to test the discriminant rule. Due to the limited number of fraud firms, this option is not feasible.

Therefore, Table 12 presents both the resubstitution and cross-validation results. Using the resubstitution method, fraudulent firms were misclassified as nonfraudulent between 23.26 and 43.02 percent of the time. These results are strong inasmuch as studies that have used the resubstitution approach and focused on financial ratios generally have misclassification errors greater than 70 percent (Kaminski et al. 2004).

However, the resubstitution results were presented only for comparison, considering they provide a model with greater potential bias. The results from the cross-validation method are discussed below.

By using the cross-validation method, the fraud firms were misclassified as non-fraudulent between 34.88 and 44.19 percent of the time. Once again, these results provide much stronger results than other fraud detection or prediction studies that used cross-validation, which generally have misclassification greater than 50 percent (Kaminski et al. 2004). This model has a larger misclassification of non-fraudulent firms as fraud firms than other studies, misclassifying approximately 28 percent of these firms as compared to as low as 14 percent in other studies. Interestingly, the overall misclassification error is as low as 31.4 percent in this study compared to 46 percent in fraud detection studies focusing on financial ratios. These results provided empirical evidence of the ability or usefulness of the fraud risk factors to detect and/or predict fraudulent financial reporting. These results support *SAS No. 99*'s assertion that not all of the fraud triangle risk factor categories need to be present for fraud to occur.

TABLE 12

DISCRIMINANT ANALYSIS

Fraud Prediction Model 1: All variables

$$FRAUD_i = \alpha + \beta_1 COMPMARG_i + \beta_2 NICFOTA_i + \beta_3 SGROW_i + \beta_4 SGROWA_i + \beta_5 AGROW_i + \beta_6 AGROWA_i + \beta_7 FATA_i + \beta_8 SALAR_i + \beta_9 SALTA_i + \beta_{10} INVSAL_i + \beta_{11} INVCA_i + \beta_{12} FINANCE_i + \beta_{13} FREEC_i + \beta_{14} LEVERAGE_i + \beta_{15} LEV_i + \beta_{16} OWNERSHIP_i + \beta_{17} 5\%OWN_i + \beta_{18} ROA_i + \beta_{19} RECEIVABLE_i + \beta_{20} INVENTORY_i + \beta_{21} FOROPS_i + \beta_{22} BOUT_i + \beta_{23} BOUTP_i + \beta_{24} BIN_i + \beta_{25} BINP_i + \beta_{26} BSIZE_i + \beta_{27} AUDCOMM_i + \beta_{28} AUDCSIZE_i + \beta_{29} NOEXPERT_i + \beta_{30} AUDINDEPP_i + \beta_{31} AUDINDNUM_i + \beta_{32} MINMEET_i + \beta_{33} AUDMEET_i + \beta_{34} INTAUD_i + \beta_{35} BLOCK_i + \beta_{36} TOTALTURN_i + \beta_{37} CEOTURN_i + \beta_{38} CEOCHAIR_i + \beta_{39} AUDCHANG_i + \beta_{40} AUDREPORT_i + \beta_{41} TATA_i + \varepsilon_i$$

Model		Resubstitution Method No Fraud %	Resubstitution Method Fraud %	Resubstitution Method Total Error	Cross-validation Method No Fraud %	Cross-validation Method Fraud %	Cross-validation Method Total Error
All variables							
	No Fraud	81.40	18.60	20.93	65.12	34.88	39.53
	Fraud	23.26	76.74		44.19	55.81	

Fraud Prediction Model 2: Removed correlated variables above 80 percent

$$FRAUD_i = \alpha + \beta_1 COMPMARG_i + \beta_2 NICFOTA_i + \beta_3 SGROW_i + \beta_4 AGROWA_i + \beta_5 FATA_i + \beta_6 SALAR_i + \beta_7 SALTA_i + \beta_8 INVSAL_i + \beta_9 INVCA_i + \beta_{10} FINANCE_i + \beta_{11} FREEC_i + \beta_{12} LEVERAGE_i + \beta_{13} LEV_i + \beta_{14} OWNERSHIP_i + \beta_{15} 5\%OWN_i + \beta_{16} ROA_i + \beta_{17} RECEIVABLE_i + \beta_{18} INVENTORY_i + \beta_{19} FOROPS_i + \beta_{20} BOUT_i + \beta_{21} BOUTP_i + \beta_{22} BIN_i + \beta_{23} AUDCOMM_i + \beta_{24} NOEXPERT_i + \beta_{25} AUDINDEPP_i + \beta_{26} AUDINDNUM_i + \beta_{27} MINMEET_i + \beta_{28} AUDMEET_i + \beta_{29} INTAUD_i + \beta_{30} BLOCK_i + \beta_{31} TOTALTURN_i + \beta_{32} CEOTURN_i + \beta_{33} CEOCHAIR_i + \beta_{34} AUDCHANG_i + \beta_{35} AUDREPORT_i + \beta_{36} TATA_i + \varepsilon_i$$

Model		Resubstitution Method No Fraud %	Resubstitution Method Fraud %	Resubstitution Method Total Error	Cross-validation Method No Fraud %	Cross-validation Method Fraud %	Cross-validation Method Total Error
Removed high correlation variables							
	No Fraud	77.91	22.09	22.76	66.28	33.72	36.63
	Fraud	23.26	76.74		39.53	60.47	

TABLE 12 (CONTINUED)

Fraud Prediction Model 3: Significant variables from descriptive statistics (Table 6)

$$FRAUD_i = \alpha + \beta_1 NICFOTA_i + \beta_2 AGROW_i + \beta_3 AGROWA_i + \beta_4 SALAR_i + \beta_5 SALTA_i + \beta_6 FREEC_i + \beta_7 5\%OWN_i + \beta_8 BOUT_i + \beta_9 BOUTP_i + \beta_{10} BSIZE_i + \beta_{11} AUDCOMM_i + \beta_{12} AUDINDEPP_i + \beta_{13} AUDINDNUM_i + \varepsilon_i$$

		Resubstitution Method			Cross-validation Method		
Model		No Fraud %	Fraud %	Total Error	No Fraud %	Fraud %	Total Error
Descriptive 10% significance							
	No Fraud	72.09	27.91	33.72	68.60	31.40	37.21
	Fraud	39.53	60.47		43.02	56.98	

