ACCOUNTING FRAUD DETECTION: IS IT POSSIBLE TO QUANTIFY UNDISCOVERED CASES?

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Abstract
Accounting fraud is defined as intentional misstatement of financial reports, in violation of generally accepted accounting principles, with the objective of making certain people act in detriment to their best interests. It is possible to identify the determinants of fraud using an econometric model, but the dependent variable (occurrence of fraud in a company) is vulnerable to misclassification: Not every case of fraud will be detected, thus false negatives are possible. This paper estimates the percentage of undiscovered frauds and also estimates a logit model to detect fraud in US companies. The dependent variable was built using the instances of fraud discovered by the Securities and Exchange Commission (SEC). We searched the Accounting and Auditing Enforcement Releases (AAERs) published by the SEC from 1 January 1998 to 23 November 2010 in order to build a sample of cases of fraud, but the model was estimated only with frauds that occurred between 1998 and 2002 (since many cases of fraud from the last years are still unknown and therefore not reported in the AAERs). The independent variables were chosen using the concept of fraud triangle. The financial statement data were obtained using Compustat. The results show that the likelihood of fraud is apparently lower when the company's auditor issues an unqualified report, but in the improved model with classification errors this variable was found to be nonsignificant. The probability that a case of fraud is not detected was estimated as 96.80%; this means just a small part of fraud cases are discovered by the SEC.

Keywords: Accounting fraud; AAER; Misclassification; Logit.

1 INTRODUCTION

In modern corporations, it is common to adopt a structure that separates ownership from management. Although the shareholders have voting rights, the daily management is actually done by professional executives appointed by the board of directors (that are themselves elected by the shareholders). In this situation emerge what Jensen and Meckling (1976, p. 5) call an *agency relationship*: "A contract under which one or more persons (the principal(s)) engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent".

In an agency relationship there usually are conflicts of interest between the principal and the agent. The decisions taken by the executives are not always the ones the shareholders would take if they were managing the company (JENSEN; MECKLING, 1976). For example, the CEO might buy a first class plane ticket, while a shareholder would probably prefer to pay a cheaper airfare. Actually, the existence of a “partial goal conflict among participants” of the relationship is an important organizational assumption of the agency theory (EISENHARDT, 1989, p. 59).

This misalignment of interests will usually incur in agency costs for the company. Some of these agency costs are monitoring costs: The principal is willing to invest in the development of a monitoring system capable of avoiding abuses by the agents. The financial statements are part of this monitoring system. Even though they are a cost (paid by the stockholders), they allow the investor access to information about the quality of the management of the company.

And what might happen when the company’s results are not as good as the shareholders expect? The managers might be fired or lose wealth, since their executive compensation will probably lose value when these poor results are published (SEN, 2007). The company itself might also get in trouble, losing access to credit or having to face loss of confidence from clients, suppliers and employees about its future. To avoid the consequences of an unsatisfactory performance, some executives might choose to falsify the financial statements.

Some high-profile cases of accounting fraud became known in the beginning of the first decade of the 21st century, shattering the trust of the investors, inasmuch as the costs of frauds are in last instance paid by the stockholders when the stock prices plummet after the announcement of fraud charges by the Securities and Exchange Commission (GERETY; LEHN, 1997). Some big companies now associated to fraud in the US are Adelphia, Enron, Tyco and WorldCom. This surge of frauds led to a legislative reform known as Sarbanes-Oxley Act (SOX), which established new standards of transparency for public companies. In spite of these measures, frauds still occur (even though their number decreased after 2002), and therefore are still a relevant theme for academic research.

To understand and avoid financial statement fraud it is necessary to know its causes. This would allow the Securities and Exchange Commission (SEC) and other similar regulatory agencies to concentrate their investigative efforts in companies that are at greater risk. This knowledge would also assist in the development of public policies and laws that fight fraud. One of the ways of studying the causes of fraud is through regression analysis, especially with binary choice models (logit and probit). This approach allows the test of hypotheses about the influence of certain variables on the occurrence of fraud.

