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RESEARCH NOTES

A Decision Aid for Assessing the Likelihood of Fraudulent Financial Reporting

Timothy B. Bell and Joseph V. Carcello

SUMMARY

The auditor's responsibility for detecting fraudulent financial reporting is of continuing importance to both the profession and society. The Auditing Standards Board has recently issued SAS No. 82, *Consideration of Fraud in a Financial Statement Audit*, which makes the auditor's responsibility for the detection of material fraud more explicit without increasing the level of responsibility.

Using a sample of 77 fraud engagements and 305 nonfraud engagements, we develop and test a logistic regression model that estimates the likelihood of fraudulent financial reporting for an audit client, conditioned on the presence or absence of several fraud-risk factors. The significant risk factors included in the final model are: weak internal control environment, rapid company growth, inadequate or inconsistent relative profitability, management places undue emphasis on meeting earnings projections, management lied to the auditors or was overly evasive, the ownership status (public vs. private) of the entity, and an interaction term between a weak control environment and an aggressive management attitude toward financial reporting. The logistic model was significantly more accurate than practicing auditors in assessing risk for the 77 fraud observations. There was not a significant difference between model assessments and those of practicing auditors for the sample of nonfraud cases.

These findings suggest that a relatively simple decision aid performs quite well in differentiating between fraud and nonfraud observations. Practitioners might consider using this model, or one developed using a similar procedure, in fulfilling the SAS No. 82 requirement to "assess the risk of material misstatement of the financial statements due to fraud."

Key Words: Fraudulent financial reporting, Decision aid.

Data Availability: Due to the confidential nature of this client information, the authors cannot release the data.

SAS No. 82, *Consideration of Fraud in a Financial Statement Audit*, provides guidance on the auditor's responsibility to "plan and perform the audit to obtain reasonable assurance about whether the financial statements are free of material misstatement, whether caused by error or fraud" (AICPA 1997). Fraud includes both fraudulent financial reporting and misappropriation of assets. The focus of this paper is on fraudulent financial reporting.[1]

Prior studies have found that failing to detect fraudulent financial reporting can expose the auditor to adverse legal and/or regulatory consequences. For example, Carcello

[1] This paper is based on data that were collected prior to the issuance of SAS No. 82. SAS No. 53, *The Auditor's Responsibility to Detect and Report Errors and Irregularities* (AICPA 1988), held auditors to a similar standard for the detection of material fraud, but used the term "irregularities" instead of "fraud." The focus of this paper, fraudulent financial reporting, was referred to as "management fraud" in SAS No. 53.

Timothy B. Bell is a Director at KPMG LLP and Joseph V. Carcello is an Associate Professor at the University of Tennessee.

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and Palmrose (1994) found a significant positive association between the presence of a financial-reporting irregularity and litigation against the auditor. Also, Feroz et al. (1991) found that an auditor's failure to consider a client's fraud potential was cited in 20 percent of the Accounting and Auditing Enforcement Releases brought against auditors. Given the adverse legal and regulatory consequences to auditors from failing to detect fraudulent financial reporting, research that can help auditors assess fraud risk is of interest to both academics and practitioners.

This study has two objectives. First, we provide evidence on the efficacy of a decision aid that could be used to assess the risk of fraudulent financial reporting. The logistic regression model reported in the paper can provide an independent assessment of the likelihood of fraudulent financial reporting that can complement the auditor's unaided risk assessment. Our model embodies a set of fraud-risk factors that demonstrated better classificatory power than a large number of alternative sets evaluated during the study. In using the model, the auditor first assesses whether these "best-model" risk factors are present for the client. The decision aid then weights and combines these individual judgments into an overall assessment of the probability of fraudulent financial reporting. Prior research suggests that properly weighting and combining fraud-risk factors is difficult for auditors (Pincus 1989; Winters and Sullivan 1994). Use of the model might reduce human bias or error associated with the weighting and combining of fraud-risk factors.

Another objective of the paper is to provide empirical evidence on the effectiveness of the risk-factor examples presented in SAS No. 53 and elsewhere in the accounting literature, at distinguishing between fraud and nonfraud engagements. This baseline evidence should be useful to researchers who may seek to evaluate the incremental effects of additional risk factors such as the examples presented in paragraph 17 of SAS No. 82. For example, researchers might want to compare the efficacy of a model based entirely on the SAS No. 82 risk factors with the model presented in this paper. Or, a better fraud-risk-assessment model might include some risk factors from the model presented in this paper combined with other factors presented in SAS No. 82.

In the next section, we review findings from prior research on the use of fraud-risk factors. In subsequent sections we discuss sample selection issues, present demographic information for our full sample of 382 fraud and nonfraud engagements, discuss the results of univariate and multivariate analyses of the discriminatory power of numerous fraud-risk factors, present our final decision aid, and present an evaluation of the final model's classificatory accuracy. In the final section, we discuss limitations of this research and present a summary and conclusions.

PRIOR RESEARCH

Prior studies on assessing the likelihood of fraudulent financial reporting have focused largely on examining a number of potential fraud-risk factors (i.e., "red flags"). Loebbecke and Willingham (1988) examined numerous SEC Accounting and Auditing Enforcement Releases to determine the presence of fraud-risk factors. From this work they developed a model (hereafter L/W model) that proposes three conditions under which fraudulent financial reporting might be perpetrated.[2] According to the L/W model, the auditor should consider the degree to which: (1) conditions (C) of the entity would allow the perpetration of fraud, (2) management is motivated (M) to perpetrate a fraud, and (3) management's ethical values are such that they might knowingly commit a dishonest or criminal act (attitude) (A). The fraud-risk factors identified during examination of the Enforcement Releases were mapped into these three components of the L/W framework.