Fraud Prediction Model 4: Significant variables from logit regression (Table 7)

$$FRAUD_i = \alpha + \beta_1 NICFOTA_i + \beta_2 OWNERSHIP_i + \beta_3 5\%OWN_i + \beta_4 ROA_i + \beta_5 RECEIVABLE_i + \varepsilon_i$$

		Resubstitution Method			Cross-validation Method		
Model		No Fraud %	Fraud %	Total Error	No Fraud %	Fraud %	Total Error
Logit 10% significance (high correlations removed)							
	No Fraud	75.58	24.42	29.65	72.09	27.91	33.14
	Fraud	34.88	65.12		38.37	61.63	

Fraud Prediction Model 5: Significant variables from logit regression using only significant descriptive statistics (Table 8)

$$FRAUD_i = \alpha + \beta_1 FREEC_i + \beta_2 5\%OWN_i + \beta_3 AUDINDEPP_i + \varepsilon_i$$

		Resubstitution Method			Cross-validation Method		
Model		No Fraud %	Fraud %	Total Error	No Fraud %	Fraud %	Total Error
Logit using only descriptive 10% significance							
	No Fraud	69.77	30.23	36.63	67.44	32.56	38.37
	Fraud	43.02	56.98		44.19	55.81	

Fraud Prediction Model 6: Significant variables from stepwise logit regression (Table 9)

$$FRAUD_i = \alpha + \beta_1 OWNERSHIP_i + \beta_2 5\%OWN_i + \beta_3 AUDINDEPP_i + \beta_4 CEOCHAIR_i + \varepsilon_i$$

		Resubstitution Method			Cross-validation Method		
Model		No Fraud %	Fraud %	Total Error	No Fraud %	Fraud %	Total Error
Stepwise Logit 10% significance (high correlations removed)							
	No Fraud	73.26	26.74	29.65	72.09	27.91	31.40
	Fraud	32.56	67.44		34.88	65.12	

Fraud Prediction Model 7: Significant variables from stepwise logit regression using only significant descriptive statistics (Table 10)

$$FRAUD_i = \alpha + \beta_1 AGROWA_i + \beta_2 SALTA_i + \beta_3 FREEC_i + \beta_4 5\%OWN_i + \beta_5 BOUT_i + \beta_6 AUDINDEPP_i + \varepsilon_i$$

		Resubstitution Method			Cross-validation Method		
Model		No Fraud %	Fraud %	Total Error	No Fraud %	Fraud %	Total Error
Stepwise Logit using only descriptive 10% significance							
	No Fraud	67.44	32.56	34.88	66.28	33.72	36.63
	Fraud	37.21	62.79		39.53	60.47	

Fraud Prediction Model 8: Significant variables from descriptive statistics, logit, and stepwise logit (summarized in Table 11)

$$\begin{aligned} FRAUD_i = \alpha &+ \beta_1 NICFOTA_i + \beta_2 AGROW_i + \beta_3 AGROWA_i + \beta_4 SALAR_i + \beta_5 SALTA_i + \beta_6 FREEC_i \\ &+ \beta_7 OWNERSHIP_i + \beta_8 5\%OWN_i + \beta_9 ROA_i + \beta_{10} RECEIVABLE_i + \beta_{11} BOUT_i + \beta_{12} BOUTP_i \\ &+ \beta_{13} BSIZE_i + \beta_{14} AUDCOMM_i + \beta_{15} AUDINDEPP_i + \beta_{16} AUDINDNUM_i + \beta_{17} CEOCHAIR_i + \varepsilon_i \end{aligned}$$

		Resubstitution Method			Cross-validation Method		
Model		No Fraud %	Fraud %	Total Error	No Fraud %	Fraud %	Total Error
10% Significant variables all models							
	No Fraud	74.42	25.58	26.16	69.77	30.23	34.88
	Fraud	26.74	73.26		39.53	60.47	