In the US, when a fraud is discovered, the SEC publishes an Accounting and Auditing Enforcement Release (AAER) detailing the case and announcing the measures that were or will be taken. For example, the AAER #1,627 explains the nature of a series of secret loans taken by Dennis Kozlowski (former CEO of Tyco), and announces that the SEC has filed a lawsuit against the individuals involved. For this reason, we used the AAERs to build a list of cases of fraud that will then be used to estimate a logit model together with other variables and financial data obtained in Compustat.

One of the problems of this approach is that there are cases of fraud that still have not been discovered, and some of them probably will never be. This generates misclassification problems in the dependent variable. There are companies incorrectly excluded from the list of cases of fraud. These errors harm the model, biasing the estimates of the parameters. It is therefore possible that the hypotheses tests are affected, making the conclusions misleading. To minimize this problem Hausman, Abrevaya and Scott-Morton (1998) developed a method that is capable of estimating the probability that a case of fraud is not discovered.

The objective of this paper was to estimate the percentage of undiscovered frauds in US companies. We also wanted to verify if the results obtained using a traditional logit model are qualitatively different from those obtained using a logit model that accounts for classification errors. To accomplish these goals, we performed a univariate analysis to identify which variables are different in the companies charged with fraud. We employed the variables that were statistically different in the two aforementioned logit models. We compared the results and performed a statistical test to verify if the percentage of undiscovered frauds is different from zero.

2 THEORETICAL BACKGROUND AND VARIABLES

There are several types of fraud. When the employee of a small shop abuses the trust his boss has in him or her and commits embezzlement, he or she is engaging in a fraudulent act. When a person receives benefits from the government without being entitled to them, he or she is also involved in a fraud. Both cases involve the conscious distortion of truth or concealment of material fact with the objective of inducing other people to act to the detriment of their own interests. These are the elements that characterize fraud (PEDNEAULT, 2009).

When an executive intentionally distort financial statements, he is also committing fraud. There is a conscious act that induces other people to act to the detriment of their own interests, like paying a high price for common stock that are actually worth much less. These cases are known as financial statement fraud (ALBRECHT et al., 2009).

It is important to add that financial statement frauds (FSF) are perpetrated by violating Generally Accepted Accounting Principles (GAAP). If there is no violation of GAAP, then it is a case of earnings management, which is also harmful to investors but resorts only to legal means (DECHOW; SKINNER, 2000).

To estimate a logit model for fraud detection, it is necessary to identify a set of variables that explain the occurrence of fraud. There are concepts and theories that explain white-collar crime and some of them can also be employed as a starting point to understand the causes of accounting fraud, thereby serving as a guide for the selection and organization of independent variables. It is common the use of the fraud triangle, originally proposed by Donald R. Cressey to explain the occurrence of white-collar crime. This author believes that these crimes occur when three factors are present: Financial need (pressure), opportunity and rationalization. In the early 1980’s, Steve Albrecht adapted this theory to the study of financial statement fraud (CHOO; TAN, 2007). We classify the variables used in this study in these three groups. In the next subsections, we describe the variables that were statistically significant in the Wilcoxon test or in the two-proportion z-test.

2.1 Pressure

The pressure (financial need) is related to the situation of the company and its managers. It is expected that companies that have been unable to attain the expectations of the market are more susceptible to fraud, since the managers are under pressure to perform well. For this reason, indicators of performance and financial security can be used for fraud detection, in association with other evidences. Enron, for example, was a highly leveraged company that required its executives to obtain (and report) large profits in order to be able to pay interests and fulfill contractual bonds (CHOO; TAN , 2007).