Loebbecke et al. (1989) assessed the above model using 77 cases of material financial reporting fraud collected in a survey of U.S. audit

[2] Other similar frameworks that discuss the conditions under which fraudulent financial reporting might be perpetrated have appeared in the literature (e.g., Romney et al. 1980; Uecker et al. 1981).

partners from a large international audit firm.[3] A majority of the 77 fraud cases were discovered during the mid-to-late 1980s shortly before the survey was administered. However, some cases date as far back as the late 1960s. Loebbecke et al. (1989) reported that at least one risk factor was present in all three L/W model components for a majority (88 percent) of the 77 fraud cases. They were not able to assess the discriminatory power of their model and its individual risk factors because their sample contained only cases where fraud had been discovered. With a fraud-only sample, it is not possible to estimate the rate of false positives resulting from the application of the model to nonfraud engagements.

The L/W model was tested by Bell et al. (1991). The full C, M, and A model that contained all 46 risk factors produced a false-positives rate in excess of 25 percent. The best model of the alternatives assessed by Bell et al. (1991) was the model where the three components—C, M, and A—contained only those risk factors from their original mapped sets that were significant stand-alone classifiers of the occurrence of fraud. That model correctly classified 74 percent of the fraud cases, while misclassifying only 11 percent of the nonfraud cases. As discussed in a later section of this paper, using the "high-risk" cutoff of .25, our final model correctly classifies 80 percent of the fraud cases, while misclassifying 11 percent of the nonfraud cases (see Figure 1 presented later in this paper).

In the next section, we discuss the approach used by Bell et al. (1991) to select a sample of nonfraud engagements to supplement the sample of 77 fraud engagements studied by Loebbecke et al. (1989), and we present information about the demographics of the final sample of 382 fraud and nonfraud engagements.

SAMPLE SELECTION AND ENGAGEMENT DEMOGRAPHICS

The sample of 382 fraud and nonfraud engagements used in the Bell et al. (1991) study was also used in this study. Bell et al. (1991) applied the following approach to select a sample of nonfraud engagements to supplement the sample of 77 fraud engagements studied by Loebbecke et al. (1989). During audit planning in the summer of 1990, 500 audit engagements were sampled randomly from the population of U.S. audit clients for the same international audit firm whose "fraud cases" were sampled by Loebbecke et al. (1989). The sample was stratified so that industries were represented in the same proportions found in the population of the firm's audit engagements. Engagements were randomly drawn from each industry. Four hundred twenty-five surveys were returned and 305 usable responses were available after culling 81 engagements that were not full-scope audits, 32 cases where subjects did not complete the survey instrument because clients had recently changed to other auditors, and seven engagements where fraud had been encountered by the auditor during the recent past. Auditors' judgments about the presence or absence of each of the 46 risk factors contained in the L/W model were collected for these 305 "nonfraud" engagements. Respondents included 233 (76.4 percent) partners, 71 (23.3 percent) managers, and one (0.3 percent) senior auditor.[4]

As discussed previously, the majority of the 77 fraud cases used in the Loebbecke et al. (1989) study occurred in the mid-to-late 1980s. However, some of the fraud observations occurred as far back as the late 1960s. Given the infrequency of fraudulent financial reporting, a relatively long time period was required to identify a sample of fraud observations of reasonable size. During the model-estimation phase of the study we tested for possible differences in the propensity for fraud for different time periods. We added a dummy variable indicating those frauds that occurred prior to 1985 and found that it was not significant.

[3] Loebbecke et al. (1989) found that only about one-half of the 376 responding partners had ever encountered a material irregularity of any kind, including both management fraud and defalcations. Of the responding partners who had experienced at least one material irregularity, they had, on average, experienced 1.4 material financial-reporting frauds throughout their careers. Other information presented in that study indicated the partners had worked on approximately 225 engagements on average throughout their careers. This information implies a base rate of material fraudulent financial reporting of approximately 0.6 percent of all audit engagements. Detailed information about sample selection, sample demographics, response rates, etc., is given in Loebbecke et al. (1989).

[4] All of the respondents to the Loebbecke et al. (1989) study—the source for the fraud cases used in this study—were partners.

Several of the risk factors evaluated in the study control for the client's "current" environmental conditions, e.g., "industry is declining with many business failures." Whether the relationship between these environmental risk factors and the occurrence of fraud is stable over time, and whether all significant environmental risk factors have been considered, cannot be determined conclusively from our study.

Table 1 presents demographic information for the combined sample of 77 fraud engagements and 305 nonfraud engagements. Panel A presents sample frequencies and related percentages by industry and type of ownership. Most of the industry proportions are comparable for the fraud and nonfraud samples. Exceptions are Banking, High Tech, and Savings & Loans where higher proportions were found in the fraud sample, and Education, Government, and Other Not-for-Profit where a higher proportion was found in the nonfraud sample. We tested several industry-categorical variables during the model-specification stage of the research and found that they did not have significant incremental classificatory power.

Panel A of Table 1 presents a comparison of the ownership characteristics (public vs. private) for the fraud and nonfraud samples. Since there is typically more pressure on public companies than private companies to produce earnings, it is not surprising that there is a higher proportion of public companies in the fraud sample (50.6 percent) than in the nonfraud sample (14.4 percent). For the industries Banking, High Tech, and Manufacturing, the fraud sample has a higher proportion of publicly owned companies.

Panel B of Table 1 shows the number of years the audit firm had been the auditor for the sampled engagements. First-year audits are more prevalent in the fraud sample (22.1 percent) than in the nonfraud sample (8.5 percent). Also, there is a higher proportion of frauds in engagements where the audit firm had been the auditor for six to 10 consecutive years. In the model-estimation stage of the study, we tested several categorical variables indicating auditor longevity and found that their incremental effects were not significant.

UNIVARIATE ANALYSES OF FRAUD-RISK FACTORS

The fraud-risk factors analyzed in this study are the same 46 factors contained in the L/W model discussed above. Twenty-one of these risk factors were similar to those presented in SAS No. 53 (presented in Table 2). The remaining 25 risk factors were similar to factors discussed in the extant literature (presented in Table 3).