Sensitivity Analysis

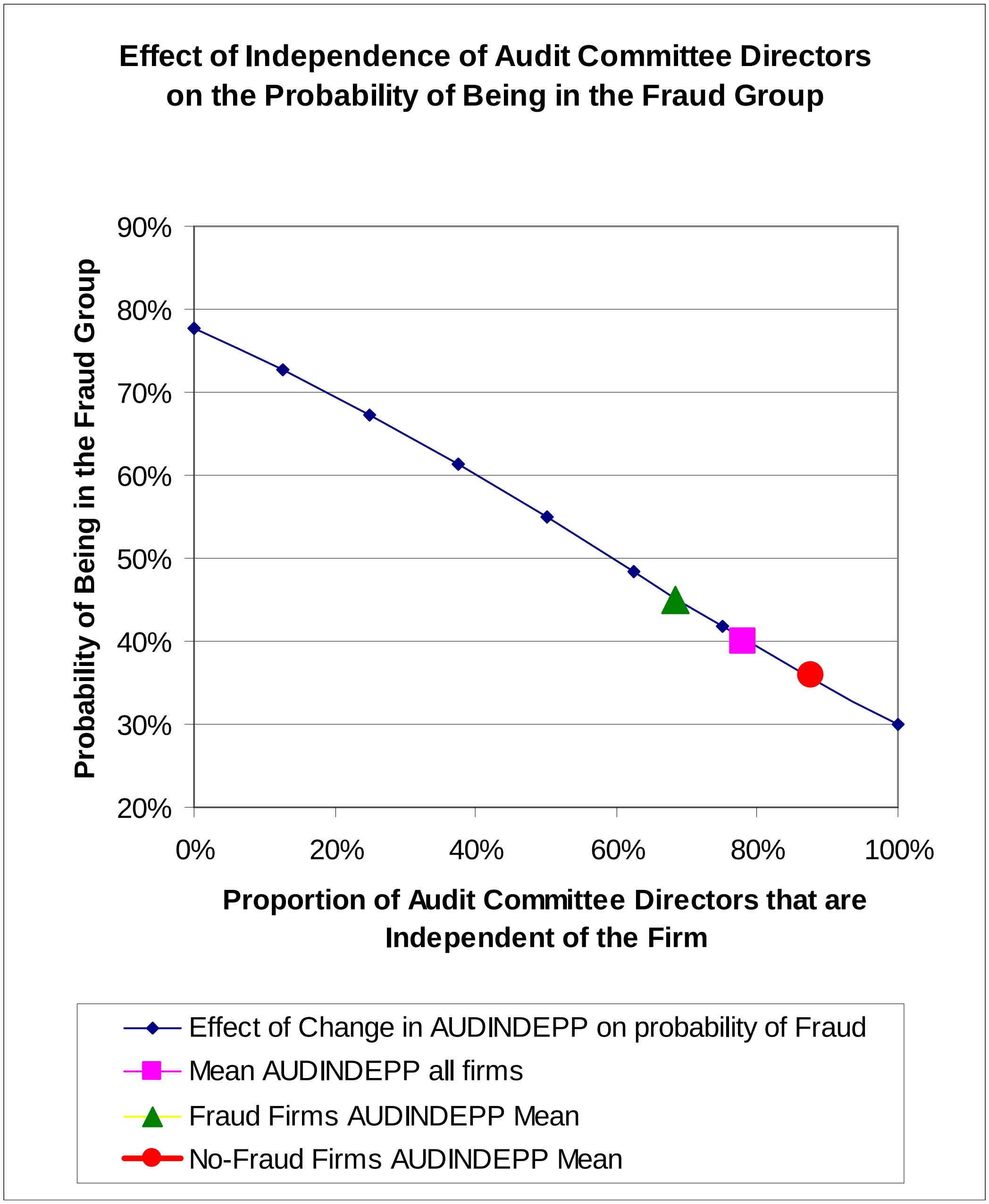
The results from the univariate and logistic analysis applied to test EP1 identified multiple variables that potentially have discriminatory value. Using these significant variables to test EP2 resulted in four variables providing the greatest discriminatory ability in classifying firms as fraud firms correctly. These variables are *AUDINDEPP*, *5%0WN*, *OWNERSHIP*, and *CEOCHAIR*. To test the sensitivity of these results, the probability of a firm being in the fraud group based on the proportion of *AUDINDEPP*, *5%0WN*, *OWNERSHIP*, and *CEOCHAIR* was derived. For each variable's proportional relationship to the probability of being in the fraud group, the other variables in the model are held at their mean.

Figures 8 through 11 report the probability of a firm being in the fraud group based upon independent changes in the proportion of the variable, while holding the remaining variables at their mean. These results reveal the power and importance of each of these variables in predicting the probability of fraud.

The results in Figure 8 reveal that when the proportion of independent audit committee directors (*AUDINDEPP*) is approximately 12 percent of the audit committee, the probability of a firm being in the fraud group is approximately 73 percent. When the proportion of *AUDINDEPP* is 25 percent of the audit committee, the probability of a firm being in the fraud group is approximately 67 percent. When the proportion increases to the mean value of approximately 78 percent, the probability of being in the fraud group decreases to 40 percent. Lastly, as *AUDINDEPP*increases to 100 percent, the probability of being in the fraud group decreases to 30 percent. These results reveal that as the proportion of independent audit committee directors is increased, the probability of financial statement fraud is reduced. These results are consistent with Robinson (2002) and mandated changes to audit committee composition (i.e., Sarbanes-Oxley).