To capture the elements of pressure in the model, we used several different indicators. The first of them is the Altman’s *Z* score, a proxy for risk of financial distress (ALTMAN, 1968; ERICKSON; HANLON; MAYDEW, 2006; FANNING; COGGER, 1998; KIRKOS; SPATHIS; MANOLOPOULOS, 2007; SPATHIS, 2002; SUMMERS; SWEENEY, 1998). We expect companies with higher *Z* scores to be in better financial situation and therefore less likely to resort to fraud. We also used several variables that attempt to measure the companies’ ability to cover their liabilities, since companies that have trouble paying their debts (and therefore have financial problems) may recourse to FSF in order to obtain financial resources, either in the capital markets or through loans. One of these variables is the cash scaled by total assets (GAGANIS, 2009); we instead adopt the cash change scaled by total assets (Δ*CASHTA*). We expect it to be negatively related to the likelihood of fraud. Also similar is the working capital (i.e. current assets minus current liabilities) divided by total assets (*WCTA*), used by Beneish (1997, 1999a and 1999b), Fanning and Cogger (1998), Spathis (2002), Kirkos et al. (2007) and Gaganis (2009). We also expect this variable to be negatively related to fraud. Kaminski, Wetzel and Guan (2004) and Fanning and Cogger (1998) used the ratio formed by the accounts receivables divided by the total assets (*ARTA*). We believe that companies with higher change in this variable (Δ*ARTA*) are less financially secure, and therefore present a higher likelihood of fraud. Another indicator of financial security is the ratio of sales to accounts receivables (*SALAR*), used by Summers and Sweeney (1998), Spathis (2002), Skousen and Wright (2006) and Kirkos et al. (2007). We expect it to be negatively related to the likelihood of fraud. Kaminski et al. (2004) used yet another proxy for financial security, given by interest expenses divided by total liabilities. We used the change in this variable (Δ*IETL*) as a predictor of financial statement fraud.

Another variable that can be used is *FATA*, the ratio of fixed assets to total assets (KIRKOS et al., 2007). It is the fixed assets (e.g. equipment and factories) that generate revenues for the company, and therefore we expect that companies with a large value invested in fixed assets are less likely to engage in fraud, since they are in better position to generate real revenue in the future. Another variable, proposed by Gaganis (2009) and negatively correlated to *FATA,* is obtained dividing the current assets by the total assets (*CATA*). Its change was also used in this study (Δ*CATA*).

Some authors suggest using the cost of goods sold divided by the sales (KAMINSKI et al., 2004). We expect the change in this variable (ΔCOGSAL) to be positively related to the likelihood of fraud, since an increase in the cost of goods sold can signal a decrease in the company's ability to compete.

Spathis (2002) and Kirkos et al. (2007) use in their models a variable obtained by dividing the net profit by the sales. We use the change in this variable (ΔNPSAL) as a predictor of FSF. The rationale behind this variable is that a decrease in profitability creates pressure that might cause the company to recourse to fraud. A similar variable is the change in EBIT (earnings before interest and taxes) scaled by total assets (Δ*EBITTA*). [1]

2.2 Opportunity

The second element of the fraud triangle is the opportunity, which should not be understood only as lack of regulation or bad corporate governance. According to Choo and Tan (2007), the intense emphasis on monetary success by the American society may cause managers to actively seek means to bypass the institutional mechanism created to repress fraud. This means that even when opportunity is not present, in some cases managers will create them. Pressure for success generates opportunities for criminal behavior. The managers of Cendant, a company charged with fraud, kept a yearly spreadsheet with "opportunities" available to inflate operational revenue, and also listed the values that should be obtained in each of these opportunities (CHOO; TAN, 2007).

In our model, the variable that represents the opportunity to fraud is a dummy for auditor change (ETTREDGE et al., 2008; FANNING; COGGER, 1998; SKOUSEN; WRIGHT, 2006), here abbreviated as *AUDCH*. According to Summers and Sweeney (1998), it is possible that a company that engages in fraud will change its auditor to diminish the

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[1] This scaling is actually done using the average total asset of the period in which the EBIT was obtained. So, for year *t*, the EBIT is scaled by $(TA_t + TA_{t-1})/2$.

likelihood of getting caught.

2.3 Rationalization

In a competitive social and corporate environment where profit is sought at any cost, it is easier to admit fraud as an acceptable way to be successful. Rationalization consists in the possibilities managers have to justify their fraudulent acts to themselves. Bernie Ebbers, former CEO of WorldCom, once said that the creation of a code of conduct for his company would be a colossal waste of time (CHOO; TAN, 2007). If he refused to create a code of ethics to avoid "wasting time", what would not he do to guarantee his year-end bonus?