For each of the 46 risk factors, we tested for significant classificatory power using 2×2 contingency tables and the related Chi-square test of independence. The two variables for each contingency table were "auditor risk-factor judgment" and "occurrence of fraud," and the two levels for each variable were present/absent. Actually, there are three possible outcomes: (1) auditor finds fraud, (2) auditor does not find fraud that is subsequently discovered by others, and (3) auditor does not find fraud and no fraud is later discovered. We coded both outcomes (1) and (2) as fraud because we were most interested in the relationship between the auditors' judgments about the presence of risk factors and the ultimate occurrence of fraud, whether discovered or undiscovered by the auditor.[5]

Each fraud-risk factor was presented to auditor-subjects in the form of a question: e.g., For this engagement, does management place an undue emphasis on meeting earnings projections? The questionnaire provided two responses—Yes and No—and required the subject to choose one response. We used a binary scale rather than a Likert scale with three or more points because we wanted the auditor-subjects to form final conclusions about the presence or absence of risk factors even when such judgments were difficult. [6]

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[5] As presented in Loebbecke et al. (1989, 14, Table 7), 84 percent of the 77 sample fraud cases were discovered by the auditors. Eight percent of the sample fraud engagements were not discovered by the auditor. Respondents did not answer this question for another 8 percent of the sample fraud engagements.

[6] Respondents were asked to leave the answer blank for any question where they could not make a judgment about whether the risk factor was present. Our dataset contains only a handful of missing items, which indicates that auditors were able to make these difficult judgments most of the time.

TABLE 1
Sample Demographics

Panel A: Client Industries and Ownership Characteristics

	Private		Fraud Public		Total		Private		Nonfraud Public		Total	
	Count	**Percent**	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**
Agribusiness	3	3.9	0	0.0	3	3.9	7	2.3	1	0.3	8	2.6
Banking	2	2.6	8	10.4	10	13.0	14	4.6	9	3.0	23	7.5
Education, Gov't., & Other Not-for-Profit	3	3.9	0	0.0	3	3.9	73	23.9	0	0.0	73	23.9
Financial Services	5	6.5	0	0.0	5	6.5	9	3.0	3	1.0	12	3.9
High Tech	2	2.6	5	6.5	7	9.1	10	3.3	4	1.3	14	4.6
Health Care	1	1.3	1	1.3	2	2.6	13	4.3	1	0.3	14	4.6
Insurance	2	2.6	1	1.3	3	3.9	13	4.3	1	0.3	14	4.6
Manufacturing	3	3.9	11	14.3	14	18.2	47	15.4	4	1.3	51	16.7
Merchandising	4	5.2	3	3.9	7	9.1	28	9.2	6	2.0	34	11.1
Real Estate	1	1.3	2	2.6	3	3.9	11	3.6	2	0.7	13	4.3
Savings & Loans	5	6.5	3	3.9	8	10.4	11	3.6	5	1.6	16	5.2
Other	7	9.1	5	6.5	12	15.6	25	8.2	8	2.6	33	10.8
Totals	38	49.4	39	50.6	77	100.0	261	85.6	44	14.4	305	100.0

Panel B: Number of Years Firm Has Been Auditor

	Fraud		Nonfraud	
	Count	**Percent**	**Count**	**Percent**
1st Year	17	22.1	26	8.5
2 – 5 Years	30	39.0	121	39.7
6 – 10 Years	25	32.5	64	21.0
> 10 Years	5	6.5	91	29.8
No Response	0	0.0	3	1.0
Totals	77	100.0	305	100.0

The results of our univariate analyses are presented in Tables 2 and 3. The 21 factors listed in Table 2 (in abbreviated form) correspond closely to the factors presented in SAS No. 53. Results for the 25 additional factors, which were similar to other factors presented in the fraud literature, are presented in Table 3.

Table 2 (SAS No. 53 factors) presents the absolute and relative (percentage) frequencies of "risk-factor-present" responses for the 77 fraud and 305 nonfraud cases. The related Chi-square statistics, phi coefficients, and observed significance levels are also presented in the table. The Chi-square statistic is used to test the significance of the relationships between individual risk-factor judgments and occurrence of fraud. The phi coefficient is a measure of the extent of association between risk-factor judgments and occurrence of fraud and can be interpreted similar to the Pearson correlation.[7] In the far right-hand column of each table an "NS" is given for each factor that is not significant at the .01 level. Also, if a risk factor is significant, but the relative frequency of "yes" responses is higher for the nonfraud sample, a "WS" is given in the far right-hand column indicating "wrong sign."

Table 2 shows that 13 of the 21 risk factors from SAS No. 53 are significant. The strongest factors and their respective phi coefficients are: management lied to the auditor or was overly evasive when responding to audit inquiries (.48); weak internal control environment (.46); management's attitude unduly aggressive (.42); management places undue emphasis on meeting earnings projections (.41); and significant difficult-to-audit transactions or balances are present (.40). It is interesting to note that the variable "significant and unusual related-party transactions are present" was not significant. The reason this factor is not significant is that its rates of occurrence in both the fraud (28.6 percent) and the nonfraud samples (25.3 percent) were nearly equivalent. Although significant and unusual related-party transactions may be contributing factors in some frauds, absent other risk factors their mere presence does not appear to elevate the risk of fraud.

Table 3 shows that the proportions of "risk-factor-present" responses for the fraud and nonfraud samples are significantly different for nine of the 25 additional fraud-risk factors. The strongest of the 25 additional risk factors is "auditor's experience with management indicates a degree of dishonesty," with a phi coefficient of .40. The lack of significance for some of these 25 factors might be due to the infrequent occurrence of the particular risk factor. In particular, a number of the "attitude" risk factors in Table 3 are rarely present. For example, the risk factor "top management is considered to be highly unreasonable" only was present for four of the frauds and five of the nonfrauds.

