Using Financial Statement Data to Identify Factors Associated with Fraudulent Financial Reporting

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Abstract

Based on stepwise-logistic models, this study finds that financial leverage, capital turnover, asset composition and firm size are significant factors associated with fraudulent financial reporting. Prediction results suggest that these models outperform a naive strategy of classifying all firms as nonfraud firms for all levels of relative costs of type I and type II errors. The models also correctly identify a large percentage of fraud firms and misclassify a relatively small percentage of nonfraud firms when realistic relative error costs are assumed.

Introduction

Increasing fraudulent financial reporting among public companies in the past decade has focused public attention on the corporate financial reporting process. According to the 1993 fraud survey of KPMG Peat Marwick, 76% of companies admit having experienced fraud during the past year and consider fraud to be a major problem for business today. Sixty-seven percent of respondents also believe the incidence of fraud will increase. The consequences of fraudulent practices can erode public confidence in the reliability of financial reporting as a means to assess a firm's future prospects.

This problem has been a major concern of policy makers. Many initiatives have been introduced to improve financial reporting. For example, between February 1985 and January 1987, the Financial Accounting Standards Board issued nine statements of financial accounting standards to enhance the quality of generally accepted accounting principles. The Securities and Exchange Commission (SEC) issued eleven financial reporting releases and ten staff accounting bulletins during the same time period. In 1987, the National Commission on Fraudulent Financial Reporting, formed by the Congress, released 49 recommendations for prevention and early detection of fraudulent financial reporting.

This issue is also a significant concern for auditors whose major function is financial statement attestation. Although the professional standards do not unambiguously specify that an auditor has a duty to detect management fraud, the Statement on Auditing Standards No. 53 impose the responsibility on an auditor to plan his examination to search for errors or irregularities that would have material effects on the financial statements and to exercise due skill and care in conducting the examination. These standards lead financial statement users to believe that auditors' opinions certify an absence of material fraudulent financial reporting. Therefore, an auditor is likely to be sued by stockholders if an auditor fails to detect or detects but fails to report material omissions or misstatements of financial statements. These lawsuits can damage both wealth and reputation of an auditor.[1]

Regardless of the public and the policy makers' concern over management's fraudulent practices, there has been little published research that assess the probability of fraudulent financial reporting. Loebbecke et al (1989) develop a management-fraud assessment model for auditors. Although their model provides a list of indicators related to fraud, the model involves a great deal of subjective judgement and a great deal of nonpublic information which is available only to auditors or insiders of a firm. Investors and policy makers cannot use their model to identify firms engaging in fraudulent financial reporting.

A question of interest to the public is whether we can use financial statements, which are readily and publicly available, to identify factors associated with fraudulent financial reporting. This study answers this question by using financial statement data to develop parsimonious models that identify factors associated with fraudulent financial reporting. The models should be useful not only for auditors but also for investors and policy makers. Investors can avoid potential losses by using the models to screen firms with high fraud potential. The SEC can use the models to help identify fraudulent financial reporting firms for investigation or to identify high fraud-potential firms for closer monitoring. Auditors can use the models as an additional decision aid to identify clients that commit fraudulent financial reporting and to screen potential clients.

The remainder of this article is organized as follows. Sample selection is presented, followed by research design. Empirical results are then discussed, followed by conclusions.

Sample Selection

This section is divided into two parts: the selection of fraudulent financial reporting firms and the selection of nonfraudulent financial reporting firms.

Selection of Fraudulent Financial Reporting Firms

Firms involving in fraudulent financial reporting are obtained from Accounting Series Releases (ASR) issued between 1974 and 1981, and Accounting and Auditing Enforcement Releases (AAER) issued between 1982 and 1991.[2] These releases summarize the SEC's accounting-based enforcement actions. Accounting violations in the ASR and the AAER are examined to ensure that (a) the SEC charged an intentional material misstatement and pursued injunctive actions under the fraud provisions of the Securities Exchange Act of 1934, (b) the case was a financial statement related fraud, and (c) the court found sufficient evidence of fraud, therefore, entered final judgement of permanent injunction. This examination results in 280 preliminary sample firms.

