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Fraudulently Misstated Financial Statements and Insider Trading: An Empirical Analysis

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ABSTRACT: This study investigates the relationship between insider trading and fraud. We find 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. Moreover, we present evidence that a cascaded logit model, incorporating insider trading variables and firm-specific financial characteristics, differentiates companies with fraud from companies without fraud.

Key Words: *Insider trading, Fraud risk assessment, Cascaded logit, SAS No. 82.*

Data Availability: *The list of sample firms may be obtained from the first author. The remainder of the data are available from public sources.*

I. INTRODUCTION

STATEMENT on Auditing Standards (SAS) No. 82, *Consideration of Fraud in a Financial Statement Audit* (American Institute of Certified Public Accountants 1997), asserts that auditors are responsible for planning and performing the audit to obtain reasonable assurance that the client's financial statements are free of material misstatement caused by fraud. Failure to detect financial statement fraud during the course of an audit can result in both damage to the auditor's reputation and significant litigation costs (Palmrose 1987). In order to obtain reasonable assurance that the client's financial statements are free of material misstatement resulting from fraud, SAS No. 82 directs auditors to consider risk factors ("red flags") relating to fraudulent reporting. This risk assessment is intended to influence the choice of audit procedures.

Prior research on financial statement fraud has generally focused on identifying such "red flags" (Romney et al. 1980; Sorenson et al. 1983) and combining these indicators into models for assessing the potential for financial statement fraud (Bell et al. 1991; Loebbecke

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et al. 1989; Beasley 1996). This study focuses on the association between financial statement fraud and a specific risk factor not identified as a "red flag" in SAS No. 82 or in prior empirical research—insider trading. We hypothesize that during the period of the fraud's occurrence, insiders in companies with fraudulent financial statements will strategically reduce their net position in the entity's stock. Specifically, we expect insiders to reduce their position by buying less stock and selling more stock in the entity during the period of the fraud.

Trading triggered by non-public (inside) information is prohibited by the Securities and Exchange Act of 1934. However, managers who commit financial statement fraud are likely to use their knowledge about the fraud to protect or increase their wealth. Managers who fraudulently issue misstated financial reports are likely to trade based on their knowledge of the impact of the fraud on the financial statements and on current prices if they believe that the impact will eventually be revealed. These managers could engage in both the fraud and the illegal insider trade with the expectation that neither would be discovered. Their inside trade would be rationalized by personal liquidity needs and the future realization of the fraud's impact (but not the fraud) could be excused as a bad economic outcome.

Our results indicate that insiders in companies with fraudulent financial statements reduce their net position in the entity's stock through a high level of stock sales activity. We find significant differences in insider trading activity and in several control variables between a matched sample of fraud-discovered firms and no-fraud firms. These results are relevant to auditors attempting to assess the risk of fraud in clients' financial statements. Auditors' assessments of fraud are likely to be enhanced if those assessments incorporate insider trading during the year under audit as well as firm-specific financial characteristics.

The remainder of this article proceeds as follows. Hypotheses are developed and stated in section II. The criteria utilized for sample selection are described in section III. In section IV, we discuss our research methodology. Results of statistical tests are given in section V and section VI contains our conclusions.

II. HYPOTHESIS DEVELOPMENT

The "red flag" literature warns auditors of certain management attitudes or characteristics that are expected to be associated with financial statement fraud (Bell et al. 1991; Romney et al. 1980; AICPA 1997; Sorenson et al. 1983). Some of these factors include excessive interest by management in maintaining or increasing the company's stock price through aggressive accounting practices, a commitment by management to achieve unrealistic forecasts, a lack of support for the entity's values or ethics, and a known history of securities law violations. Bell et al. (1991) and Loebbecke and Willingham (1988) describe this subset of "red flags" as indicators of an attitude or "tone at the top" that fosters the commission of a fraud. To the extent that such an attitude abets illegal acts in general, it is reasonable to assume that this same attitude abets illegal insider trading.