In the next section, we discuss the results of our multivariate analysis of the 46 fraud-risk factors. We present our final multivariate model for assessing the likelihood of fraudulent financial reporting, and we compare the final model's sample classifications with unaided assessments made by the auditors associated with these engagements.

MULTIVARIATE ANALYSIS OF FRAUD-RISK FACTORS

Logistic Regression Model

We used the results from the univariate analyses to guide our development of the final logistic regression model. Combinations of the risk factors that were significant in the univariate analyses were tested in many different models. Other factors that were not significant on a stand-alone basis were added and tested, as well as numerous interaction terms. In order to estimate, test, and compare alternative logistic regression models, we randomly divided the total sample of 382 cases into an estimation sample and a holdout sample. The estimation sample contained 37 fraud cases and 143 nonfraud cases. The holdout sample contained 40 fraud cases and 162 nonfraud cases. We estimated literally hundreds of models using the estimation sample, and assessed and compared their predictive abilities using the holdout sample. Due to the large number of risk factors included in this study (n = 46 plus "ownership status" and all possible interactions), estimating and comparing predictive abilities of all possible models was

[7] The phi coefficient is computed by taking the square root of the Chi-square statistic divided by the sample size.

TABLE 2
Auditor Judgments for L/W Risk Factors
(derived from SAS No. 53)

Risk Factors from SAS No. 53	Fraud Cases (n = 77) Present	%	Nonfraud Cases (n = 305) Present	%	Pearson Chi-Sq.	Phi Coef.	Prob.
Weak Internal Control Environment	50	64.9	47	15.4	79.6	.46	.000
Management Characteristics							
Management decisions dominated by a single person or small group	67	87.0	195	63.9	15.2	.20	.000
Management's attitude unduly aggressive	28	36.4	13	4.3	66.1	.42	.000
Management turnover is high	7	9.1	18	5.9	1.0	.05	.312 NS
Management places undue emphasis on meeting earnings projections	28	36.4	14	4.6	63.4	.41	.000
Management's reputation in the business community is poor	10	13.0	6	2.0	18.6	.22	.000
Operating and Industry Characteristics							
Inadequate or inconsistent relative profitability	30	39.0	35	11.5	32.9	.29	.000
Sensitivity of operating results to economic factors is high	24	31.2	83	27.2	0.5	.04	.490 NS
Rate of change in industry is rapid	30	39.0	75	24.6	6.4	.13	.012 NS
Industry is declining with many business failures	25	32.5	59	19.3	6.2	.13	.013 NS
Organization is decentralized without adequate monitoring	9	11.7	6	2.0	15.4	.20	.000
Doubts about entity's ability to continue as a going concern	23	29.9	30	9.8	20.7	.23	.000
Engagement Characteristics							
Many contentious or difficult accounting issues	26	33.8	57	18.7	8.2	.15	.004
Significant difficult-to-audit transactions or balances are present	32	41.6	21	6.9	61.9	.40	.000
Significant and unusual related-party transactions are present	22	28.6	77	25.3	0.4	.03	.552 NS
Misstatements detected in prior period's audit	4	5.2	5	1.6	3.4	.09	.066 NS
New client with no prior audit history or sufficient information not available from predecessor auditor	15	19.5	29	9.5	6.0	.13	.014 NS
Other Red Flags from Paragraph 12							
Management has been overly evasive when responding to audit inquiries	30	39.0	9	3.0	87.0	.48	.000
Management has engaged in frequent disputes with auditors	16	20.8	6	2.0	40.1	.32	.000
Compensation arrangements are based on recorded performance	15	19.5	35	11.5	3.5	.10	.063 NS
Accounting personnel exhibit inexperience or laxity in performing duties	32	41.6	34	11.2	39.8	.32	.000

NS = Not significant at the .01 significance level.

TABLE 3
Auditor Judgments for Additional L/W Risk Factors
(derived from extant literature)

Additional Risk Factors in Three L/W Model Components	Fraud Cases (n = 77) Present	%	Nonfraud Cases (n = 305) Present	%	Pearson Chi-Sq.	Phi Coef.	Prob.
Conditions							
Company entered into one or an aggregate of material transactions	19	24.7	58	18.4	1.6	.06	.213 NS
Company involved in purchase, sale, or merger of/with another company	3	3.9	85	27.9	19.9	–.23	.000 WS
Company recently entered into a significant number of acquisition transactions	1	1.3	19	6.2	3.0	–.09	.083 NS
Company is in a period of rapid growth	34	44.2	41	13.4	36.8	.31	.000
Company has inexperienced management	15	19.5	18	5.9	14.4	.19	.000
A conflict of interest exists within the company and/or its personnel	12	15.6	7	2.3	23.0	.25	.000
Motivation							
There are adverse conditions in the client's industry	30	39.0	136	44.6	0.8	–.05	.373 NS
Company is subject to significant contractual commitments	18	23.4	56	18.4	1.0	.05	.320 NS
Company is confronted with adverse legal circumstances	11	14.3	14	4.6	9.4	.16	.002
Company holdings represent a significant portion of management's personal wealth	7	9.1	99	32.5	16.7	–.21	.000 WS
Management personnel perceive their jobs are threatened by poor performance	10	13.0	49	16.1	0.4	–.03	.504 NS
Attitude							
Officers of the company have entered into collusion with outsiders	1	1.3	1	0.3	1.1	.05	.292 NS
There is need to cover up an illegal act	1	1.3	5	1.6	0.0	–.01	.830 NS
Auditor's experience with management indicates a degree of dishonesty	21	27.3	6	2.0	59.9	.40	.000
There is undue concern with the need to maintain or improve the reputation/image of the company	1	1.3	28	9.2	5.4	–.12	.020 NS
Management displays a propensity to take undue risk	4	5.2	7	2.3	1.8	.07	.174 NS
Management personnel engage in an inappropriate lifestyle	2	2.6	3	1.0	1.2	.06	.266 NS
Top management is considered to be highly unreasonable	4	5.2	5	1.6	3.4	.09	.066 NS
Management displays a significant lack of moral fiber	4	5.2	7	2.3	1.8	.07	.174 NS
Client personnel exhibit strong personality anomalies	8	10.4	0	0.0	32.4	.29	.000
Management places undue pressure on the auditors	14	18.2	12	3.9	19.7	.23	.000