Fraudulent financial reporting firms are excluded from the sample if there are insufficient financial statement data for computing financial ratios for a fraud year or for the year preceding a fraud year.[3] A fraud year is the year that fraudulent financial reporting first started.[4] Financial statement data for the fraud year is the original data before any restatement. This criterion excludes 172 firms for a fraud year and 175 firms for the preceding year. Firms in the financial services industry are excluded because certain financial statement variables (e.g., accounts receivable, inventories) are not available for these companies.[5] Companies are also excluded if they changed their fiscal year end during these two years. Five firms are further excluded because of this criterion.

A final sample consists of 103 firms for the fraud-year sample and 100 firms for the preceding-year sample. Twenty three firms are exchange-listed firms and the rest are over-the-counter firms. Fraud year spans from 1970 to 1990, with 54% of sample firms during 1981-1985. Most firms are in durable manufacturing and services industries. Further analysis indicates the following industries as having higher concentration of fraud firms: (a) computer and data processing services (12 firms, SIC code 737), (b) scientific and medical instrument manufacturing (11 firms, SIC code 38), (c) household appliances and electronic equipment manufacturing (10 firms, SIC code 36), and (d) computer manufacturing (10 firms, SIC code 357).

Selection of Nonfraudulent Financial Reporting Firms

Each fraud firm is matched with a nonfraud firm on the basis of industry and time period. Firms in the same industry are subject to similar business environment and similar accounting and reporting requirements (St. Pierre and Anderson 1984). A nonfraud firm is randomly drawn from COMPUSTAT firms that are in the same industry (same four-digit SIC code) as a fraud firm. If the number of firms within the four-digit SIC code is less than ten, then firms within the same three-digit (or two-digit, if necessary) SIC code are added. Financial statement variables of nonfraud firms are obtained from the same time period as fraud firms in order to control for general macroeconomic factors that affect the financial prospects of all companies and the probability of a company's involving in fraud (Palmrose 1987). This one-for-one matching process is used here in an effort to enhance the discriminatory power of the models.

Nonfraudulent financial reporting companies are also required to have sufficient financial statement data, and not to change their fiscal year end during the matching time period. This selection process results in 103 nonfraud firms for a fraud year and 100 nonfraud firms for the preceding year.

Research Design

This section is divided into three parts: variables for estimating models of fraudulent financial reporting, model estimation method, and assessment of models' predictive ability.

Variables for Estimating Models of Fraudulent Financial Reporting

The National Commission on Fraudulent Financial Reporting (1987, p.159) states that "Fraudulent financial reporting has traditionally been associated with companies experiencing financial difficulties." Kinney and McDaniel (1989, p.74) also state that "Management of firms in weak financial condition are more likely to window dress in an

Table 1

Descriptive Statistics of the Ten Variables for Sample of Fraud Firms and Nonfraud Firms.

Variables	Mean		Standard Deviation		t-statistic[a]	Prob
	Fraud	Nonfraud	Fraud	Nonfraud		> t
TLTA	0.6096	0.4868	0.2954	0.2213	3.3277	0.0005
NITA	-0.0774	0.0139	0.3642	0.1882	-2.2596	0.0126
RETA	-0.1007	0.1531	0.7144	0.3553	-3.1812	0.0009
CATA	0.6403	0.5913	0.2222	0.2153	1.6095	0.0545
RVTA	0.2551	0.2270	0.1588	0.1419	1.3371	0.0913
IVTA	0.2349	0.1993	0.1847	0.1621	1.4710	0.0714
WCTA	0.2486	0.3050	0.3158	0.2534	-1.4148	0.0793
SATA	1.2465	1.4608	0.8046	0.8769	-1.8004	0.0366
LOGTA	16.8359	17.9699	2.1726	1.8811	-3.9461	0.0001
Z-Score	1.2917	1.4966	0.7864	0.8725	-1.7439	0.0413

[a] This t-statistic is based on the assumption of unequal variances.

attempt to disguise what may be temporary difficulties." These two studies suggest financial condition as an important factor in assessing the risk of fraudulent financial reporting.

This study identifies ten financial statement ratios/variables commonly used in prior studies to measure a firm's financial condition. Table 1 presents results of two-sample t-test based on these variables. The variables seem to measure the following seven aspects of a firm.