Although the vast majority of corporate insiders adhere strictly to insider trading rules and have legitimate, and legal, rationale for trading in their company's stock, empirical evidence suggests that insiders sometimes appear to engage in informed trading (Larcker et al. 1983; Odaiyappa and Nainar 1992; Penman 1982).[1] Sorenson et al. (1983, 99) contend that those individuals who perpetrate a fraud may use insider trading as a tool to extract

[1] The definition of a corporate insider varies across SEC rules and sections. For example, in connection with tender offers, an insider is defined as any party with material non-public information (Section 14(e)-3). In this study, we use the criteria of Section 16(b), which designates an insider as an officer, director, or 10 percent beneficial owner.

personal gains from a fraud. As such, one would expect greater insider trading activity in the presence of fraud than if fraud were not present. An alternative argument is that insiders will engage in less trading activity to avoid SEC scrutiny. However, an individual who is willing to engage in fraud is expected to possess low personal ethics (Ponemon 1993, 2), low risk aversion, and/or to have a downwardly biased assessment of the probability of detection. The personal characteristics that lead to the commission of fraud are also likely to lead to violations of insider trading rules. Insiders can exploit their private knowledge of overpriced stock resulting from fraudulent financial information by either selling securities in anticipation of subsequent price declines and/or reducing their purchases of securities.

Given the vigilance the SEC maintains over insider trades, insiders are aware that increases in reported buying or selling activity may draw unwanted scrutiny.[2] Nevertheless, insiders must trade if they are to benefit from their information. We expect that in the presence of fraud, insiders will strategically reduce their net position in the entity's stock. Specifically, in the presence of fraud, insiders are expected to engage in high levels of sales and low levels of purchases of company stock. As a lack of purchasing activity does not require any reports to be filed with the SEC, insiders should not be inhibited in this action.

If the above arguments are correct, then incorporating insider trading activity into a formal assessment of fraud risk should enhance that assessment. The following hypotheses examine the relationship between insider trading and financial statement fraud in the context of an auditor's risk assessment.

H1: Auditors' risk assessment of financial statement fraud will be enhanced through the inclusion of insider trading activity in their model.

In their assessment of fraud risk, auditors should specifically evaluate in their model whether insiders are reducing their net position in the entity's stock, consistent with the following hypotheses:

H1a: In the presence of fraud, insiders will engage in a high level of sales activity in their entity's stock.

H1b: In the presence of fraud, insiders will engage in a low level of purchasing activity in their entity's stock.

III. SAMPLE SELECTION AND DESCRIPTION

The Wall Street Journal Index was reviewed for the period 1980 through 1987 to identify companies for which an illegal act was reported. For each instance of an illegal act, the article cited in the *Wall Street Journal* was examined to determine if the act was a fraudulent one or of another nature.[3] This procedure resulted in the collection of information on 184 companies for which fraud had been detected.[4] CUSIP numbers for 73 companies were unavailable and 41 companies with CUSIPs were not found on Compustat (mainframe or CD versions) for either the year prior to the occurrence of fraud or the year of occurrence.

[2] Section 16 of the Securities and Exchange Act requires insiders to report any stock transaction to the SEC.

[3] An inherent limitation in the study of fraud is the inability to identify all companies in which fraudulent acts occur. Frauds caught by the auditor and corrected within the company are generally not revealed publicly. Frauds not detected by the auditor but discovered later are more likely to appear in the press and increase the auditor's litigation risk. Frauds never discovered are not available for study. This study compares firms with discovered frauds that are publically revealed to firms that do not have publicly revealed frauds.

[4] Professional standards (AICPA 1997) and prior research (Loebbecke et al. 1989; Sorenson et al. 1983) have noted that inventories and receivables are important in assessing audit risk due to fraud. In order to investigate these variables, the banking and insurance industries were excluded from the sample.

TABLE 1
Summary of Filters for Fraud Sample

Sample Selection Filters	
Companies with fraud reported in the *Wall Street Journal*	184
Companies without a CUSIP	(73)
Companies not on Compustat during the years of interest	(41)
Companies in Compustat with incomplete information	(19)
Companies for which fraud was reported in the Final Sample	51

Complete information could not be found on Compustat or in other sources (*Standard and Poor's Stock Reports,* Standard and Poor's Corporation, (1973–1988) or *Moody's Industrial Manual,* Moody's Investors Service, (1973–1988) for 19 companies. Information from *Who Audits America: Corporations and Accountants* (Who Audits America, 1976–1988) was extracted to augment the auditor information retrieved from Compustat.

Fifty-one companies with complete information are included in the final sample of fraud-discovered companies. Table 1 displays information about the sample selection filters, and the resulting number of companies for this study. The average time between perpetration of the fraud and its discovery was 3.02 years.

The fraud-discovered companies were matched with a control sample for hypothesis testing. Since industry membership is reported to influence the likelihood of litigation (Stice 1991), and since the "red flag" literature suggests that industry membership is a factor that affects the likelihood of fraud, the fraud-discovered companies were matched with the control companies based on their SIC code.[5] Differences in company size could also influence the analyses performed. Rather than matching several control companies to each fraud-discovered company to analyze the effect of size, we minimized the data collection task and controlled for size by matching a single control company to the fraud-discovered company.