For Skousen and Wright (2006), the accruals level is representative of the management's way of making decisions about financial statements. When earnings management is seen as normal, more serious actions might be the next step. These authors also explain that excessive use of accruals is often cited in auditing reports. For this reason, we used a dummy variable (*UQUAL*) that is equal to 1 if the auditing report presents an unqualified opinion and 0 if it presents an unqualified opinion with additional language.

2.4 Similar studies

There are several papers that used probit and logit models to estimate the likelihood of FSF or identify the variables that influence this likelihood. Some of them also used AAERs to build the dependent variable (ABBOTT; PARK; PARKER, 2000; BRAZEL et al., 2005; CRUTCHLEY; JENSEN; MARSHALL, 2007; ERICKSON et al., 2006; ETTREDGE et al., 2008; JOHNSON; RYAN; TIAN, 2003; LENNOX; PITTMAN, 2010; MILLER, 2006; SKOUSEN; WRIGHT, 2006). Other authors used the cases of fraud publicized by the press, either alone or jointly with AAERs (BEASLEY, 1996; BENEISH, 1997; BENEISH, 1999; LEE; INGRAM; HOWARD, 1999; SUMMERS; SWEENEY, 1998).

Papers using probit and logit often aim at verifying the impact of a given variable on the occurrence of fraud. Erickson et al. (2006), for example, studied the effect of stock option on fraud. The results of this article indicate that, contrary to what is often believed, there are no consistent evidence that stock-based incentives contribute to the occurrence of accounting fraud. These results were confirmed by the papers of Gerety and Lehn (1997) and Crutchley et al. (2007), but not by Erickson, Hanlon and Maydew (2004). More recently, Feng, Ge and Luo (2011) found evidence supporting the hypothesis that CFOs get involved in fraud because they succumb to pressure from CEOs, and not because they want to increase their income from equity incentives.

There are also papers that employed methodologies to estimate the probability that a case of fraud is not detected (WANG, 2004; WANG, 2008). These working papers used a method proposed by Poirier (1980), in which the probability of fraud and the probability of fraud detection are estimated separately. The models used by Wang require the identification of a set of variables that influence the likelihood of fraud detection. Our paper, on the other hand, estimated the unconditional likelihood of fraud detection (without the use of an additional set of independent variables).

Some papers used artificial intelligence techniques to detect frauds. It is common the use of neural networks for this purpose (FANNING; COGGER; SRIVASTAVA, 1995; FANNING; COGGER, 1998; OGUT et al., 2009). Some studies employed fuzzy logic (DESHMUKH; TALLURU, 1997), while others adopted hybrid methods like fuzzy neural networks (LIN; HWANG; BECKER, 2003). At last, there are articles that used several different fraud detection methods with the intent of comparing them (GAGANIS, 2009; KIRKOS et al., 2007).

One of the shortcomings of studies using artificial intelligence is the difficulty in testing hypotheses. It is not possible, for example, to test whether the likelihood of fraud is related to executive compensation. On the other hand, several studies concluded that artificial intelligence methods can identify the occurrence of fraud with higher accuracy when compared to probit and logit models (GOTTLIEB et al., 2006; OGUT et al., 2009). The choice of tools depends on the objectives of the researcher. In this paper, since our objective is to estimate the likelihood of a fraud being undetected and test the hypothesis that this likelihood is different from zero, we have chosen a logit model.

3 METHOD

This paper presents an empirical model. The data regarding financial statements were obtained in Compustat. The following sections describe how the AAERs published by the SEC were used to identify the companies charged with fraud in the US and explain the method used to estimate the likelihood of a fraud being not detected.

3.1 Data

The companies accused of FSF were identified by an analysis of the Accounting and Auditing Enforcement Releases published by the SEC from 1 January 1998 to 23 November 2010. All the reports where read in search of material misstatements.