Financial Leverage

This aspect is measured by TLTA (total liabilities/total assets). Higher leverage is typically associated with higher potential for violations of loan agreements and less ability to obtain additional capital through borrowing. Christie (1990) reports that leverage is positively correlated with income-enhancing accounting policies. If these income-increasing accounting policies are not sufficient to avoid a violation of debt covenants, managers may be motivated to understate liabilities or overstate assets. Sign of this variable is, therefore, expected to be positive. Results in Table 1 confirms this expectation, i.e., fraud firms have higher financial leverage than nonfraud firms.

Profitability

This aspect is measured by NITA (net income/total assets) and RETA (retained earnings/total assets). Lower profit may give management an incentive to overstate revenues or understate expenses. Kreutzfeldt and Wallace (1986) find that firms with profitability problems have significantly more errors in their financial statements than other firms. Sign of these two variables is, therefore, expected to be negative. Results in Table 1 provides supporting results that fraud firms are less profitable than nonfraud firms.

Asset Composition

This aspect is measured by CATA (current assets/total assets), RVTA (receivables/total assets), and IVTA (inventory/total assets). Examination of fraud firms' financial statements seem to indicate that current assets of these firms consist mostly of receivables and inventories. This finding is consistent with Feroz, Park and Pastena (1991) who find that overstatements of receivables and inventory represent about three-fourths of the SEC enforcement cases. St. Pierre and Anderson (1984) also find a high frequency of lawsuits against auditors involving inventories and receivables. Simunic (1980) argues that audit fees, which may proxy for risk of undetected false financial statements, are higher for firms with relatively large amounts of receivables and inventories because those accounts are the subject of most lawsuits against auditors. Sign of these variables is, therefore, expected to be positive. Results in Table 1 confirm this expectation, i.e., fraud firms seem to have higher CATA, RVTA and IVTA than nonfraud firms.

Liquidity

This aspect is measured by WCTA (working capital/total assets). Lower liquidity may provide an incentive for managers to engage in fraudulent financial reporting. This argument is supported by Kreutzfeldt and Wallace (1986) who find that firms with liquidity problems have significantly more errors in their financial statements than other firms. Sign of this variables is, therefore, expected to be negative. Table 1 shows that fraud firms seem to have lower liquidity than nonfraud firms.

Capital Turnover

This aspect is measured by SATA (sales/total assets). The turnover represents the sales generating power of a firm's assets. It also measures management's ability to deal with competitive situations. Managers of fraud firms may be less competitive than management of nonfraud firms in using firm's assets to generate sales. This inability to compete successfully may provide an incentive for engaging in fraudulent financial reporting. Sign of this variables is, therefore, expected to be negative. Results in Table 1 support this expectation, i.e., fraud firms have smaller capital turnover than nonfraud firms.

Size

This aspect is measured by LOGTA (natural logarithm of book value of total assets at the end of the fiscal year). Feroz, Park and Pastena (1991) find that most target firms of the SEC enforcement actions are over-the-counter firms which are relatively smaller. Sign of this variables is, therefore, expected to be negative. Table 1 provides supporting evidence, i.e., fraud firms are, on average, smaller than nonfraud firms.

Overall Financial Position

This aspect is measured by Z-score (Altman 1968). This score measures the bankruptcy probability of a firm. The elements of Z-score with their associated weightings (in parentheses) are as follows: working capital/total assets (.012), retained earnings/total assets (.014), earnings before interest and taxes/total assets (.033), market value of equity/book value of total debt (.006), and sales/total assets (.010). Although certain variables mentioned in 2 through 5 above are part of Z-score, an inclusion of Z-score in model estimation stage enables us to assess the relative contribution of Z-score versus an individual variable comprising the score. Sign of Z-score is expected to be negative. In other words, firms with poorer financial condition (smaller Z-score) are more likely to engage in fraudulent financial reporting. Table 1 shows supporting result that fraud firms have smaller Z-score (worse financial condition) than nonfraud firms.

Model Estimation Method

Two prediction models are estimated: a model for the fraud-year sample and a model for the preceding-year sample. The fraud-year model is estimated on 206 firms (103 fraud firms and 103 nonfraud firms). The preceding-year model is estimated on 200 firms (100 fraud firms and 100 nonfraud firms). Both models are estimated by the logistic procedure. This procedure fits a linear regression model by the method of maximum likelihood which applies a transformation to the dependent variable. It is appropriate for estimating a model with a dichotomous dependent variable. McFadden (1973) indicates that this method yields estimators that are asymptotically efficient even in small samples. The dependent variable of these logistic models takes the value of 1 for a fraud firm and 0 for a nonfraud firms.