The control sample was drawn from the pool of companies on the Compustat data files. As Beasley (1996, 451) notes, a control company would be misclassified if a fraud is subsequently determined to have an occurred in the sample period. To guard against this misclassification potential, *The Wall Street Journal Index* was reviewed for a period of seven years subsequent to the year of the fraud occurrence.[6] No instances of fraud were noted for the control companies in the no-fraud sample.

During the audit planning process, the most recent non-fraudulent financial data available to company auditors would have been the prior period financial statements. Therefore, matching for the control group was performed based on the financial statements from the year before the fraudulent act occurred (pre-fraud financial statements).

IV. RESEARCH METHOD AND DESCRIPTION OF VARIABLES

Cascaded logit analysis is used to examine whether insider trading activity is a useful incremental indicator of the incidence of fraud. This method allows groups of factors that represent a shared underlying construct to be consolidated into a single index representing

[5] Of the 51 companies in the fraud-discovered sample, we were able to match 40 companies in the control sample by four-digit SIC code, eight companies by three-digit SIC code, and three companies by two-digit SIC code.

[6] We chose a period of seven years for subsequent review of the no-fraud sample companies because it represented the average time (three years) for the fraud-discovered sample between the perpetration of the fraud and its disclosure plus two standard deviations (two years).

the influence of that construct. As multiple measures are available to insider trading activity, and as none of these measures are thought to independently capture the underlying construct of insider trading activity, the cascaded logit is the method of choice. Bell et al. (1991) employed the cascaded logit approach to statistically model the influence of groups of related factors on the assessment of fraud.

The goal of this research is to examine the usefulness of insider trading activity as a factor to be used by external auditors in assessing the likelihood of fraud occurrence as required under SAS No. 82. Our application of cascaded logit analysis involves the estimation of three separate logit models. The first logit model will classify firms into fraud and no-fraud categories based upon financial statement characteristics that have been documented as diagnostic in prior studies. The second logit model will classify firms into fraud and no-fraud categories based upon insider trading variables. These two logit models represent the first-tier models in cascaded logit analysis. Each of these first-tier models generates an index, ranging from zero to one, of the risk of fraud based on the variables included in the model. Weights for the two indices are estimated and combined in the final (second-tier) logit model. The ability to weight groups of factors to assess their incremental contribution based upon maximum likelihood estimates makes the cascaded logit analysis preferable to a single stage logit approach.[7]

The first tier of logit models is based upon groupings of factors that jointly represent a relevant characteristic. There are two such groups in this research: a financial statement characteristics group and an insider trading characteristics group. The variables included in each of these groups are described below.

Financial Statement Variables

Financial Condition

Poor financial condition (Bell et al. 1991; Loebbecke et al.1989) may motivate unethical insiders to take actions intended to improve the appearance of the company's financial position, perhaps to reduce the threat of loss of employment, or to garner as many resources as possible before termination. In addition to motivating the commission of fraud, poor financial condition may indicate a weak control environment, a condition that allows the perpetration of a fraud (AICPA 1997). Loebbecke et al. (1989) found that 19 percent of the fraud companies in their sample were experiencing solvency problems.

The measurement of a company's financial condition is operationalized by using Altman Z scores (Altman and McGough 1974). Alternative measures of financial health have been proposed (e.g., Ohlson 1980; Blum 1974), but Hammer (1983) demonstrates that the various models in the literature do not differ significantly in their ability to predict business failure. Hence, Altman's Z is utilized in the model as a control variable for differences in financial condition between fraud and no-fraud firms. Altman's Z score is computed as:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + .6X_4 + 1.0X_5 \qquad (1)$$

where:

X_1 = (current assets − current liabilities)/total assets,

[7] A single-stage logit model with both financial and insider trading variables was also estimated for diagnostic purposes. The single-stage logit model produces higher concordance measures and R^2s than the final-tier model of the cascaded logit method, but statistical significance of the final-tier model is greater than that of the single-stage model.

X_2 = retained earnings/total assets,
X_3 = earnings before interest and taxes/total assets,
X_4 = market value of equity/BV of total liabilities, and
X_5 = sales/total assets.

The calculation of Altman's Z is based on information from the year prior to the year of fraud occurrence.