FIGURE 8

EFFECT OF INDEPENDENT AUDIT COMMITTEE DIRECTORS ON THE PROBABILITY OF BEING IN THE FRAUD GROUP

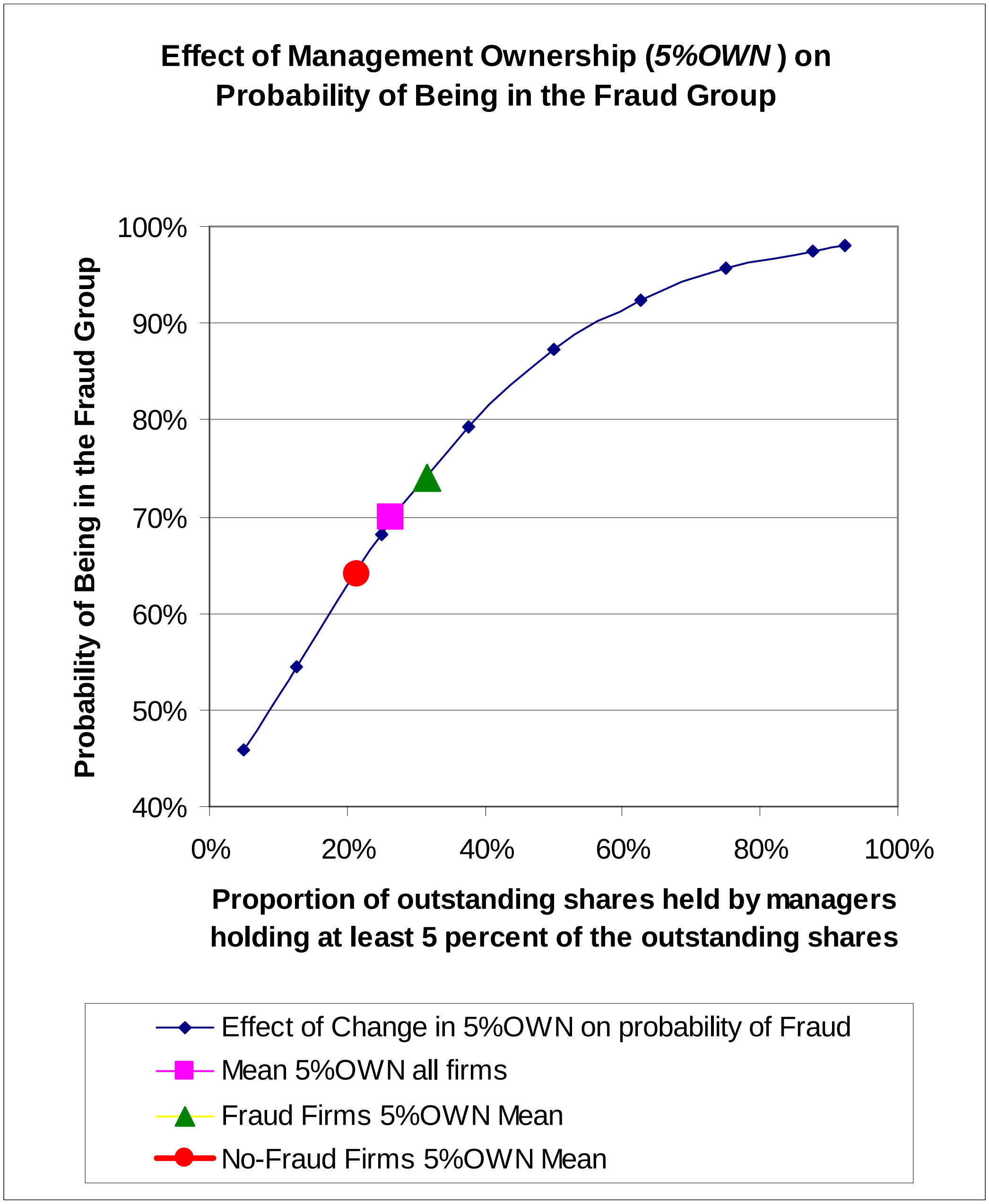


The results in Figure 9 indicate that when the proportion of ownership held by management who hold greater than 5 percent of the outstanding shares (*5%OWN*) increases, the probability of fraud increases. When *5%OWN* is approximately 12 percent of the firm's outstanding shares, the probability of a firm being in the fraud group is 55 percent. When the proportion increases to the mean value of approximately 26 percent of firm ownership, the probability of being in the fraud group increases to 70 percent. And as *5%OWN* increases to 75 percent, the probability of being in the fraud group increases to 96 percent. These results reveal that a curvilinear relationship exists between the probability of a firm being in the fraud group and the proportion of management ownership greater than 5 percent. See Figure 9 below.

FIGURE 9

EFFECT OF 5% OWNERSHIP ON THE PROBABILITY OF

BEING IN THE FRAUD GROUP

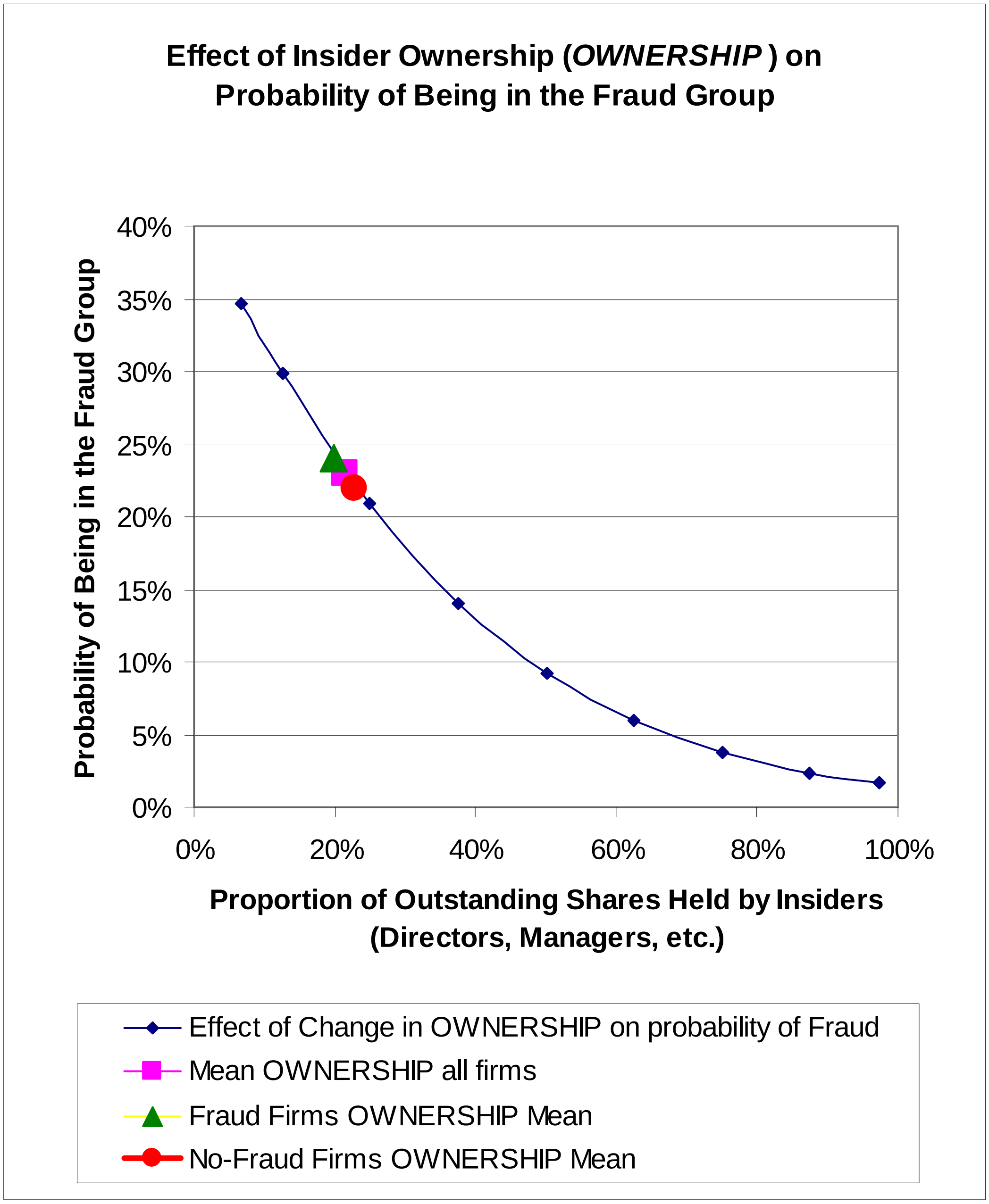


The results in Figure 10 indicate that when the proportion of insider ownership (management and directors) decreases, the probability of being in the fraud group increases. When insider ownership (*OWNERSHIP)* is equal to 75 percent ownership of the firm's outstanding shares, the probability of being in the fraud is 4 percent. When *OWNERSHIP* decreases to its mean value of approximately 21 percent, the probability of fraud increases to 23 percent. This analysis reveals a strong relationship between the probability of being in the fraud group and insider ownership.