The ten variables are screened by a stepwise model-estimation method.[6] This stepwise method starts with a forward selection of a variable with the largest chi-squared statistic followed by a backward elimination of an insignificant variable. We specify that a variable enters the models and stays in the models if its chi-squared statistic is significant at < 0.10 level. The reason for using this method is that we want to build the most parsimonious model that still explains the data. The rationale for minimizing the number of variables in the model is that the resultant model is more likely to be statistically stable, and is more easily generalized. The more variables included in a model, the greater the estimated standard errors become and the more dependent the model is on the observed data.[7]

Assessment of Models' Predictive Ability

The jackknife method (Altman et al., 1981) is used to obtain the predicted probability (score) of fraudulent financial reporting. This method requires holding out one firm from the sample and estimating the logistic function on the basis of all of the remaining firms. This function is then used to compute the probability of fraudulent financial reporting for the holdout firm. The fraud probability is computed for each of the 206 firms in the fraud-year sample and for each of the 200 firms in the preceding-year sample. This procedure results in relatively unbiased prediction of fraudulent financial reporting for all sample firms.

There are two reasons for using the jackknife method. First, Lachenbruch and Mickey (1968) suggest that this method produces nearly unbiased estimates of probabilities of misclassification. They also demonstrate that the traditional holdout procedure of using two subsets of observations, where one subset is used to estimate the function and then predict on the other subset (cross-validation) is not considered to be superior to the jackknife procedure.[8] Second, this study has a relatively small sample size of fraud firms (100-103 firms). If part of these firms were used as a holdout sample for cross-validation, the number of firms available for model estimation would have been significantly reduced. This reduction can adversely affect the models' explanatory power and statistical stability.

The expected misclassification costs, developed by Dopuch et al. (1987), is then computed. According to Dopuch et al., the fraud score is compared to a cutoff score that minimize the expected cost of misclassification. The cost-minimizing cutoff score is selected iteratively by calculating the expected misclassification costs per the equation below, using each of the scores (probability estimates) obtained through the jackknife method as a candidate cutoff score. Firms with estimated probabilities above the cutoff score are classified as fraud firms. Firms with estimated probabilities less than or equal to the cutoff score are classified as nonfraud firms. If a fraud firm is classified as a nonfraud firm, the error is considered as type I. If a nonfraud firm is classified as a fraud firm, the error is considered as type II. The expected cost of misclassification is computed as follows:

$$EC = P_I * P(\text{fraud}) * C_I + P_{II} * P(\text{nonfraud}) * C_{II}$$

where EC = expected cost of misclassification,

P_I = probability of type I error (classifying a fraud firm as nonfraud),

P(fraud) = prior probability of fraudulent financial reporting,

C_{HI} = cost of a type I error,

P_{II} = probability of type II error (classifying a nonfraud firm as fraud),

P(nonfraud) = prior probability of fraudulent financial reporting not occurring,

C_{II} = cost of a type II error.

The probabilities of type I and II errors (P_I and P_{II}) are calculated by dividing the number of type I and II errors (produced by classifying sample firms based on the cutoff score) by the number of fraud and nonfraud firms, respectively. The prior probability of fraudulent financial reporting (P(fraud)) is computed by dividing the number of fraudulent financial reporting cases per the SEC enforcements during the period 1974-1991 (280 firms) by the average number of the SEC filing companies during this same period (13,500 firms). This computation results in approximately 2% for P(fraud) and, therefore, about 98% for P(nonfraud).

The costs of type I and type II errors are incorporated into the above equation under alternative assumptions about the relative cost of type I and II errors ranging from 1:1 to 30:1. These relative costs have been widely used in the literature. Higher cost of type I error relative to type II error (e.g., 30:1) seems to represent a more realistic assumption because losses incurred by investors as a result of investing in fraud firms, that are misclassified as nonfraud, are normally far greater than the opportunity cost of not investing in nonfraud firms as a result of misclassifying them as fraud firms.

Following Dopuch et al. (1987), this study assesses the predictive ability of the models by comparing the expected cost of model misclassification with the expected cost of a naive strategy of classifying all firms as nonfraud firms.

Empirical Results

This section is divided into two parts. The first part describes the estimated models. The second part presents model prediction results.