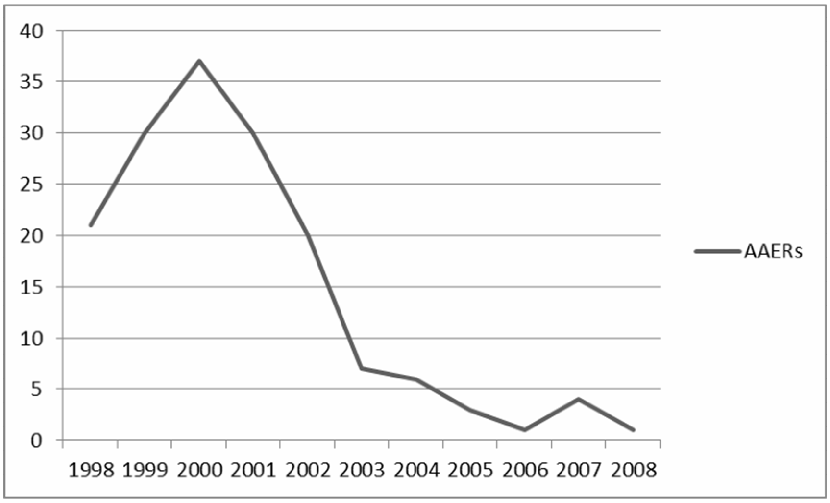
If the company was accused of fraud, we carefully read the release to identify the first fraud year – that is, the first year in which a materially false statement was published. There was care in checking the fiscal years of the accused companies. Compustat adopts a simple rule: If the fiscal year finishes between 1 January and 31 May, then it is considered as being the previous calendar year. For example, a statement closed in 31 March 2000 is stored in the database as being of the year 1999. Therefore, if a fraud was first identified in this statement, then the first fraud year is 1999. In other words, we made an effort to match the list of frauds and their years with the data provided by Compustat.

We removed all the occurrences of violation of the Foreign Corrupt Practices Act (FCPA) from the sample. The FCPA prohibits the practice of bribing foreign officials. Since bribery is illegal, the money used to such ends does not pass through official accounting; the company might recourse to some kind of financial report violation in order to hide the destination of these resources. This can materially affect the financial statements of the company. Unfortunately, not every AAER issued because of FCPA violations state which financial statements were affected; sometimes, the amount channeled to bribes is negligible. Because of these problems, they were all removed from the sample.

We also ignored the occurrences of stock options backdating. The main reason was the difficulty of finding explanatory variables related to this kind of fraud, which is much more designed to benefit certain executives than to mislead the general public about the financial health of the company. Including stock options backdating in this study would just mix two different phenomena in the same dependent variable. Nevertheless, the practice of backdating stock options might also distort financial statements.

Due to technical limitations, we kept in the sample only companies listed in three stock exchanges (NYSE, NASDAQ and AMEX). This means that companies traded over the counter were excluded, as well as those with no data available in Compustat.

A financial statement fraud is usually discovered only several years after it has begun. It is therefore very difficult to have a meaningful sample of companies that issued falsified financial statements in recent years. Any attempt to do so would increase the number of cases of misclassification, since many more companies would be incorrectly labeled as honest. Therefore, we also opted to remove from the sample those instances of fraud that occurred before 1998 and



after 2002. As can be seen in

Figure 1, the number of frauds discovered after 2002 apparently felt abruptly. Instead of signaling a true reduction in the number of fraud cases, this fall more likely shows the SEC's inability to report recent cases.