FIGURE 10

EFFECT OF OWNERSHIP ON THE PROBABILITY OF

BEING IN THE FRAUD GROUP



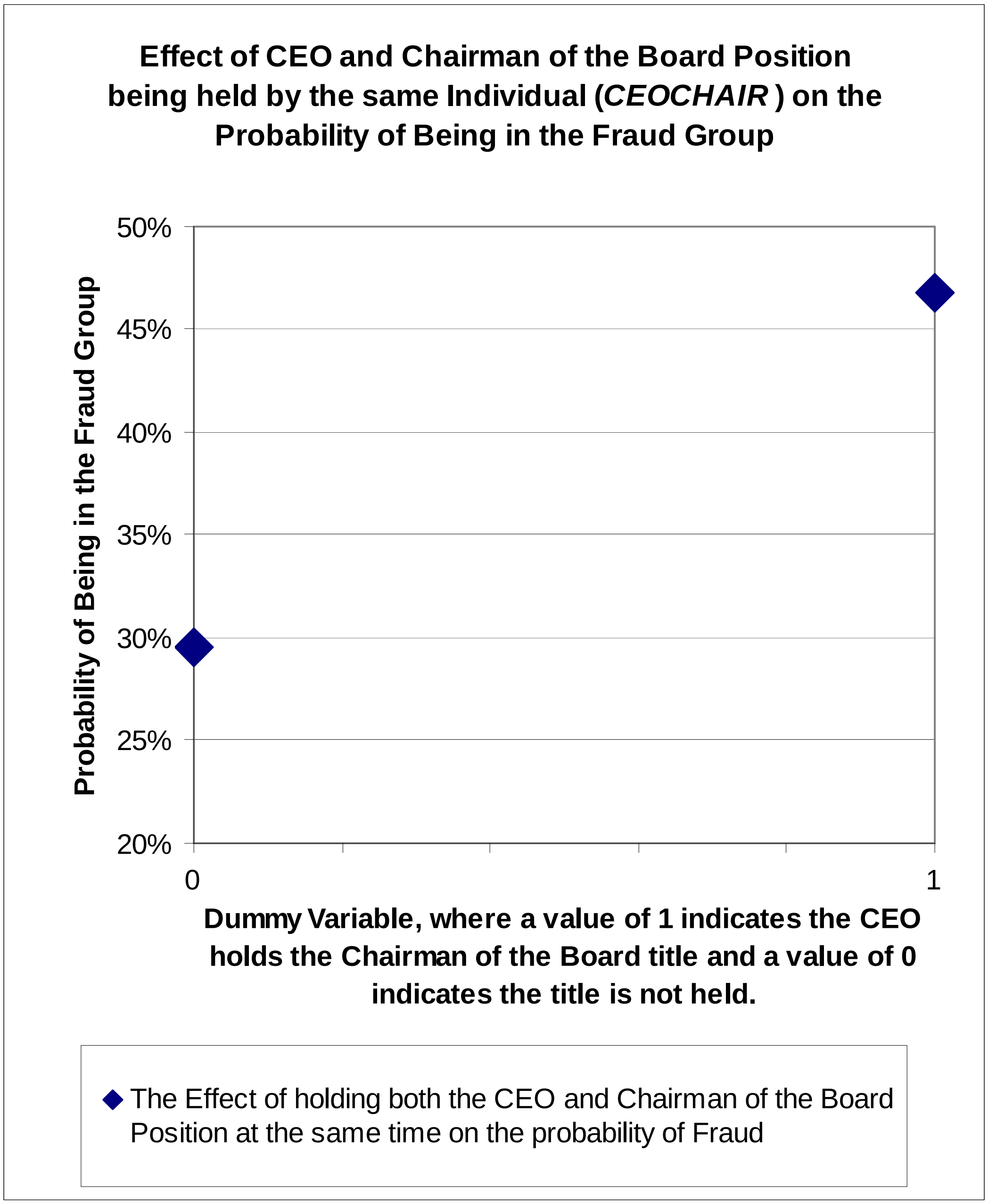
The Figure 11 results indicate that the relationship between CEOs who hold the CEO position and both the CEO and Chairman of the Board positions (*CEOCHAIR*) is correlated with a higher probability of being included in the fraud group. When the CEO holds the Chairman of the Board position (*CEOCHAIR* equals one), the probability of being in the fraud group is 47 percent; otherwise (CEO does not hold Chairman of the Board title, *CEOCHAIR* equals zero) the probability of being in the fraud group is 30 percent. This result reveals the power that an individual who holds both the CEO and Chairman of the Board positions may have. As CEOs accumulate positions/titles, they are eliminating individuals who could potentially contend with them. This potentially eliminates a check or balance among the executives.

FIGURE 11

EFFECT OF CEO/CHAIRMAN OF THE BOARD POSITIONS

HELD BY THE SAME INDIVIDUAL ON THE PROBABILITY OF

BEING IN THE FRAUD GROUP



Implications

The above analysis demonstrates that the fraud risk factors are useful in identifying fraud firms. In particular, three pressure fraud risk factors and one opportunity fraud risk factor were found to be useful in classifying firms as either fraud or no-fraud firms. These variables are *AUDINDEPP*, *5%0WN*, *OWNERSHIP*, and *CEOCHAIR*. Specific implications relating to the significant fraud risk factors follow.

The results reveal that as the percentage of independent audit committee members increases, the likelihood of fraudulent financial statements decreases. This result supports recent legislation (Sarbanes-Oxley) that has mandated an independent audit committee. However, research needs to be done on how independence is defined and how this study's definition of audit committee independence may affect fraud research.

When firms have high management ownership (*5%0WN)*, high insider ownership (*OWNERSHIP)*, and/or a CEO who holds the Chairman of the Board position (*CEOCHAIR)*, the likelihood of fraud increases. This implies that firms that have a concentration of power should be carefully scrutinized by parties of interest. Further, legislation may be needed to prevent the CEO from holding the chairman of the board position to limit the power of individuals.