(Continued on next page)

TABLE 3 (Continued)
Auditor Judgments for Additional L/W Risk Factors
(derived from extant literature)

Additional Risk Factors in Three L/W Model Components	Fraud Cases (n = 77) Present	%	Nonfraud Cases (n = 305) Present	%	Pearson Chi-Sq.	Phi Coef.	Prob.
Management has engaged in opinion shopping	7	9.1	1	0.3	23.0	.25	.000
Management displays a hostile attitude toward the auditors	1	1.3	6	2.0	0.2	–.02	.696 NS
Management displays significant disrespect for regulatory bodies	7	9.1	4	1.3	13.3	.19	.000
Management displays significant resentment of authority	1	1.3	5	1.6	0.0	-.01	.830 NS

NS = Not significant at the .01 significance level.
WS = Wrong sign, opposite of expectations.

prohibitively costly. The model that achieved the highest level of classificatory accuracy is presented in Table 4.

As shown in Table 4, the "best model" contains the following variables: weak internal control environment, rapid company growth, inadequate or inconsistent relative profitability, management places undue emphasis on meeting earnings projections, management lied to the auditor or was overly evasive, the ownership status (public vs. private) of the entity, and an interaction term between a weak control environment and an aggressive management attitude toward financial reporting.[8]

Assessments of Model Performance

The "hit rates" for the final model using both the estimation and holdout samples and an array of consecutive cutoff points are presented in Table 5. The cutoff points represent the predicted probabilities of fraud that are derived from the application of the logistic regression model. For example, using a cutoff value of .40 (i.e., predict "fraud" for all observations where the model-generated probability of fraud is 40 percent or greater), 73 percent of all fraud observations and 96 percent of all nonfraud observations are correctly classified.

Since the selection of any one cutoff point would be arbitrary in the absence of conclusive information about costs of misclassification to the auditor, we evaluated the classificatory accuracy of our model using numerous cutoff points. We assessed classificatory accuracy at every cutoff point between .05 and .95 (scaled in increments of .05), and we considered additional cutoff points in the two tails of the distribution.

Figure 1 graphically depicts the relative frequency of engagements (fraud/nonfraud) in different risk categories. The overall distribution in Figure 1 has been separated into five subjective categories ranging from very low risk to very high risk, and within-sample classifications and holdout-sample predictions have been combined. The cutoffs used for the five risk categories were selected based on "natural breaks" in the distribution of fraud probabilities. We attempted to identify thresholds where misclassification rates changed significantly.

The model correctly classifies the majority of cases assigned to the low- and high-risk categories. The very-low-risk category pertains to cases for which the probability of fraud is .017 or lower, and contains 55 percent of the nonfraud cases and 5 percent of the fraud cases. The very-high-risk category includes cases for which the

[8] The variable "inadequate or inconsistent relative profitability" and the interaction between "weak control environment" and "aggressive management attitude toward financial reporting" were marginally significant. However, they are included in our final model as both variables contributed to classificatory accuracy, and because we were not particularly concerned with the individual significance of any one predictive variable.

probability of fraud is .75 or higher, and contains 44 percent of the fraud cases and 2 percent of the nonfraud cases. The low-risk category applies to clients with probabilities of fraud between .017 and .10 and contains an additional 14 percent of the nonfraud cases and 3 percent of the fraud cases. The high-risk category applies to clients with probabilities ranging from .25 to .75 and contains an additional 36 percent of the fraud cases and 9 percent of the nonfraud cases.

The overall assessment of the risk of fraud becomes increasingly tenuous for cases where the probability of fraud falls between .10 and .25. The risk of fraud for clients with probability values within this "gray" area, where some significant risk factors are present, is considered

TABLE 4
Logistic Regression Model[a]

Chi-Square for Model (7 degrees of freedom)	86.59
p-value	.0001
Pseudo R^2	.48

Independent Variable	**Estimated Coefficient—Estimation Sample**	**Standard Errors**	**Chi-Square**	**p Level**[b]
Intercept	–4.04	.59	47.54	.0001
WKCONTROL	2.16	.62	11.93	.001
RAPGROWTH	1.26	.61	4.28	.02
INADPROFIT	0.89	.66	1.82	.09
UNDEMEARN	1.75	.74	5.69	.01
EVASMGMT	1.35	.74	3.29	.03
OWNSTATUS	2.22	.58	14.77	.0001
WKCTRLXAGGMGMT	2.05	1.36	2.28	.07

		Model[c] **Predictions**	
		Fraud	**Nonfraud**
Actual	Fraud	30	7
	Nonfraud	20	123

[a] Estimated on a randomly drawn sample of 37 fraud and 143 nonfraud cases.
[b] The significance tests are one-tailed.
[c] Based on prior probabilities similar to the relative subsample frequencies of 20 percent/80 percent for the fraud/nonfraud samples respectively.