Financial Performance

A primary orientation assumed to be guiding corporations is profitability. Gordon (1964) notes that the profitability orientation is tempered by the manager's own utility maximization. That utility is partially defined by job security, which is maximized by means of producing smooth or increasing earnings streams. Implied is the expectation that management will be able to maintain or improve past levels of profitability, regardless of what those levels were. This expectation, if not met by actual performance, provides a motivation for financial statement fraud. Loebbecke et al. (1989) found that profit relative to industry was inadequate for 35 percent of companies with fraud in their sample. Financial performance is measured using return on assets (ROA) and serves as a control variable for performance differences between fraud and no-fraud firms in the sample. ROA is calculated as net income before extraordinary items in the year prior to the occurrence of the fraud divided by total assets at the end of that year.

Growth

Rapid growth is expected to be associated with the incidence of fraud (Beasley 1996; Bell et al. 1991; Loebbecke et al.1989; Loebbecke and Willingham 1988). The vast majority of managers in high-growth companies do not commit fraud. However, unethical managers may be induced to misstate financial statements when growth slows or reverses in order to maintain the appearance of consistent growth. Moreover, sustained growth occurs in combination with changes in company structure (Pugh et al. 1968) and such changes result in increased uncertainty in roles and responsibilities (Baucus and Near 1991). Such uncertainty may motivate the perpetration of a fraud. Loebbecke et al. (1989) found that 29 percent of frauds in their sample were in high-growth companies.

The arguments above suggest that rapid growth and sustained growth could influence the likelihood of fraud in different ways. Rapid growth is thought to lead to weaknesses in internal control, while sustained growth is accompanied by structural changes that create role and responsibility uncertainty. Control variables representing each type of influence are used. First, a continuous variable (GROWTH) is used as the proxy for sustained growth. Second, a dichotomous variable (CLASSG) is used to address the issues associated with rapid growth. The continuous variable, GROWTH, is computed as the simple average of the percentage growth in sales over a three-year window ending in the year before the fraud occurred. The classificatory variable is created by assigning the variable a value of 1 if the company's sales growth in the year before the fraud occurred is in the top quartile of growth relative to all companies in the same three-digit industry in the Compustat population and zero otherwise.

Receivables/Inventory

SAS No. 47, *Audit Risk and Materiality in Conducting and Audit* (AICPA 1984, AU312.29), states that any account that requires subjective judgment in determining its value increases audit risk. Accounts receivable and inventory are noted as two such accounts due to the subjective judgment involved in estimating uncollectible accounts and obsolete inventory. Because subjective judgment is involved in determining the value of these accounts, management may use these accounts as tools for financial statement manipulation. Loebbecke et al. (1989) found that the inventory account and accounts receivable were involved in 22 percent and 14 percent, respectively, of frauds in their sample.

The change in the ratio of receivables (inventory) to sales is computed as the ratio of receivables (inventory) to sales in the year t less the ratio of receivables (inventory) to sales in t − 1, where t is the year prior to the fraud occurrence. Specifically, the variables RECEIV and INVENT are measured, respectively, as $R_t/S_t - R_{t-1}/S_{t-1}$ and $I_t/S_t - I_{t-1}/S_{t-1}$, where R is accounts receivable, I is Inventory and S is Sales.

Auditor Change

Although the vast majority of auditor changes are for legitimate reasons, the risk of audit failure and subsequent litigation is higher during an initial engagement than in subsequent years (Stice 1991; St. Pierre and Anderson 1984).[8] Sorenson et al. (1983) suggest that a client may even change auditors in order to reduce the likelihood of detection of a financial statement fraud. Loebbecke et al. (1989) found that 36 percent of the frauds in their sample were perpetrated in the first two years of an auditor's tenure. The auditor change variable (CHANGE) is operationalized as a dichotomous variable representing a new client (1), or an established client (0). A client is considered new if the auditor has been with the client for two years or less.

Insider Trading Variables

Trading activity is gathered from magnetic tapes acquired from the Securities and Exchange Commission. The dollar amount, number of shares and number of transactions for purchasing (P_{Money}, P_{Shares}, P_{Trans}) and selling (S_{Money}, S_{Shares}, S_{Trans}) by insiders during the fiscal year of the fraud occurrence are reflected in six independent variables. In addition, the net amount (sales minus purchases) of dollars and shares traded (N_{Money}, N_{Shares}), as well as the total number of stock transactions (T_{Trans}), are analyzed.

