Do Analysts Anticipate Accounting Fraud?

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April 2007

We thank workshop participants at the 2005 AAA and AFAANZ Annual meetings, CUNY Baruch College, Emory University, the Australian Graduate School of Management, and Monash University for their helpful comments. We are grateful for the research assistance of Ron Harris, Xiaolan Wang, and Prasant Gondipalli. We appreciate funding from the University of Southern Queensland and CUNY Baruch College. We thank I/B/E/S/Firstcall for providing analyst recommendations.

Data Availability: Please contact the authors.

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ABSTRACT: We examine whether analysts anticipate the public disclosure of accounting frauds by studying a sample of companies that have committed fraud as evidenced by the Security and Exchange Commission (SEC) issuance of an Accounting and Auditing Enforcement Release (AAER). We use survival analysis to determine when analysts drop coverage and revise their recommendations down prior to the public disclosure of fraud. Our analyses indicate some evidence that analysts anticipate fraud and use different signals to inform investors about different fraud types. For example, firms that commit larger frauds are significantly more likely to have analysts drop coverage earlier in the period preceding the public announcement, but are not significantly more likely to show downward revisions in recommendations. We also find that analysts appear to be fooled by fictitious frauds – they are no more likely to drop coverage or revise down earlier prior to public disclosure for firms that commit these frauds versus firms that do not commit fictitious frauds. Finally, our results show that the decision and timing of dropping coverage is not correlated with revision of forecasts, indicating that analysts consider different variables for the two decisions.

Keywords: Accounting fraud, analyst recommendations, analyst revisions, survival analysis.

Data Availability: Please contact the authors.

I. INTRODUCTION

We know that some firms commit accounting frauds and that these frauds distort financial statements and move price away from the fundamental value of the firm if market participants are misled. Consistent with this pattern of events, there is evidence that stock prices decrease when accounting frauds are revealed (Dechow et al. 1996; Feroz et al. 1991). Because analysts are sophisticated users of financial statements who use fundamental analysis of accounting numbers to develop their reports (Block 1999), we expect that analysts are a group likely to detect accounting frauds. Our study examines a set of firms that have committed accounting fraud to determine whether sell-side equity analysts anticipate the fraud and reveal this negative information by revising their recommendations down or dropping coverage of the firm prior to public disclosure. Specifically, we use survival analysis to study the timing of these decisions prior to a public disclosure of the fraud and examine what types of accounting fraud are related to analysts' decisions to revise recommendations or drop coverage.

The examination of such evidence is important because it helps us understand analysts' ability to anticipate and convey information about accounting fraud. If analysts reveal this bad news prior to a public disclosure of the fraud, they may help bring prices back to fundamental values and enhance market efficiency. This ability to detect accounting problems should be considered especially important when a company is manipulating financial statements to the point of accounting fraud. Further, if we consider analysts to be an extra layer of protection for investors or as an additional mechanism for corporate governance, an early and informed reaction to corporate fraud provides additional evidence of analysts' contribution to market efficiency. Finally, evidence of analysts' recommendation revisions or dropping coverage prior to a public disclosure may provide the Securities and Exchange Commission (SEC) with a useful monitor for fraudulent corporate behavior. Given the current debate in the press regarding the quality of analyst research and the resulting increase in regulation in the brokerage industry, it is important to understand analysts' contributions in situations where accounting fraud has occurred.

We examine a set of companies that have committed an accounting fraud over the period 1995 through 2002 as evidenced by the SEC's issuance of an Accounting and Auditing Enforcement Release (AAER). We use the issuance of an AAER as a proxy for the existence of accounting fraud in accordance with several prior studies (e.g. see Bonner et al. 1998; Dechow et al. 1996; Feroz et al. 1991). We classify the types of accounting fraud committed by our sample of companies using the fraud taxonomy developed by Bonner et al. (1998)[1]. We focus on two signals analysts may use to communicate accounting problems: revisions of recommendations and dropping coverage of the firm.[2] We determine the first public disclosure of the accounting fraud for each firm and use survival analysis to analyze the timing of analysts' decisions to drop coverage and revise their recommendations downward prior to the public disclosure. We expect that analysts will revise their recommendations down and drop coverage *earlier* for firms that commit more egregious frauds.

Overall, the results of our survival analyses provide evidence that analysts anticipate some types of accounting fraud and communicate this bad news to the market prior to public disclosure but may be fooled by managers who commit fictitious frauds. We also find that analysts are more likely to drop coverage earlier for firms that commit frauds with larger impact on revenues and net income but no more or less likely to revise forecasts downward. Likewise, analysts are more likely to drop coverage earlier in our study period for firms who commit frauds related to overvalued assets, but less likely to revise recommendations down, both consistent with McNichols and O'Brien (1997) argument of analysts self-selection in coverage and resulting censoring of the distribution of analyst recommendations. It is also interesting to note the timing of the decision to drop coverage is not correlated with the timing of the decision to revise down, indicating that these may be separate and distinct signals from analysts.