These results imply that *SAS No. 99* is correct in its usage of Cressey's Fraud Triangle. Furthermore, *SAS No. 99* suggests that if any of the fraud triangle elements are present, then the likelihood of fraud increases. This study was only able to identify two elements of the fraud triangle that differed among fraud and no-fraud firms. This finding appears to support *SAS No. 99*'s assertion that not all elements of the fraud triangle need to be present for fraud to occur. It also supports *SAS No. 99*'s assertion that rationalization is difficult to observe. Future studies should choose or seek to identify alternative proxies for rationalization.

According to this study's findings, standard setters, stockholders, investors, academics, and any other users of publicly available information should take additional precautions when companies have audit committees with a low percentage of outside directors, high management ownership exceeding 5 percent, high cumulative percentage ownership in the firm held by insiders, or a CEO who holds both the CEO and Chairman of the Board position. The remaining chapter discusses the results and limitations of this study.

CHAPTER V

SUMMARY, LIMITATIONS, AND SUGGESTIONS

Summary

Much attention has recently been focused on fraud committed by business executives and on the accounting firms that failed to detect and report financial statement fraud. This failure has resulted in a loss of public confidence in audited financial statements and created an environment where users of financial statements are questioning the procedures utilized to detect financial statement fraud.

Prior to the recent accounting scandals, the American Institute of Certified Public Accountants' (AICPA) Fraud Task Force directed the Accounting Standards Board (ASB) to consider revising *Statement of Auditing Standards (SAS) No. 82*, "Consideration of Fraud in a Financial Statement Audit." This was based on academic research, recommendations from the accounting profession, and recommendations provided by other financial reporting stakeholders. This process, as well as other pressures, resulted in the issuance of *SAS No. 99*, "Consideration of Fraud in a Financial Statement Audit" (which supersedes *SAS No. 82*). While the auditor's responsibility for detecting fraud remains unchanged, *SAS No. 99* is intended to focus auditing guidance and thus increase auditor effectiveness in detecting fraud.

SAS No. 99 was intended to serve as the cornerstone of the ASB's anti-fraud program. It was enhances the accounting profession's most decisive steps in combating fraud. The standard was intended to result in a greater emphasis on professional skepticism, a partner-led discussion of fraud assessment with all of the members of the audit engagement team as part of the planning process, and additional procedures to obtain information needed to identify the risks of material misstatement due to fraud, including inquiries of management and others, and analytical procedures.

This study focused specifically on the *SAS No. 99* processes wherein the auditor 1) gathers information needed to identify risks of material misstatement, 2) assesses these risks after taking into account an evaluation of the entity's programs and controls, and 3) responds to the results. Under *SAS No. 99*, the auditor must gather and consider much more information to assess fraud risks than in the past (Ramos 2003). This process involves gathering information and assessing firms' fraud risk factors.

The theory behind the *SAS No. 99* fraud risk factors was developed by Donald R. Cressey in the late 1940s. Cressey surmised that three conditions are present when fraud occurs:

1. Pressure – management or other employees may have an incentive or be under pressure, which provides a motivation to commit fraud.
2. Opportunity – circumstances exist (i.e., the absence of controls, ineffective controls, or the ability of management to override controls) that provide an opportunity for fraud to be perpetrated.
3. Rationalization – those involved in a fraud rationalize a fraudulent act as being consistent with their personal code of ethics. Some individuals possess an attitude, a character, and/or a set of ethical values that allow them to knowingly and intentionally commit a dishonest act (Ramos 2003).

This study empirically examined the fraud risk factors adopted by the Accounting Standards Board in *SAS No. 99* and developed a model that is useful in discriminating between fraud and no-fraud firms. A cross-sectional logistic regression analysis of matched sample firms was used to evaluate the usefulness of the fraud risk factors. In addition, differences between fraud risk factor means were compared between fraud and no-fraud firms. The result was to identify fraud risk factors that are useful in discriminating fraud and no-fraud firms. This phase of testing involved identifying and testing proxies for pressure, opportunity, and rationalization. The identified proxies were examined for a sample of firms that have been convicted of fraud and compared with a sample of no-fraud firms. This phase identified several pressure and opportunity fraud risk factors that may be useful in discriminating between fraud and no-fraud firms. These variables included *5%OWN, AUDINDEPP, FREEC, CEOCHAIR, NICFOTA, OWNERSHIP*, *FINANCE,* and *ROA.*

After identifying the significant fraud risk factors from the logistic and means analyses, the study applied multiple discriminate analysis to the significant variables to develop a prediction model. This phase of the study followed the theory developed in the bankruptcy prediction studies (initiated by Altman 1968). This phase involved using the empirically relevant fraud risk factors identified in the first phase to develop a fraud prediction model. As shown in Table 12, the fraud prediction model that performed best used the significant variables identified in the stepwise regression logit model. These variables included *5%0WN*, *OWNERSHIP*, *CEOCHAIR,* and *AUDINDEPP*. These variables represent only two legs of the fraud triangle. The first three fraud risk factors are proxies for pressure, while the last fraud risk factor proxies for opportunity.

It is interesting that none of the fraud risk factor proxies for rationalization were significantly different among fraud and no-fraud firms. This may indicate that better proxies for rationalization need to be identified or that pressure and opportunity are the only two variables that must be present for fraud to occur. This is in line with *SAS No. 99*'s assertion that if any fraud risk factors are present, greater attention should be given to that firm.

The prediction model is able to correctly classify fraud firms 72 percent of the time. This finding is very important as Kuruppu *et al*. (2003) noted that the Altman bankruptcy model, when applied to matched samples such as this study, only has an accuracy rate of between 40 and 50 percent. This shows that the fraud risk factor model is a stronger analytical tool at identifying fraud firms. Additionally, studies that have expanded the financial ratios used by Altman (1969), such as Persons (1995) and Kaminski *et* al. (2004), have only correctly identified fraud firms in the year prior to the fraud 20 to 40 percent of the time.