Estimated Models

The final stepwise logistic models for fraud year and for preceding year are presented in Table 2. Both final models consist of four explanatory variables: TLTA, SATA, CATA and LOGTA. The estimated coefficients of these variables have expected signs and are highly significant (< 0.05 level). Among these four variables, TLTA, which measures financial leverage, has the highest significance level (< 0.001). The results reported in the table seem to suggest that fraud firms differ from nonfraud firms in four important aspects: (a) they have higher financial leverage, i.e., more likely to violate loan agreements, (b) they have lower capital turnover, i.e., less competitive in using assets to generate sales, (c) their assets consist of a higher proportion of current assets, especially inventories and accounts receivable, and (d) they are smaller than nonfraud firms.

Table 2

Estimated Stepwise-Logistic Models for the Preceding-Year Sample and the Fraud-Year Sample.

Variables	Expected Sign	Preceding Year Coefficients	Preceding Year Chi-Square (p-value)	Fraud Year Coefficients	Fraud Year Chi-Square (p-value)
Intercept	N/A	2.4925	2.0952 (0.1478)	1.3935	0.6615 (0.4160)
TLTA	+	2.7993	12.4168 (0.0004)	2.7837	14.5580 (0.0001)
SATA	-	-0.6370	8.6574 (0.0033)	-0.6807	9.8204 (0.0017)
LOGTA	-	-0.2418	8.5239 (0.0035)	-0.1808	4.9507 (0.0261)
CATA	+	1.7737	4.2335 (0.0396)	1.8746	5.4251 (0.0198)
Model Chi-Square			35.2140 (0.0001)		31.3530 (0.0001)
R-Value			0.3133 (0.01)		0.2860 (0.01)

Table 2 also presents two goodness-of-fit measures for the models. The first measure is the model chi-square which is based on the likelihood ratio test and can be interpreted similar to the F-test for a linear regression. The model chi-square is 31.353 for the fraud-year model and 35.214 for the preceding-year model. Both chi-squared statistics are significant at < 0.0001 level. The other measure is the R-Value which represents the predictive ability of a model and can be interpreted in a manner similar to the multiple correlation coefficient in a linear model, after an adjustment for the number of estimated parameters.9 R-Value is 0.2860 for the fraud-year model and 0.3133 for the preceding-year model. Both statistics are significant at < 0.01 level. In addition to Table 2 results, the stepwise procedure indicates that the residual chi-square of variables not in these models is insignificant (at 0.10 level). This result is in accordance with Bartolucci and Fraser (1977) who suggest that model building should cease when the residual chi-square is insignificant.

Model Prediction Results

Table 3 presents predictive results. Cost of model errors is lower than cost of errors from naive strategy for every relative cost of type I and type II errors. The percentage of type I error indicates that as the relative cost of type I and type II errors increases, the models correctly classify more fraud firms (e.g., 97% type I error for 1:1 relative cost of errors vs. 36% type I error for 30:1 relative cost). Although the percentage of type II error rises as the relative cost of type I and type II errors increases, the percentage is relatively small, 0-21%. In addition, as the relative cost of type I and type II errors increases, there is greater percentage reduction in expected costs from using the models vs. naive strategy.

In sum, these results suggest that the models developed here provide superior predictive results, i.e., they always outperform naive strategy. There are also significant cost-savings by using these models vs naive strategy especially when relative error costs are assumed to be at least 20:1.

Comparison between preceding-year and fraud-year models indicates that there is virtually no difference between these two models when the relative costs of type I and II errors are low, i.e., 1:1 and 5:1. The differences between the two models become more evident when the relative costs of errors are at least 10:1, a more realistic range of relative error costs. These differences are: (a)

Table 3

Predictive Ability of the Estimated Model for Both Sample Years Based on the Jackknife Method.