WKCONTROL = weak internal control environment
RAPGROWTH = rapid company growth
INADPROFIT = inadequate or inconsistent relative profitability
UNDEMEARN = undue emphasis on meeting earnings projections
EVASMGMT = management lied to the auditors or was overly evasive
OWNSTATUS = the ownership status (public vs. private) of the entity
WKCTRLXAGGMGMT = interaction between a weak control environment and an aggressive management attitude toward financial reporting

TABLE 5
Classificatory Accuracy

Estimation Sample[a]			Holdout Sample[c]		
Predicted Probability of Fraud from Model[b]	Percentage of Observations Correctly Classified: Fraud	Nonfraud	Predicted Probability of Fraud from Model	Percentage of Observations Correctly Classified: Fraud	Nonfraud
.99	8	100	.99	23	99
.98	11	100	.98	23	99
.97	13	100	.97	28	99
.96	19	100	.96	30	99
.95	24	100	.95	30	99
.90	27	100	.90	33	99
.85	30	99	.85	33	98
.80	38	99	.80	40	98
.75	43	98	.75	45	98
.70	46	97	.70	48	98
.65	54	97	.65	50	98
.60	57	97	.60	50	98
.55	62	96	.55	55	96
.50	65	96	.50	55	96
.45	73	96	.45	55	95
.40	73	96	.40	55	95
.35	78	92	.35	65	92
.30	78	92	.30	65	92
.25	81	88	.25	80	90
.20	81	88	.20	80	90
.15	84	86	.15	83	88
.10	95	71	.10	90	67
.05	95	61	.05	95	59
.04	95	55	.04	95	55
.03	95	55	.03	95	55
.02	95	55	.02	95	55
.01	100	0	.01	100	0

[a] Estimated on a randomly drawn sample of 37 fraud and 143 nonfraud cases.
[b] The cutoff points represent the predicted probabilities of fraud that are derived from the application of the logistic regression model. For example, using a cutoff value of .40 (i.e., predict "fraud" for all observations where the model-generated probability of fraud is 40 percent or greater), 73 percent of all fraud observations are correctly classified, and 96 percent of all nonfraud observations are correctly classified.
[c] Estimated on a randomly drawn sample of 40 fraud and 162 nonfraud cases.

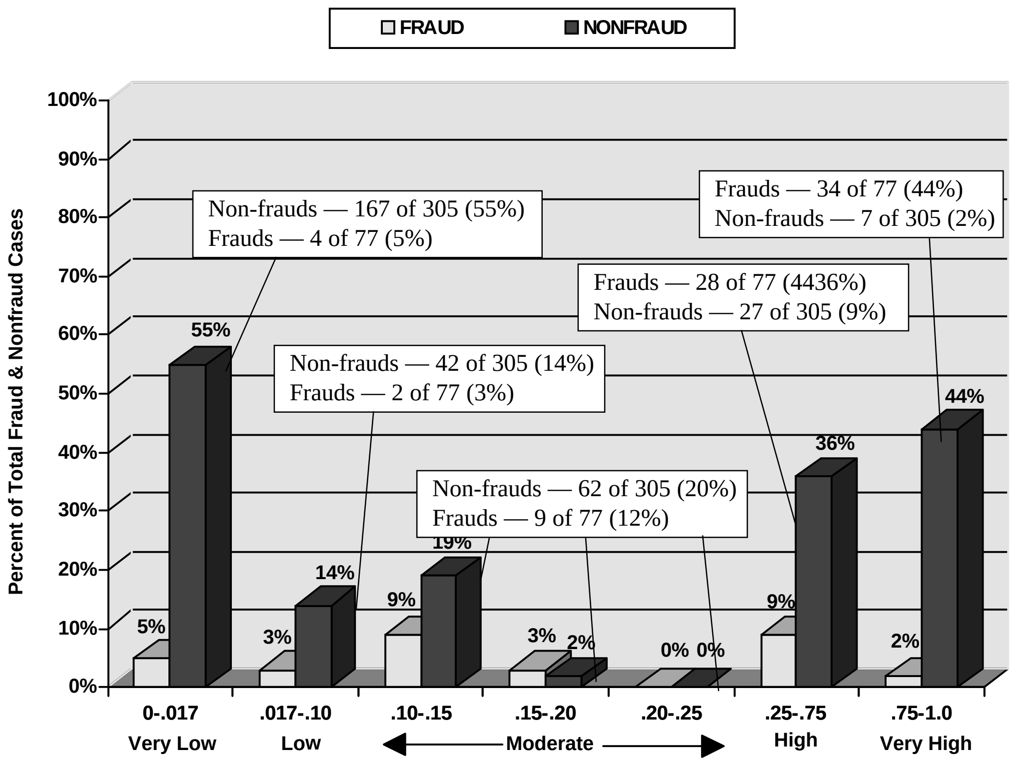
moderate. Although the model's usefulness as an aid to the fraud assessment for clients with a fraud probability within this range is limited, only 20 percent of the nonfraud cases and 12 percent of the fraud cases are involved.

The combined high- and very-high-risk categories capture 62 of the 77 fraud cases (80 percent) and include only 34 of the 305 nonfraud cases (11 percent). The combined low- and very-low-risk categories contain 209 of the 305 nonfraud cases (69 percent) and only 6 of the 77 fraud cases (8 percent).

Comparison of Decision Aid and Unaided Auditor Judgments—Fraud Cases

As a further means of evaluating the efficacy of our decision aid, we compared model predictions against auditors' unaided risk

FIGURE 1
Percent of Fraud and Nonfraud Cases within Risk Categories
(estimation and holdout samples combined)