In addition to a higher identification rate of fraud firms, the fraud risk factor model developed in this study is more accurate in correctly identifying no-fraud firms. The overall effect is that the fraud risk factor has a lower misclassification error of fraud and no-fraud firms than the other prediction models. Given the high costs associated with misclassifying fraudulent firms, the need or demand for an accurate analytical model for identifying fraudulent firms is immense. The developed fraud prediction model can be used as a valuable analytical tool in evaluating and identifying fraudulent firms. Most importantly this study used publicly available data, thus allowing private investors who are not privy to proprietary information to assess the likelihood of a firm issuing fraudulent financial statements. Further, the use of Cressey's theory in the development of the *SAS No. 99* fraud risk factors appears to be substantiated by these results.

The results of this study provide evidence of the usefulness of the *SAS No. 99* fraud risk factors and support the use of Cressey's fraud triangle. This evidence should be of interest to regulators, standard setters, investors, academics, and the accounting profession as they further define and refine analytical procedures and methods for identifying fraudulent firms.

The results of this study are of interest to academics, standard setters, and users of financial statement data. The results show that Cressey's theory is at least in part correct and can be used in developing proxies for fraud risk factors. This is important in light of the ASB using the fraud triangle theory in *SAS No. 99.* The development of the fraud prediction model based upon the fraud triangle is of interest to academics, standard setters, and users of financial statement data since the model permits the use of publicly available data (unlike the proprietary data that auditors and other insiders may have access to) to assess the likelihood that a firm will be involved in the preparation of fraudulent financial statements (similar to Altman's Z-score [1968]).

Limitations

As with most fraud studies, a limitation of the sample selection process involved the potential misclassification of no-fraud firms. This misclassification results from the possibility that financial statement fraud might have occurred but has yet to be detected and subjected to SEC investigation. This results in a dichotomous dependent variable for fraud. All cases of financial statement fraud are in publicly traded companies, where the supporting financial and proxy statements are available.

Another limitation resulted in the operationalization of the *SAS No. 99* fraud risk factors. The proxies for the fraud risk factors may not be truly measuring the fraud risk factor or there may be stronger unidentified proxies for the fraud risk factors. This is particularly evident in that none of the proxies for rationalization were significantly different among fraud and no-fraud firms.

The significant findings for audit committee independence support the suggestions made by the Blue Ribbon Committee and the Sarbanes-Oxley Act of 2002; however, with the advent of Sarbanes-Oxley this measure, as currently defined, may have lost its predictive ability and a new measure may need to be developed.

Suggestions for Future Research

This study extends the previous literature of financial statement fraud by examining the *SAS No. 99* fraud risk factors that are modeled after Cressey's fraud triangle. In addition, the study extends the research by developing a discriminatory model using the fraud risk factors to discriminate between fraud and no-fraud firms. However, many interesting questions could be examined by future research. Listed below are possible future research avenues.

SAS No. 99 identifies two types of fraud: financial statement fraud and asset misappropriation. Future research could focus on developing a model to identify firms with asset misappropriation based on the *SAS No. 99* fraud risk factors. Similar work has been done relating to *SAS No. 82* but has yet to be tied to Cressey's fraud triangle.

This study identified several fraud risk factors recognized in the literature as having discriminatory value, yet they were not useful in discriminating between fraud and no-fraud firms. It may be interesting to see if any of these variables are useful in discriminating between firms with asset misappropriation and no-misappropriation.

While this study has stronger results than other prediction studies using MDA and/or ratio analysis, there remains the potential to identify stronger proxies for the fraud risk factors and to develop a stronger model for detecting financial statement fraud.

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APPENDIX

LIST OF FRAUD AND MATCHED NO-FRAUD FIRMS

Initial Fraud Year	#	Fraud Firm	Matched Firm (No-Fraud)
1992	1	AMP INC	MOLEX INC
1992	2	COLLINS INDUSTRIES INC	SUPREME INDS INC
1992	3	DIAGNOSTEK INC	LILLIAN VERNON CORP
1992	4	GRACE (W R) & CO	AIR PRODUCTS & CHEMICALS IN
1992	5	JO-ANN STORES INC	HOUSE OF FABRICS INC
1992	6	KENDALL SQUARE RESH CORP/DE	CYCOMM INTERNATIONAL INC
1992	7	RANDOM ACCESS INC	PEAK TECHNOLOGIES GRP
1992	8	STRUCTURAL DYMICS RESEARCH	ELECTRONIC ARTS INC
1993	9	CYPRESS BIOSCIENCE INC (aka IMRE Corp)	LIPOSOME COMPANY INC
1993	10	FASTCOMM COMMUNICATIONS CORP	CASCADE COMMUNICATIONS CORP
1993	11	NORTHSTAR HEALTH SVCS INC	CLINICORP INC
1993	12	PINNACLE MICRO INC	CAMBEX CORP
1993	13	T2 MEDICAL INC	ABBEY HEALTHCARE GROUP INC
1994	14	ABS INDUSTRIES INC	AMPCO-PITTSBURGH CORP
1994	15	CALIFORNIA MICRO DEVICES CP	EA INDUSTRIES INC
1994	16	CENTENNIAL TECHNOLOGIES INC	VOICE CONTROL SYSTEMS INC
1994	17	DONNKENNY INC	DANSKIN INC
1994	18	KNOWLEDGEWARE INC -CL A	BOOLE & BABBAGE INC
1994	19	MICRO WAREHOUSE INC	EGGHEAD.COM INC-OLD
1994	20	MIDISOFT CORP	MERIDIAN DATA INC
1994	21	SUNRISE MEDICAL INC	MINE SAFETY APPLIANCES CO
1994	22	SYSTEM SOFTWARE ASSOC INC	COMPUWARE CORP
1995	23	IGI INC	PDK LABS INC
1995	24	MATERIAL SCIENCES CORP	BMC INDUSTRIES INC/MN
1995	25	OAK INDUSTRIES INC	METHODE ELECTRONICS -CL A
1995	26	THOR INDUSTRIES INC	ARCTIC CAT INC
1996	27	CEC INDUSTRIES CORP	MERITAGE CORP
1996	28	FINE HOST CORP	TACO CABANA -CL A
1996	29	INAMED CORP	STERIS CORP
1996	30	LERNOUT & HAUSPIE SPEECH PD	EXPERT SOFTWARE INC
1996	31	PHYSICIAN COMPUTER NETWK INC	CERPLEX GROUP INC
1996	32	SIGNAL TECHNOLOGY CORP	KEITHLEY INSTR INC
1996	33	SUNBEAM CORPORATION	PILLOWTEX CORP
1996	34	UNISON HEALTHCARE CORP	RETIREMENT CARE ASSOC INC
1997	35	ACCELR8 TECHNOLOGY CORP	BRILLIANT DIGITAL ENTMT INC
1997	36	AURA SYSTEMS INC	FIREARMS TRAINING SYS -CL A
1997	37	CANDIE S INC	WALKER (B.B.) CO
1997	38	CYBERGUARD CORP	PUMATECH INC
1997	39	ENRON CORP	ADAMS RESOURCES & ENERGY IN
1997	40	GUILFORD MILLS INC	ITHACA INDUSTRIES INC
1997	41	HBO & CO	REYNOLDS & REYNOLDS -CL A
1997	42	HYBRID NETWORKS INC	TRICORD SYSTEMS INC
1997	43	INTL THOROUGHBRED BREEDERS	FAMILY GOLF CENTERS INC