Relative Costs of Type I and Type II Errors	Cut-Off Probability	Estimated Error Rates		Cost of Model Errors Relative to Cost of Errors from Naive Strategy [c]
		Type I [a]	Type II [b]	
1:1 Preceding Year	0.9212	0.9700	0.0000	0.9700
1:1 Fraud Year	0.9199	0.9709	0.0000	0.9700
5:1 Preceding Year	0.9212	0.9700	0.0000	0.9700
5:1 Fraud Year	0.9199	0.9709	0.0000	0.9710
10:1 Preceding Year	0.7862	0.8500	0.0200	0.9480
10:1 Fraud Year	0.9199	0.9709	0.0000	0.9710
20:1 Preceding Year	0.6505	0.6200	0.0800	0.8160
20:1 Fraud Year	0.6018	0.5340	0.1359	0.8670
30:1 Preceding Year	0.5416	0.3600	0.2100	0.7030
30:1 Fraud Year	0.6018	0.5340	0.1359	0.7560

[a] Type I error is defined as classifying fraud firms as nonfraud firms.
[b] Type II error is defined as classifying nonfraud firms as fraud firms.
[c] Naive strategy is defined as classifying all firms as nonfraud firms.

Relative to naive strategy, the expected cost of the preceding-year model is lower than that of fraud-year model, and (b) The preceding-year model has lower rate of type I error than the fraud-year model for the relative error costs of 10:1 (12% lower) and 30:1 (17 % lower).

These findings in (a) and (b) seem to suggest that it is easier to detect firms with a high potential of committing fraud (based on the preceding-year model) than to detect fraud firms (based on the fraud-year model). This higher detection rate of high fraud-potential firms is good news for investors, auditors, and regulators. Based on a 30:1 relative error cost, investors can avoid 64% of high fraud-potential firms while risking only 21% of rejecting potentially good-investment firms. Auditors may choose not to accept these high fraud-potential clients while risking only 21% chance of rejecting misclassified low fraud-potential clients. Likewise, the SEC may closely monitor all of these identified high fraud-potential firms while risking only 21% chance of incurring unnecessary monitoring costs on misclassified low fraud-potential firms. This close monitoring may eventually deter these high fraud-potential firms from actually engaging in fraudulent financial reporting.

We also estimate the stepwise-logistic models using variables in a change form. A change form for a fraud year is $variable_t$ - $variable_{t-1}$ where t is fraud year and a change form for a preceding year is $variable_{t-1}$ - $variable_{t-2}$. The goodness-of-fit and the prediction results of these change-form models are inferior to those discussed above.[10]

Conclusions

This study responds to the concerns of the public and the policy makers by identifying several financial statement ratios/variables as being associated with fraudulent financial reporting. Samples of fraud and nonfraud firms are matched on the basis of industry and time period. The results of parsimonous stepwise-logistic models indicate that financial leverage, capital turnover, asset composition and firm size are significant factors influencing the likelihood of fraudulent financial reporting.

The predictive ability of the models are tested and found to outperform a naive strategy of classifying all firms as nonfraud firms for all levels of relative costs of type I and type II errors. The models also correctly identify a large percentage of fraud firms and misclassify a relatively small percentage of nonfraud firms when realistic relative error costs are assumed.

The evidence suggests that accounting data are useful to identify fraudulent financial reporting. The models developed in this study should be useful for the SEC in identifying firms for fraud investigation and identifying high fraud-potential firms for closer monitoring. Likewise, investors can avoid potential losses by using the models as an additional aid for investment decisions. These models could also help auditors assess the likelihood of fraudulent financial reporting of their clients. Auditors could then choose to reject high fraud-potential clients or adjust audit procedures and audit fees to compensate for this increased risk.

Suggestions for Future Research

Future research may replicate this study by using quarterly financial statements. Using quarterly data may reduce the sample size but the data can provide an early indication of factors leading to fraudulent financial reporting. Another interesting extension is to investigate factors associated with fraudulent financial reporting among financial services firms. These firms are structurally different and may require a different set of financial ratios. Finally, more work can be done examining the motives for fraudulent financial reporting. Better understanding of these motives can help investors and analysts be more aware of conditions that potentially lead to fraudulent practices and can aid stockholders in designing a management compensation package that discourages such practices. 🕮