Categorization of Fraud and Nonfraud Observations
Categorized by Risk Category

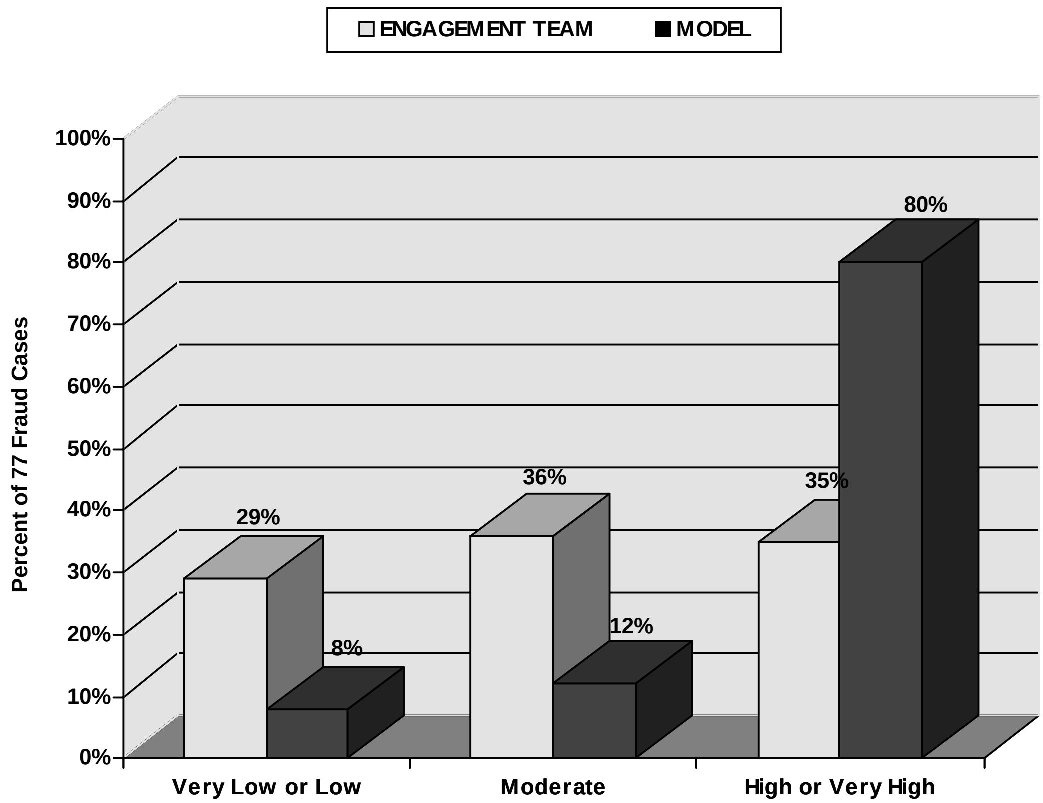
assessments. For the sample of fraud observations described earlier in the paper, the auditors were asked to respond to the following question: During engagement planning, was the sense of the engagement team that the likelihood of a material irregularity occurring was high, moderate, or low?"

Figure 2 shows the model classifies 80 percent of the fraud engagements as high or very high risk. The auditors said they classified only 35 percent of the fraud engagements as high risk during audit planning. The model classified 12 percent of the fraud observations as moderate risk and 8 percent as low/very low risk. The comparable percentages of frauds classified as moderate or low risk, based on the auditors' unaided planning-stage assessments, were 36 percent and 29 percent, respectively. Subject to possible limitations of this research discussed in the paper's final section, this evidence suggests the logistic regression model outperforms unaided auditor assessments in identifying fraudulent financial reporting.

Comparison of Decision Aid and Unaided Auditor Judgments—Nonfraud Cases

There may be situations where the risk of fraudulent financial reporting is considered high during the planning stage of the audit, and yet no fraud is uncovered during the audit. We

FIGURE 2
Fraud Observations
Comparison of Auditor Planning-Stage
Unaided Risk Assessments and
Logistic Regression Model Risk Assessments



Fraud-Risk Categories

tested the model's ability to identify these "high risk/no fraud" cases by comparing the unaided auditor risk assessments for the 305 nonfraud cases with our model classifications. In the nonfraud survey the auditor-subjects were asked to indicate whether the risk of fraud for the sample engagement was high, moderate, or low. One respondent did not answer the question. Table 6 presents the cross-classification of unaided auditor assessments and model predictions for the remaining 304 nonfraud cases. Auditors' unaided assessments comprise the rows in the cross-classifications, and model classifications by risk categories comprise the columns.

Table 6 shows that all three engagements assessed as high risk by the auditors were also classified as high risk by the model.[9] For the 263 engagements where auditors indicated low risk, our model classified 192 (73 percent) as low risk. Column percentages indicate that 92 percent of the cases for which the model indicated low risk were also assessed as low-risk engagements by the auditors. Although model

[9] We have combined the model-generated very-low- and low-risk categories, and the very-high- and high-risk categories for the purpose of making comparisons with unaided auditor assessments in Table 6.

TABLE 6
Comparison of Model-Estimated Risk by Auditors' Assessments for Nonfraud Cases
(Goodman-Kruskal Gamma Measure of Association = .64, Z = 4.01, p < .0001)

Auditors' Assessments	Model-Estimated Risk: High n	High Row%	High Col%	Moderate n	Moderate Row%	Moderate Col%	Low n	Low Row%	Low Col%	Totals
High	3	100	9	0	0	0	0	0	0	3
Moderate	14	37	41	8	21	13	16	42	8	38
Low	17	6	50	54	21	87	192	73	92	263
Totals	34			62			208			304 *

* One respondent did not give an assessment.

classifications and auditors' unaided assessments were generally consonant, an examination of the off-diagonal elements of Table 6 indicates a tendency on the part of the auditors to assign clients to risk categories that are lower than the model-generated classifications. For example, the risk category assigned by the model was higher than the auditor's assessment in 85 cases. The auditor's risk assessment was "moderate risk" while the model's classification was "low risk" for only 16 cases.

We used the Goodman-Kruskal Gamma (G) statistic to measure the association between model classifications and auditors' unaided assessments (Siegel and Castellan 1988). The G-statistic is .64 for the nonfraud sample cases, which is significant at the .0001 level (Z = 4.01).[10] In contrast, the G-statistic for the 77 fraud cases is .26, which is not significant at the .10 level (Z = .76). These results indicate that auditors' unaided assessments and model classifications were similar for nonfraud cases but not for fraud cases where auditors tended to assign clients to lower risk categories than the model.