Descriptive Statistics

Descriptive statistics for each variable are presented in table 2 for the fraud-discovered and no-fraud-discovered samples. The mean is considerably larger than the median for many of the insider trading variables. This is due to a number of companies having no transactions by insiders, combined with a few companies that have substantial insider transactions. To minimize the influence of extremely large observations, we truncated observations to three standard deviations from the mean. Variables affected by this truncation include P_{Money}, P_{Shares}, S_{Money} and S_{Shares}. Even with the truncation, the insider trading variables do not approximate a normal distribution. Thus, both parametric and non-parametric statistical tests were performed. The non-parametric Wilcoxon Rank Sum test provided higher levels of significance as compared to the t-test for those variables found to be significant. For consistency across financial statement and insider trading variables, only the t-test is reported. Where appropriate, t-tests are adjusted for unequal variances in the two samples. Fortunately, logistic model coefficient estimates are not sensitive to departures from normality in the independent variables (Hosmer and Lemeshow 1989).

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[8] Stice (1991) defines audit failure as a subsequent circumstance which calls into question the quality of the audit or that brings to light evidence of a substandard audit. Undetected fraud would be an example of such audit failure.

TABLE 2
Descriptive Statistics and Comparison of Means for Fraud and Control Samples

		Mean	*Difference*	*Median*	*Std. Dev.*
CHANGE	Fraud = F	0.078		0	0.272
	No Fraud = NF	0.059	.019	0	0.238
RECEIV	F	−0.001		−0.002	0.038
	NF	−0.004	.003	−0.004	0.027
INVENT	F	0.004		−0.003	0.037
	NF	−0.013	.017**	−0.009	0.029
Z	F	1.557		1.509	0.654
	NF	1.474	.083	1.382	0.656
GROWTH	F	0.197		0.150	0.183
	NF	0.164	.033*	0.142	0.127
CLASSG	F	0.275		0	0.451
	NF	0.255	.020	0	0.440
ROA	F	0.075		0.065	0.046
	NF	0.046	.029***	0.047	0.062
S_{Money}	F	3,050,120		215,547	7,377,563
	NF	940,040	2,110,080*	44,080	3,343,451
S_{Shares}	F	235,600		30,920	754,387
	NF	55,586	180,014*	4,750	132,088
S_{Trans}	F	25.039		16	27,379
	NF	15.020	10.019**	6	23.688
P_{Money}	F	584,454		71,250	1,211,743
	NF	334,006	250,448	3,360	1,318,987
P_{Shares}	F	97,999		17,174	195,836
	NF	73,726	24,273	2,900	222,962
P_{Trans}	F	22.137		12	32.127
	NF	17.196	4.941	4	29.478

TABLE 2 (Continued)

		Mean	*Difference*	*Median*	*Std. Dev.*
N_{Money}	F	−2,465,666		−31,994	7,154,117
	NF	−606,034	−1,859,632*	−2,693	3,407,114
N_{Shares}	F	−137,602		0	690,661
	NF	18,140	−155,742	0	257,570
T_{Trans}	F	47.176		41	51.691
	NF	32.216	14.960	12	49.664

Significance levels: *** < .01, ** < .05, * < .1.

Z = Altman Z score;

GROWTH = simple average of the percentage growth in sales over the three years prior to the occurrence of fraud;

CLASSG = 1 if sales growth in the year prior to the occurrence of fraud is in the top 25% of the companies in industry, 0 otherwise;

RECEIV = $(receivables_t/sales_t) - (receivables_{t-1}/sales_{t-1})$ where t is the year prior to the occurrence of the fraud;

INVENT = $(inventory_t/sales_t) - (inventory_{t-1}/sales_{t-1})$ where t is the year prior to the occurrence of the fraud;

ROA = net income before extraordinary items for year prior to occurrence to fraud/total assets (end of year);

CHANGE = 1 if new auditor in the year prior to fraud occurrence or the prior year, 0 otherwise;

P_{Money}, P_{Shares}, P_{Trans} = dollars spent purchasing shares, number of shares purchased, number of purchase transactions in year of fraud occurrence, respectively;

S_{Money}, S_{Shares}, S_{Trans} = dollars received through selling shares, number of shares sold, number of sales transactions in year of fraud occurrence, respectively.

N_{Money}, N_{Shares}, T_{Trans} = net dollar flow (purchases minus sales) in trading activity, net flow of shares (purchases minus sales), total number of transactions (purchases plus sales).