The remainder of the paper continues as follows. Section II discusses the issuance of an AAER by the SEC and the determination of the public disclosure of a fraud. Section III discusses prior research and research questions. Section IV describes the sample and descriptive statistics. Section V presents our empirical results and Section VI concludes.

II. SEC ENFORCEMENT RELEASES AND PUBLIC DISCLOSURE OF FRAUD

We use the issuance of an AAER to determine the sample of firms for our study. SEC enforcement actions are an objective method of identifying companies with fraudulent financial reporting, and as such AAERs provide an advantage over alternative measures of earnings management, such as restatements or accrual levels, where accounting fraud may not exist. Further, AAERs provide a description of the nature of the fraud, which is necessary for identifying and classifying fraud schemes. According to their website (www.sec.gov), the SEC brings between 400-500 civil enforcement actions against individuals and companies each year. These include violations not related to accounting fraud, such as insider trading and providing false or misleading information about securities and the companies that issue them. The SEC obtain evidence of possible violations of securities laws from many sources, including its own surveillance activities, the self-regulatory organizations (e.g. NASD) and other securities industry sources, press reports, and investor complaints. In 2003, McKinsey & Co. was commissioned to examine problems at the SEC and found that the SEC generates just 33 percent of its enforcement cases internally. The remaining cases are spurred by external sources including 15 percent of the cases the SEC uncovers by reading newspaper reports of firm transactions. Informal SEC investigations are begun privately. Information is gathered through interviewing witnesses, examining brokerage records, reviewing trading data, and other methods. If the SEC issues a formal order of investigation, it may compel witnesses by subpoena to testify and produce books, records, and other relevant documents. Following the formal investigation, the SEC may authorize its staff to file a case in federal court or bring an administrative action. Individuals and companies charged may choose to settle the case or contest the charges.

Enforcement releases have increased dramatically over the last few years, from 126 AAERs issued in 2001 to 239 issued in 2003. In our sample of firms, the average time between the end of the accounting fraud and the release of the first AAER by the SEC is approximately three years. Public disclosure of the accounting fraud is the key event in our study of analysts' decisions to revise recommendations or drop coverage. Public disclosure of the fraud can occur in several different ways, including the announcement of an SEC investigation, auditor resignation or lawsuit, and company announcements of accounting irregularities or restatements.

III. PRIOR RESEARCH AND RESEARCH QUESTIONS

Few prior papers have examined how the market reacts to the announcement of accounting fraud. Feroz et al. (1991) examine a sample of 58 firms that were issued AAERs between 1982 and 1989 and find that abnormal returns average negative 13 percent over the two days surrounding the public disclosure of the fraud. They argue that the market reaction is due to revised expectations of future earnings related to the revised current earnings level as well as expected costs related to the fraud (litigation and reputation costs). Further, there may be an expectation that a greater extent of earnings manipulation will be revealed prior to the release of the AAER. Dechow et al. (1996) also examine firms subject to SEC enforcement for fraud between 1982 and 1992 and find an average stock price drop of nine percent on the day the fraud is first announced. In addition, Dechow et al. (1996) provide some evidence of analysts' ability to detect the accounting fraud.[3] The authors find a drop in analyst following in the two years leading up to the public announcement of an accounting fraud, indicating that some analysts may have detected the fraud and reacted by ceasing coverage. However, they also find an increase in forecast dispersion following the announcement of alleged earnings manipulations, but not before. This suggests that the group of analysts that continue to cover these firms do not detect and signal the fraud in their earnings forecasts prior to its public disclosure.

Given the limited evidence regarding analysts' reactions to accounting fraud, we review prior research of forms of earnings manipulation less severe than fraud. Griffin (2003) examines the reactions of four groups of informed investors to the announcement of class action lawsuits that lead to a corrective disclosure. He defines a corrective disclosure as typically involving “a material restatement of company revenues or expenses and/or a correction of a financial statement disclosure that, under federal securities law, plaintiffs allege should have been made or better represented earlier so as to make the financial statements not misleading.” Griffin finds that analyst following decreases *after* the corrective disclosure and very limited evidence that analysts revise their forecasts downward prior to a corrective disclosure. The largest revisions occur in the month of the corrective disclosure and forecast errors decrease significantly in the month of the disclosure, but not before. Palmrose et al. (2004) also provide evidence that analysts revise forecasts significantly downward *after* a restatement announcement. Additional studies conclude that analysts fail to anticipate subsequent earnings declines associated with high accruals, and that they do not revise their forecasts in anticipation of predictable accrual reversals (Barth and Hutton 2004; Teoh et al. 2002; Bradshaw et al. 2001). For example, Bradshaw et al. (2001) find evidence that analysts’ earnings forecasts do not incorporate the predictable future earnings declines associated with high accruals. Analysts (and auditors) do not appear to anticipate the future earnings reversal and do not alert investors to future earnings problems.