SUMMARY, LIMITATIONS, AND CONCLUSIONS

Summary of the Results and Implications

Our results indicate that a relatively simple mathematical model correctly classifies a majority of both fraud and nonfraud sample cases included in this study. Use of the model reported herein can assist the auditor's unaided fraud-risk assessment by independently weighting and combining significant fraud-risk factors that the auditor has judged are present for the audit client. The model employs risk factors and weights that have demonstrated superior classificatory accuracy using a large sample of past audit engagements. Using the model as an independent check on their unaided fraud-risk assessments, auditors may be able to reduce biases introduced through inappropriate weighting of fraud-risk factors. For example, when model-generated and unaided risk assessments are discordant, auditors would be challenged to rethink their assessments and consider whether they gave sufficient weight to important risk factors known to be present.[11]

Where a firm has been the client's auditor for some time, the risk-factor judgments required to use the decision aid can be made without great difficulty. Also, for new clients or prospective

[10] The G-statistic ranges from –1 to +1 and should be interpreted in a manner similar to a Pearson correlation. We used the Z-test to evaluate the significance of the computed G-score.

[11] Recent research (Eining et al. 1997, 16) suggests that a decision aid such as the one presented here is more likely to be used by practicing auditors when it is supported by a "constructive dialogue" feature. Eining et al. (1997) combined a logit model very similar to the model presented in this paper with constructive dialogue in an integrated expert system and found that practicing auditors were more likely to rely on the recommendations of the model. Eining et al. (1997) present five features of a useful constructive dialogue: (1) judgment decomposition, (2) prior judgment, (3) rule presentation, (4) reassessment opportunity, and (5) deviation justification.

clients, our model identifies those risk factors that should be of primary concern to the auditor when making a client acceptance/rejection decision, when making inquiries of the predecessor audit firm, and when forming the initial audit plan.

The model presented in this paper produced impressive hit rates when applied to a large sample of fraud and nonfraud engagements. The "best model" correctly classified 69 percent (80 percent) of the sample engagements into the low- and very-low- (high- and very-high-) risk categories. The model appears less effective as a tool for assessing fraudulent financial reporting at what we characterize as the moderate-risk category, but only 20 percent of the nonfraud and 12 percent of the fraud engagements included in our sample were assigned to this category.

Limitations

Assessments of the model's discriminatory power could be overstated due to possible hindsight bias inherent in the judgments made by the auditors associated with the fraud engagements. Although Loebbecke et al. (1989) exercised care when collecting risk-factor judgments for the sample of fraud engagements by asking subjects to answer "yes" only for those factors that were apparent during audit planning, there is no way to ensure the complete elimination of hindsight bias. Also, because model cutoffs were chosen based on researcher judgment, they might not be the cost-minimizing cutoffs.

Since our data were gathered before the issuance of SAS No. 82, we were unable to explicitly consider the risk-factor examples presented in the new SAS during our development of the decision aid. However, we cross-matched the 46 L/W model risk factors used in this study with the 37 risk-factor examples presented in paragraph 17 of SAS No. 82.[12] In our judgment, for 27 (73 percent) of the 37 SAS No. 82 fraud-risk factors, an L/W model risk factor is similar to the analogous SAS No. 82 risk factor. Also, each of the significant risk factors comprising our final model corresponds with a risk factor contained in SAS No. 82. Additional research is needed to assess the incremental discriminatory power of SAS No. 82 risk factors over the set of factors included in our final model.

In order to have a sufficient number of fraud observations to develop our model, fraud engagements were drawn from a number of years whereas nonfraud engagements were identified from one particular year. The use of different time periods for the fraud and nonfraud samples might be problematic if the relationship between the risk factors and the incidence of fraud changes over time.

Conclusions

In conclusion, the analyses presented in this paper indicate that several risk factors presented in the authoritative guidance and elsewhere in the literature are not particularly effective in discriminating between fraud and nonfraud engagements. The set of insignificant risk factors includes: "high management turnover," various indicators of industry-wide performance such as "rapid industry growth" or a "declining industry," and engagements involving "significant and unusual related-party transactions" or "compensation arrangements tied to reported earnings."

The factors that were effective discriminators of fraudulent financial reporting were: (1) rapid growth, (2) weak control environment, (3) management overly preoccupied with meeting

[12] Paragraph 17 of SAS No. 82 presents examples of risk factors relating to misstatements arising from fraudulent financial reporting, grouped into the following three categories: (1) *management's characteristics and influence over the control environment*, (2) *industry conditions*, and (3) *operating characteristics and financial stability*. Many of the SAS No. 82 risk-factor examples are similar to examples that were presented in SAS No. 53 or other sources studied in this research. For example, two of the fraud-risk factors included in our final logistic regression model are "the company is in a period of rapid growth," and "management places undue emphasis on meeting earnings projections." Similar risk factors presented in SAS No. 82 are *unusually rapid growth or profitability, especially compared with that of other companies in the same industry*, and *a practice by management of committing to analysts, creditors, and other third parties to achieve what appear to be unduly aggressive or clearly unrealistic forecasts*. SAS No. 82 states, "Although the fraud-risk factors described in paragraphs 17 and 19 cover a broad range of situations typically faced by auditors, they are only examples" (AICPA 1997, para. 14). SAS No. 82 does not preclude the auditor from evaluating other risk factors, nor does it preclude the use of similar, but not identical, risk factors such as those given in SAS No. 53.

earnings projections, (4) management that lied to the auditors or that was overly evasive, (5) ownership status, and (6) an interaction between a weak control environment and an aggressive management attitude toward financial reporting. SAS No. 82 suggests a number of actions the auditor might consider in response to a heightened risk of fraud. These actions include assigning more experienced personnel to the engagement team, considering further the appropriateness of management's selection and application of significant accounting principles and policies, and adjusting the nature, timing, and extent of audit procedures.

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