Inventory levels (INVENT) for the fraud-discovered companies increased while the inventory levels of the control sample declined in the year before the fraud. This result is consistent with the findings of Albrecht and Romney (1986). The fraud-discovered companies have a mean ROA of 7.5 percent which is significantly higher than the control sample mean of 4.6 percent. The GROWTH variable suggests that the fraud-discovered companies experienced greater sustained growth than the control sample over the previous three years. However, while Bell et al. (1991) found rapid growth to be significantly related to the perpetration of fraud, the fraud-discovered companies in this sample were not in a period of rapid growth (CLASSG) any more than the control sample. Fraud-discovered companies did not have recent auditor changes (CHANGE) more often, were not in greater financial distress (Z), and did not have different rates of change in receivables (RECEIV) than their control sample counterparts. Prior research found fraud-discovered companies had a greater average level of financial distress than a no-fraud control sample (Bell et al. 1991), but no significant difference in the average of the change in receivables relative to sales (Albrecht and Romney 1986).

Tables 2 indicates that trading activity was higher for the fraud-discovered companies than for the companies in the matched sample for all three measures of sales activity (S_{Money}, S_{Trans}, S_{Shares}), supporting H1a. Hypothesis 1b is not supported as purchasing activity is not significantly lower for the fraud-discovered sample (P_{Money}, P_{Trans}, P_{Shares}) than for the control sample. It is interesting to note, however, that when purchasing activities are netted with sales activities, the net money (N_{Money}) invested by insiders in their entity's stock declined significantly for fraud-discovered companies as compared to the control sample. Insiders from the fraud-discovered companies engage in nearly 50 percent more trades per year than insiders of the matched companies in the year of the perpetration of a fraud.[9]

Table 3 presents the correlations among financial and insider trading variables for the fraud-discovered companies and control companies. Each measure of insider trading activity is based on the same set of events, so correlations among these variables are expected to be high. Few of the correlations among the insider trading variables are insignificant. It is notable that N_{Money} and P_{Money} are not significantly correlated, indicating that insider selling activities may overwhelm purchasing activities. Among the financial statement variables, GROWTH is negatively correlated with the Z score and positively correlated with rapid growth (CLASSG) and ROA. GROWTH is also positively correlated with INVENT and ROA. The correlation of GROWTH with INVENT may be indicative of inventory obsolescence. In addition to its association with GROWTH, ROA is also positively related to rapid growth (CLASSG), increasing proportions of inventory (INVENT), decreasing proportions of receivables (RECEIV), and more stock transactions by insiders (P_{Trans}, S_{Trans}, or T_{Trans}). Both ROA and INVENT are positively correlated with FRAUD, as are measures of insider sales transactions.

V. RESULTS

This section presents the results of the cascaded logit analysis. The first-tier models are represented as:

[9] In the post-fraud occurrence period, fewer significant differences are found among the financial characteristics. Fraud-discovered companies still exhibit significantly higher growth and higher ROA. Insiders still engage in more buying and selling transactions. Fraud-discovered company insiders purchase fewer dollars of stock and fewer shares of stock than the insiders of the matched companies which is consistent with H1b. Stock sales activities of insiders of fraud companies continue to be above the level of the matched group.

TABLE 3
Correlation Matrix for the Combined Fraud and Control Samples

	FRAUD	*Z*	*GROWTH*	*CLASSG*	*RECEIV*	*INVENT*	*ROA*	*CHANGE*	P_{Money}	P_{Shares}	P_{Trans}	S_{Money}	S_{Shares}	S_{Trans}	N_{Money}	N_{Shares}	T_{Trans}
FRAUD	1.0																
Z	.06	1.0															
GROWTH	.11	−.20**	1.0														
CLASSG	.02	.02	.51***	1.0													
RECEIV	.04	−.07	−.13	−.23**	1.0												
INVENT	.25**	−.13	.33***	.02	.28*	1.0											
ROA	.26***	.01	.38***	.16*	−.20**	.19*	1.0										
CHANGE	.04	−.02	.13	.01	.00	.00	.05	1.0									
P_{Money}	.10	.00	.03	.01	.17	.01	.06	.16*	1.0								
P_{Shares}	.06	.01	.01	.10	.08	.00	.23**	.18*	.30***	1.0							
P_{Trans}	.08	.07	−.04	−.01	−.01	−.01	.21**	−.04	.49***	.29***	1.0						
S_{Money}	.18*	−.03	−.02	−.13	.00	.05	.13	−.02	.22**	.40***	.30***	1.0					
S_{Shares}	.17*	−.02	−.02	−.09	.01	.01	.07	−.03	.21**	.29***	.21**	.80***	1.0				
S_{Trans}	.19*	.07	.17*	.05	−.17*	.09	.32***	.05	−.37***	.25***	.61***	.52***	.22**	1.0			
N_{Money}	−.17*	.03	.03	.13	.05	−.05	−.12	.06	.00	−.35***	−.20**	−.97***	−.77***	−.45***	1.0		
N_{Shares}	−.15	.02	−.03	.13	.02	−.01	.01	.10	−.11	.09	−.10	−.68***	−.92***	−.13	.67***	1.0	
T_{Trans}	.15	.08	.06	.02	−.10	.04	.29***	−.05	.48***	.31***	.92***	.44***	.24***	.88***	−.35***	.30***	1.0