APPENDIX (CONTINUED)

Initial Fraud Year	#	Fraud Firm	Matched Firm (No-Fraud)
1997	44	JUST FOR FEET INC	SHOE CARNIVAL INC
1997	45	PREMIER LASER SYS -CL A	UROLOGIX INC
1997	46	SAF T LOK INC	QEP CO INC
1997	47	WIZ TECHNOLOGY INC	DIGITAL RIVER INC
1997	48	XEROX CORP	LEXMARK INTL INC -CL A
1998	49	ANICOM INC	WIRELESS XCESSORIES GRP INC
1998	50	AURORA FOODS INC	DEL MONTE FOODS CO
1998	51	BRIGHTPOINT INC	MARSHALL INDUSTRIES
1998	52	CYLINK CORP	MEDIA 100 INC
1998	53	FIRST VIRTUAL COMMUNICATIONS	KOFAX IMAGE PRODUCTS INC
1998	54	FLIR SYSTEMS INC	DRS TECHNOLOGIES INC
1998	55	LASON INC	BLACK BOX CORP
1998	56	MICROSTRATEGY INC	ENGINEERING ANIMATION INC
1998	57	RITE AID CORP	CVS CORP
1998	58	SABRATEK CORP	THERMO CARDIOSYSTEMS
1998	59	SPORT-HALEY INC	PREMIUMWEAR INC
1998	60	SYMBOL TECHNOLOGIES	CREATIVE TECHNOLOGY LTD
1998	61	THOMAS & BETTS CORP	RAYCHEM CORP
1998	62	US TECHNOLOGIES INC	NATIONAL MFG TECHNOLOGIES
1999	63	ANDRX CORP	SYNCOR INTL CORP/DE
1999	64	AREMISSOFT CORP/DE	METASOLV INC
1999	65	ENGINEERING ANIMATION INC	INFORMATION ADVNTGE SOFTWARE
1999	66	GEMSTAR-TV GUIDE INTL INC	MARTHA STEWART LIVING OMNIM
1999	67	HEALTHSOUTH CORP	CONCENTRA OPERATING CORP
1999	68	INDUS INTERTIOL INC	MANUGISTICS GROUP INC
1999	69	LEGATO SYSTEMS INC	REMEDY CORP
1999	70	PEREGRINE SYSTEMS INC	GENESYS TELECOMM LABS INC
1999	71	RENT WAY INC	PREMIUMWEAR INC
1999	72	SCHICK TECHNOLOGIES INC	AMERICAN SCIENCE ENGINEERING
1999	73	TENFOLD CORP	MICRO GENERAL CORP
1999	74	TRUMP HOTEL&CASINO RESRT INC	MANDALAY RESORT GROUP
1999	75	UNIFY CORP	ON TECHNOLOGY CORP
2000	76	800 AMERICA.COM INC	VICINITY CORP
2000	77	ASHFORD.COM INC	GEERLINGS & WADE INC
2000	78	CRITICAL PATH INC	LUMINANT WORLDWIDE CORP
2000	79	CUTTER & BUCK INC	ASHWORTH INC
2000	80	GATEWAY INC	APPLE COMPUTER INC
2000	81	MAX INTERNET COMM INC	WAVE SYSTEMS CORP -CL A
2000	82	NESCO INC	STERLING CONSTRUCTION CO INC
2001	83	DYNEGY INC	OCCIDENTAL PETROLEUM CORP
2001	84	HOMESTORE INC	SRA INTERNATIONAL INC
2001	85	KMART HOLDING CORP	TARGET CORP
2001	86	RSA SECURITY INC	KRONOS INC

VITA

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Scope and Methodology: This study empirically examined the fraud risk factors adopted by the Accounting Standards Board in *SAS No. 99* and developed a fraud prediction model that is useful in discriminating between fraud and no-fraud firms. The first phase of testing involved identifying and testing proxies for Cressey's fraud triangle (pressure, opportunity, and rationalization). A step-wise logistic regression analysis of matched sample firms was used to evaluate the usefulness of the fraud risk factors in discriminating between fraud and no-fraud firms. Notably, all data was collected from publicly available sources.

Findings and Conclusion: After identifying the significant fraud risk factors, the study applied multiple discriminate analysis to the significant variables to develop a fraud prediction model. The results indicate that users of publicly available data should take additional precautions when companies have audit committees with a low percentage of outside directors, high management ownership exceeding 5 percent, high cumulative percentage ownership in the firm held by insiders, and/or a CEO who holds both the CEO and Chairman of the Board position.

The prediction model correctly classified fraud firms 72 percent of the time. This finding is important since Kuruppu *et al*. (2003) noted that the Altman bankruptcy model, when applied to matched samples such as this study, only has an accuracy rate of between 40 and 50 percent. Additionally, studies that have expanded the financial ratios used by Altman (1969), such as Persons (1995) and Kaminski *et* al. (2004), have correctly identified fraud firms in the year prior to the fraud only 20 to 40 percent of the time. The fraud prediction model developed in this study is more accurate in correctly identifying no-fraud firms. The overall effect is that this fraud prediction model has a lower misclassification error of fraud and no-fraud firms than the other models.

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