❄❄❄ Endnotes ❄❄❄

1. Palmrose (1987) finds that management fraud is about half of the litigation cases against auditors, and these management fraud cases are most frequently resolved through large auditor payments.
2. This is the period during which the SEC issued ASR or AAER after they had concluded their investigation. This SEC-fraud-report year is one to four years after fraudulent financial reporting first occurred.
3. Financial statement data is obtained from COMPUSTAT tape, Moody's Manuals and 10K reports.
4. This fraud year always precedes the SEC-fraud-report year.
5. A possible extension is to investigate the probability of fraudulent financial reporting among financial services firms. These firms are structurally different and may require a different set of financial ratios.
6. For a more detailed discussion of the stepwise procedure, see Hosmer and Lemeshow (1989).
7. We also estimate the models using all ten variables. The results review that certain variables have extremely large estimated coeffcients and estimated standard errors. These results suggest that the full-variable modes may be overfitted and produce statistically unstable estimates. These results support the use of stepwise method.
8. A recent study that uses the jackknife method is Stice (1991).
9. R is the value such that R = (model chi-square - 2p) / (-2L(0)), where p = the number of variables in the model excluding the intercept and L(0) is the maximum log likelihood with only an intercept in the model. Thus, each added variable must increase the model chi-square by more than an average of two for R to increase.
10. We also estimate the models based on stock market variables and financial statement ratios. The inclusion of stock market variables results in a significant reduction in sample size. The goodness-of-fit and the predictability of financial-statement and stock-market-variable models based on this reduced sample are significantly lower than those of financial-statement-variable models based on a full sample as reported in this study.

❄❄❄ References ❄❄❄

1. Altman, E. I., "Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy," Journal of Finance, September, pp. 589-610, 1968.
2. Altman, E. I., Avery, R., Eisenbeis, R., and Sinkey, J., Application of Classification Techniques in Business, Banking and Finance, JAI Press, Inc. 1981.
3. Bartolucci, A. A., and Fraser, M. D., "Comparative Step-Up and Composite Tests for Selecting Prognostic Indicators Associated with Survival," Biometrical Journal, Vol. 19, pp. 437-448, 1977.
4. Christie, A., "Aggregation of Test Statistics: An Evaluation of the Evidence on Contracting and Size Hypotheses," Journal of Accounting and Economics, January, pp. 15-36, 1990.
5. Dopuch, N., R. Holthausen, and R. Leftwich, "Predicting Audit Qualifications with Financial and

Market Variables," The Accounting Review, Vol. 62, July, pp. 431-454, 1987.

6. Feroz, E. H., Park, K., and Pastena, V. S., "The Financial and Market Effects of the SEC's Accounting and Auditing Enforcement Releases," Journal of Accounting Research, Supplement, pp. 107-142, 1991.
7. Hosmer, D. W., and Lemeshow, S., Applied Logistic Regression, John Wiley & Sons, Inc, New York. 1989.
8. KPMG Peat Marwick, Fraud Survey Results 1993, New York. 1993.
9. Kinney, W., and McDaniel, L., "Charateristics of Firms Correcting Previously Reported Quarterly Earnings," Journal of Accounting and Economics, February, pp. 71-94, 1989.
10. Kreutzfeldt, R., and Wallace, W., "Error Characteristics in Audit Populations: Their Profile and Relationship to Environment Factors," Auditing: A Journal of Practice & Theory, Fall, pp. 20-43, 1986.
11. Lachenbruch, P. A., and Mickey, M. R., "Estimation of Error Rates in Discriminant Analysis," Technometrics Vol. 10, pp. 1-11, 1968.
12. Loebbecke, J. K., Eining, M. M., and Willingham, J. J., "Auditors' Experience with Material Irregularities: Frequency, Nature, and Detectability," Auditing: A Journal of Practice & Theory, Fall, pp. 1-28, 1989.
13. McFadden, D., "Conditional Logit Analysis of Qualitative Choice Behavior," Frontiers in Econometrics, Zarembka, P., ed., Academia Press, pp. 105-142, 1973.
14. National Commission on Fraudulent Financial Reporting, Report of the National Commission on Fraudulent Financial Reporting, October 1987.
15. Palmrose, Z., Litigation and Independent Auditors: The role of Business Failures and Management Fraud. Auditing: A Journal of Practice & Theory, Spring, pp. 90-103, 1987.
16. Simunic, D., "The Pricing of Audit Services: Theory and Evidence," Journal of Accounting Research, Spring, pp. 161-190, 1980.
17. St. Pierre, K., and Anderson, J., "An Analysis of the Factors Associated with Lawsuits Against Public Accountants," The Accounting Review, April, pp. 242-263, 1984.
18. Stice, J. D., "Using Financial and Market Information to Identify Pre-Engagement Factors Associated with Lawsuits Against Auditors," The Accounting