Significance Levels: *** < .01, ** < .05, * < .1.
Fraud = 1 if fraudulent company, 0 if no fraud has been discovered.
All other variables defined in table 2.

Financial Statement Factors:

$$\begin{aligned} \text{FRAUD} = \beta_0 &+ \beta_1 Z + \beta_2 \text{GROWTH} + \beta_3 \text{CLASSG} + \beta_4 \text{RECEIV} \\ &+ \beta_5 \text{INVENT} + \beta_6 \text{ROA} + \beta_7 \text{CHANGE} + \varepsilon. \end{aligned} \tag{2}$$

Insider Trading Factors:

$$\begin{aligned} \text{FRAUD} = \beta_0 &+ \beta_1 P_{\text{Money}} + \beta_2 P_{\text{Shares}} + \beta_3 P_{\text{Trans}} + \beta_4 S_{\text{Money}} \\ &+ \beta_5 S_{\text{Shares}} + \beta_6 S_{\text{Trans}} + \varepsilon \end{aligned} \tag{3}$$

where:

FRAUD = 1 if fraud-discovered group, 0 otherwise. All other variables as defined in section IV.

The first-tier model results are shown in table 4. Panel A presents the financial statement characteristics model. Panel B presents the insider trading factors model. The goal of these models is to provide indices/scores for the second-tier logit analysis. It is interesting to note that factors which were significant in both the correlation analysis and the univariate analysis, were also significant in the multivariate analysis. The variables INVENT and ROA contribute significantly to the model.

The concordance measure, which is based on all possible combinations of fraud/no-fraud companies, indicates that the financial statement factors model correctly ranks fraud companies higher than control companies 68 percent of the time. Classification accuracy using the midpoint of the index (.5) as a cutoff is approximately 60 percent.

In panel B, the insider trading factors model includes all three measures of sales activity and all three measures of purchasing activity. By including all three measures of each insider trade, the maximum information about insider trading is included in the model. Several other model specifications were tested to determine if a more parsimonious model adequately captured insiders activities. Specifically, we examined three other models of insider trading activities in terms of transactions, shares or money. In each case, the model that combines all three measures produced higher concordance measures and R^2s. While this is partially attributable to the increase in the number of variables, it is also due to the more fully capturing insider behavior. The model presented correctly ranks fraud companies higher than no-fraud companies 63 percent of the time with a classification accuracy of 58 percent. High correlations among variables in the model results in multicollinearity. In that the index is of primary interest, multicollinearity in the model is not of concern.

The second-level model is represented as:

$$\text{FRAUD} = \beta_0 + \beta_1 F_{\text{SCORE}} + \beta_2 T_{\text{SCORE}} + \varepsilon \tag{4}$$

where:

FRAUD = 1 if fraud-discovered group, 0 otherwise;
F_{Score} = score from the Financial Statement Factors model; and
T_{Score} = score from the Insider Trading Factors model.

Table 5 presents the second-tier logit results. The analysis indicates that the model performs well. Both the financial statement factors index and the insider trading factors

TABLE 4
Results of the First-Tier Logit Models

Panel A: Financial Statement Factors
(n = 102)

$$FRAUD = \beta_0 + \beta_1 Z + \beta_2 GROWTH + \beta_3 CLASSG + \beta_4 RECEIV + \beta_5 INVENT + \beta_6 ROA + \beta_7 CHANGE + \varepsilon$$

Variables	*Parameter Estimate*	*Chi-Square*
Z	.2811	.6898
GROWTH	−.8604	.1827
CLASSG	.1422	.0603
RECEIV	2.2190	.0802
INVENT	16.2649	3.7566
ROA	10.7201	4.1901
CHANGE	.1757	.0360
Intercept	−.9164	1.7411
Model R^2	.34	
Model Chi-square	13.261	
Model significance	.066	
Concordant pairs	67.8%	
Classification accuracy using a .5 cutoff value	59.8%	