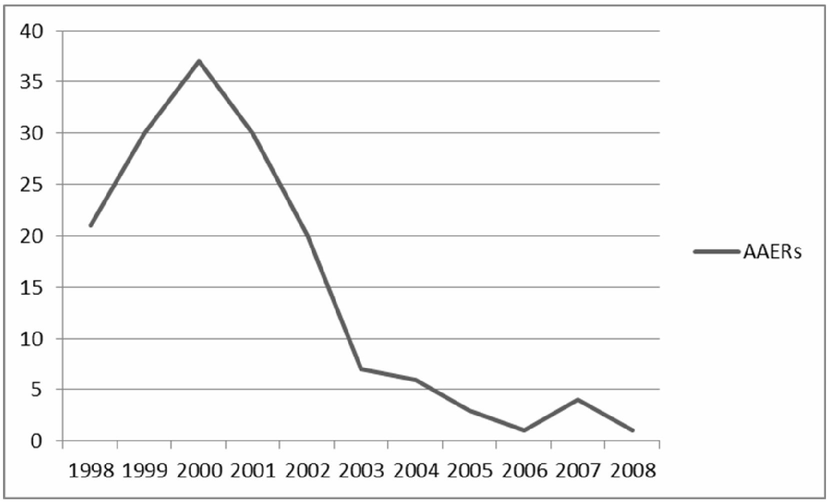


Figure 1: AAERs issued between 1998 and 2008.

Financial companies (SIC[2] codes 6000 to 6999) were also removed from the sample. The final sample contains 118 companies that fulfill all the requirements.

The models were not estimated only with the companies charged with fraud. The population of this study comprises all the companies with financial statements available in Compustat for the period ranging from the years 1998 to 2002. Companies without data for all the years were included.

3.2 Model estimation

In probit and logit models, the dependent variable $\tilde{y}_i$ is usually expressed as a function of a latent and observable variable I_i and an unknown threshold I_i^* (GUJARATI, 1995; POWERS; XIE, 2000):

$$\tilde{y}_i = 1 \text{ if } I_i > I_i^* \quad (1)$$

[2] SIC stands for *Standard Industrial Classification.* It is a code used by the SEC and other US agencies to classify industries.

$$\tilde{y}_i = 0 \text{ if } I_i < I_i^*$$

When there is misclassification in the dependent variable, the conditions above are not respected. The observed variable y_i is not the same as the real variable $\tilde{y}_i$. The model now has two new parameters α_0 and α_1:

$$\begin{aligned} \alpha_0 &= \Pr(y_{it} = 1 \mid \tilde{y}_{it} = 0) \\ \alpha_1 &= \Pr(y_{it} = 0 \mid \tilde{y}_{it} = 1) \end{aligned} \tag{2}$$

In studies about financial statement fraud, the most important error is the one shown as the parameter α_1 in the second equation. This error is the probability that a company that issued false financial statements is not classified as such (type II error). The other error (type I) is expected to be very rare and close to zero. Therefore, to make model convergence easier, this paper adopts the assumption that $\alpha_0 = 0$. Without this restriction, the expected value of y_i in a logit model is (HAUSMAN et al., 1998):

$$E(y_i \mid \mathbf{x}_i) = \Pr(y_i = 1 \mid \mathbf{x}_i) = \alpha_0 + (1 - \alpha_0 - \alpha_1)\Lambda(\mathbf{x}_i'\boldsymbol{\beta}) \tag{3}$$

The log likelihood function that was effectively maximized in this paper, based in equation 3 but with the restriction $\alpha_0 = 0$, is:[3]

$$\ln L = \sum_{y_i=0} \ln[1 - (1 - \alpha_1)\Lambda(\mathbf{x}'\boldsymbol{\beta})] + \sum_{y_i=1} \ln[(1 - \alpha_1)\Lambda(\mathbf{x}'\boldsymbol{\beta})] \tag{4}$$

The function 4 was maximized using the Newton-Raphson method. Since the residuals of the model are heteroskedastic, the variance matrix was obtained using the White (1980) heteroskedasticity-consistent estimator.

4 RESULTS

Since there are many variables related to fraud described in the literature, it would be computationally complicated to estimate a logit model with all of them simultaneously. Therefore, an important preliminary step in this study was to identify the most relevant variables. For this purpose, a variable is considered relevant when it presents smaller or larger values for companies charged of fraud (when compared to similar, non-charged companies).

To accomplish this objective, we formed a treatment group with the companies charged with fraud. We also created a control group by matching companies from the treatment group with other companies of the same industry and with similar total assets. The test used to verify if the variables are statistically different between these groups is the Mann-Whitney U test, also known as the Wilcoxon rank-sum test (MANN; WHITNEY, 1947). We applied this test to several variables, many of which are not cited in this paper. We estimated the initial model using all the variables with a p-value lower than 0.20 in the univariate test, as shown in Table 1. For the binary variables (*AUDCH* and *UQUAL*), the two-proportion z-test was used instead of the Wilcoxon test.

Table 1: Wilcoxon test and two-proportion z-test

[3] For details on how this equation was obtained, see Hausman et al (1998).

Variable	Median		z	prob > |z|
	AAER = 0	AAER = 1		
$\Delta COGSAL_{(t-1)}$	0.0035	-0.0052	1.72	.0847
$\Delta LLVEN_{(t-1)}$	0.0086	-0.0058	1.28	.1988
$\Delta EBIT_{(t-1)}$	-0.0023	0.0081	-1.69	.0909
$Z_{(t-1)}$	3.3480	5.0550	-2.72	.0066
$\Delta CASHTA_{(t-1)}$	0.0004	-0.0080	2.24	.0251
$WCTA_{(t-1)}$	0.2335	0.2452	-1.52	.1290
$\Delta RVTA_{(t-1)}$	0.0209	0.0050	1.30	.1929
$CATA_{(t-1)}$	0.5083	0.5520	-1.51	.1316
$\Delta CATA_{(t-1)}$	0.0079	-0.0076	2.04	.0414
$FATA_{(t-1)}$	0.1893	0.1585	1.72	.0850
$RECCR_{(t-1)}$	5.6110	7.4691	-1.47	.1415
$\Delta IETL_{(t-1)}$	-0.0086	-0.0007	-1.95	.0518
AUDCH	0.0583	0.2019	-3.06	.0022
UQUAL	0.6058	0.6923	-1.30	.1921

We performed a stepwise logit regression, starting with all the variables shown in Table 1. The least significant variable (the one with higher p-value) was eliminated, and the model was estimated again. This elimination procedure was repeated until all the remaining variables had a p-value lower than 15.73%.[4] The resulting model is shown in Table 2. It should be noted that the sample in each intermediary model (and also in the final model) contained only the observations with data available for all the variables used in the initial model. Adding observations after dropping a variable, although possible, could generate biased estimates. Due to the large number of missing observations, the sample was quite small, containing only 47 cases of fraud.

In the final model, only one variable (*UQUAL*) was significant at the 10% level. The model as a whole was also significant, with the likelihood ratio test rejecting the null hypothesis at the 5% level (p = .033); this means that the final model fits the data better than a model with only the intercept.

Table 2: logit model without misclassification parameter

Dependent variable: AAER

Observations: 10439

Period: 1998-2002

Variable	Parameter	Std. Error	z	P>|z|
Intercept	-4.6876	0.3035	-15.44	.000
UQUAL	-0.6460	0.3010	-2.15	.032
$\Delta CASHTA_{(t-1)}$	-1.9412	1.2454	-1.56	.119
$FATA_{(t-1)}$	-0.9709	0.6762	-1.44	.151

LR χ^2: 8.72

Prob > χ^2: .033

Log likelihood: -296.48

[4] This value was chosen because it yields the same model that would be obtained by minimizing the C_p statistic, as proposed by Mallow (2000) and Atkinson (1980).

Taking into account the possibility of misclassification, we estimated the model shown in Table 3. The only variable that was significant in the traditional logit model (Table 2) now failed to reject the two-tailed *z* test (*UQUAL*). There was no significant variable, and the likelihood ratio test also failed to reject the null hypothesis. The differences between these models show the problems that can arise when the possibility of misclassification is ignored.

The misclassification parameter (α_1) estimated was 96.80% and is statistically different from zero (p < .001). This means that just a small part of the instances of fraud are discovered and charged by the SEC.