Panel B: Insider Trading Factors
(n = 102)

$$FRAUD = \beta_0 + \beta_1 P_{Money} + \beta_2 P_{Shares} + \beta_3 P_{Trans} + \beta_4 S_{Money} + \beta_5 S_{Shares} + \beta_6 S_{Trans} + \varepsilon$$

Variables	*Parameter Estimate*	*Chi-Square*
P_{Money}	.00000007	.1167
P_{Shares}	−.00000041	.1069
P_{Trans}	−.0061	.4146
S_{Money}	.00000004	.1256
S_{Shares}	−.00000159	.6647
S_{Trans}	.0173	1.670
Intercept	−.3238	1.4579
Model R^2	.25	
Model Chi-square	6.983	
Model significance	.322	
Concordant pairs	62.7%	
Classification accuracy using a .5 cutoff value	57.8%	

All variables are defined in tables 2 and 3.

index make significant contributions to the model. However, the significance of each factor must be interpreted with caution. When a predicted value is used as an independent variable, the standard errors used in the significance tests for parameter estimates may be biased downward producing spurious inferences (Gujarati 1988). The overall model is not affected

TABLE 5
Results of the Second-Tier Logit Model

$$FRAUD = \beta_0 + \beta_1 F_{SCORE} + \beta_2 T_{SCORE} + \varepsilon$$

Variables	*Parameters Estimate*	*Chi-Square*	*PR > Chi-Square*
F_{Score}	4.1615	8.2727	.0040
T_{Score}	3.6542	3.7213	.0537
Intercept	−3.9077	11.3778	.0007
Model R^2	.39		
Model Chi-square	16.674		
Model significance	.0002		
Concordant pairs	72.2%		
Classification accuracy using a .5 cutoff value	66.7%		

F_{Score} = score from the Financial Statement Factors model.
T_{Score} = score from the Insider Trading Factors model.

by the bias and is highly significant. The weighting of each factor grouping is shown by the parameter estimates. The parameter estimates reveal that more weight is given to the financial statement factors than to the insider trading factors. The parameter estimate for the insider trading factors does show a large contribution to the overall risk assessment, supporting H1. These results also indicate that pre-fraud financial statement factors have explanatory power in assessing the likelihood of fraud prior to its occurrence. Model concordance increases from 68 percent in the first-tier model with just financial statement factors (table 4) to 72 percent in the second-tier model that includes both the financial statement factors and the insider trading factors indices. Importantly, classification accuracy increases from 60 percent in the financial statement characteristics model to 67 percent in the second-tier model.

VI. CONCLUSION

The purpose of this study was to analyze the relationship between financial statement fraud and insider trading activity to determine whether auditors could enhance financial statement fraud risk assessment by including insider trading activity in their model. Using a matched sample of fraud and no-fraud companies, we found differences in insider trading activity variables and important financial statement control variables between the two samples. As hypothesized (H1a), insiders in companies where fraud is found reduce their net position in the entity's stock by engaging in significant selling activity, regardless of whether selling activity is measured by dollars of shares sold, number of shares sold or number of selling transactions. The hypothesis (H1b) of a reduction in purchasing activity was not supported. Additionally, we find that fraud companies have significantly more inventory relative to sales, are growing faster, and have a higher return on assets than no-fraud companies in the year before the occurrence of the fraud.

The results of this study indicate that insider trading and financial statement factors are useful in a model which distinguishes companies where fraud is found from companies where fraud is not found. This is a significant contribution to both auditors attempting to detect fraud and to regulators monitoring insider trading.

There are a number of limitations to this study. First, this study examines the population of companies for which fraud was discovered after an audit. Hence, two types of fraud are not included in the fraud sample: undiscovered fraud and fraud discovered during the audit. Second, this study may have a newsworthiness bias. The study over-sampled discovered fraud with respect to the newsworthiness of the fraud. Frauds not reported in the *Wall Street Journal* were not used in this research. The extent to which this model is biased toward identifying environments that are conducive to newsworthy fraud is unknown. Furthermore, the ethical implications of fraud and the perpetration of fraud are not addressed. Future research should incorporate the study of individual ethics in relation to the perpetration of a fraud (Ponemon 1993). Third, this study did not use a hold out sample to validate the models that are presented. Further research with larger samples will be necessary to validate these results.

Finally, this study is limited in that it does not address finer classifications of fraud. Turner (1980) proposes classification of management fraud into four classes, according to whether the distortion of the financial statements is the vehicle for the fraud or a disguise of the fraud, and according to who benefits from the fraud: the company or the perpetrator. Our model does not assess the likelihood of a particular class of fraud.

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