Table 3: logit model with misclassification parameter

Dependent variable: AAER

Observations: 10439

Period: 1998-2002

Variable	Parameter	Std. Error	z	P>|z|
Intercept	-0.9370	4.8846	-0.19	.848
UQUAL	-0.7806	0.6758	-1.16	.248
ΔCASHTA$_{(t-1)}$	-2.5192	2.7317	-0.92	.356
FATA$_{(t-1)}$	-1.1602	1.1363	-1.02	.307
α_1	0.9680	0.1146	8.44	.000

Wald χ^2: 1.51

Prob > χ^2: .679

Log likelihood: -296.45

5 DISCUSSION AND CONCLUSION

The variables *UQUAL*, $\Delta CASHTA_{t-1}$ and $FATA_{t-1}$ are not usual in the extant literature. We found only one paper that used $FATA_t$, and it concluded that its coefficient was not statistically different from zero (KIRKOS et al., 2007). Gaganis (2009) used $CASHTA_{t-1}$ (instead of the change in this variable) and found that it rejected the null hypothesis of the Kruskal-Wallis test at the 5% level, but did not reported the p-value of this variable in the logit analysis.

Skousen and Wright (2006) used auditors' reports (*UQUAL*) as a proxy for rationalization, and in their analysis this variable failed to reject the null hypothesis of the Wilcoxon test (z = -0.814 and p = .208). This result is actually quite consistent with our findings (z = -1.30, p = .1921). Due to a stroke of fortune and the adoption of a stricter criterion for inclusion of a variable in their logit regression (p < .15 in the Wilcoxon test), Skousen and Wright ultimately did not used *UQUAL* in their model. Our results regarding *UQUAL* in the traditional logit model are, therefore, consistent with previous research.

Although it is important to discover which variables are somehow related to fraud, our objective was to test the hypothesis that there is a significant number of undetected cases of fraud. The misclassification parameter α_1 was estimated as 96.8% and found to be statistically different from zero (p < .001). This result confirms what common sense suggests: the SEC is unable to go after every case of fraud.

No test was ran in order to verify whether the parameter estimates from the misclassification model are statistically different from the traditional logit model, but the results are indeed qualitatively different. The variable *UQUAL* lost statistical significance (p = .248), as well as the likelihood ratio test (p = .679). These results suggest that conclusions obtained using uncorrected fraud detection models might be simply not valid.

Even though the model with classification errors had no significant variable and failed to pass the likelihood ratio test, this does not means that it is impossible to develop a good model with classification error parameters. This paper presents no attempt to do so; our objectives were to estimate the amount of error present in SEC's AAERs and to show that results obtained with traditional logit models can be misleading the financial statement fraud research. Another characteristic of the model that might explain the poor results is the small sample, limited to those observations that had all the variables that passed the Wilcoxon test or the two-proportion z-test at the 20% level.

We recommend caution in the use of uncorrected binary choice models as a decision-support tool in fraud detection. It is more adequate to use a specification that considers the possibility of misclassification problems, and doing so yields a more reliable model. It is also important to avoid the downward-biased fraud likelihood estimates generated by traditional models. These measures can contribute to more precise assessments of fraud likelihood when using econometric models. Adopting the misclassification model is quite straightforward–although not yet integrated in statistical and econometric software–and could become standard procedure in financial statement fraud research.

It is important to stress that this is not the only method that can be employed to avoid the problems that arise with misclassification. Wang (2004, 2008) was able to estimate the conditional misclassification probability using a different method. It is important to note, however, that the method proposed by Wang requires the identification of variables related to the likelihood of fraud detection. While this might allow the testing of interesting research hypotheses, it is an unnecessary burden for researchers interested just in variables related to the likelihood of fraud.

As research advances, it will be possible to use the method adopted here to study problems related to the efficiency of regulatory agencies in repressing fraud. Testing for changes in the misclassification parameter along time might allow conclusions about the efficiency of certain policies concerning fraud. When more data becomes available, it will be possible to test, for instance, whether the Sarbanes-Oxley Act increased the SEC's capability of identifying and punishing financial statement fraud.

The method employed here, however, is not able to correct specification problems in the model. If the model is underspecified (i.e. there are missing variables), then the results will nevertheless be inconsistent. There is also need for theoretical development on the causes of fraud that allows us to identify better models.

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