Overall, there is mixed evidence of analysts’ detection of future earnings declines associated with high accruals or corrective disclosures. While these studies provide some evidence on analyst reactions to unusual events, we must note that restatements and high accruals are not necessarily accounting fraud or manipulation issues. A study by the Huron Consulting Group found that the main cause of restatements in 2003 was errors in accounting for reserves and contingencies. Further, high accruals could be related to growth or other unidentified risk factors of the firm. The bulk of these papers do not examine accounting fraud so it is difficult to generalize results to our sample. A further issue with prior research is earnings forecast error or earnings forecast revision may not be the proper metric to determine whether accounting problems are discovered in advance of a public disclosure. If analysts are rewarded for forecasting the same number that management reports, whether or not that number is fraudulent, analysts' incentives to report accurate or slightly pessimistic earnings numbers may lead to no observed anticipation in forecasts (see e.g. Matsumoto 2002). Therefore, while analysts may not have an incentive to report accounting manipulations through earnings forecast revisions, they may reveal suspected or known earnings manipulations through revising their recommendations or dropping coverage.

There is however, considerable evidence that analyst activities provide valuable information to market participants. For example, McNichols and O'Brien (1997) find that analysts drop coverage of stocks that have lower ratings than those they continue to cover and that the realized performance of these dropped stocks is lower than for stocks where the analyst initiates coverage or continues coverage, indicating that the dropped coverage does reflect information about future performance. Also, Moses (1990) finds that analysts tend to drop coverage of failing firms in the year prior to a bankruptcy filing. Stickel (1995) and Womack (1996) provide further evidence that analysts' reports are informative. Each of these authors examines a sample of analyst reports and finds that positive (negative) changes in individual analyst recommendations are accompanied by positive (negative) returns at the time of their announcement. Womack (1996) also documents a post-recommendation stock price drift, which lasts up to one month for upgrades and six months for downgrades. He concludes that this indicates analysts appear to have market timing and stock picking abilities. Finally, Whisenant and Fairfield (2001) find evidence suggesting that analysts employed by the Center for Financial Research and Analysis (CFRA) are able to identify firms that are manipulating earnings. They find that CFRA identified firms tend to restate earnings more often than a sample of control firms and conclude that the firms identified are masking operational problems with aggressive accounting.

We select a sample of firms where the detection of accounting problems is especially important due to the severity of manipulation and where analysts should be most motivated to reveal negative information. Prior research supports the notion that analyst information is most important for bad news events. Frankel et al. (2006) examine analysts forecast revisions and find that analyst reports are most informative when analysts reveal bad news through negative forecast revisions. Hong et al. (2000) argue that management has stronger incentives to highlight good news than bad news, and absent analysts, they expect bad news will be reflected in price more slowly. Conrad et al. (2006) find evidence suggesting that recommendation changes are "sticky" in one direction, with analysts reluctant to downgrade securities. Therefore analysts play a more significant role in the dissemination of bad news given managers' lower likelihood of revealing bad news. They provide evidence that analysts appear to detect bad news and communicate to this to market participants before management or other sources do. We examine two measures of communicating this negative information: revisions in recommendations, the magnitude of those revisions and dropped coverage. These measures are more compelling than those based on earnings forecasts because they are less likely to be affected by analyst incentives to forecast management reported earnings.

We also recognize that there are several possible explanations for why we may not observe analysts detecting and informing investors of accounting problems. One reason is the cost of detecting accounting fraud. Some research into the prediction of earnings management (see e.g. Bartov et al 2001; Dechow et al. 1995) implies that it is both difficult and costly for analysts to detect all but the most clear-cut cases of aggressive accounting. Additional reasons include a lack of ability or experience and incentives to please management and increase personal compensation. In the case of fraudulent reporting, we expect that observations of no revisions or no dropped coverage are more likely to represent lack of ability rather than incentives. We expect that the incentive for analysts to report bad news would be highest in cases where accounting fraud is detected, especially more egregious fraud, due to the higher expected costs of reputational punishment that could be incurred for not reporting this bad news. We use several measures in our study to proxy for the egregiousness of the fraud, including fraud size, whether the fraud involves fictitious transactions, whether the fraud moves the firm from a loss to a profit, number of frauds and fraud length.

To summarize, we expect that analysts are more likely to revise their recommendations downward and drop coverage at an earlier date prior to public disclosure of the fraud for firms with more egregious frauds due to lower costs to detect and higher costs to reputation for not reporting the fraud (see section IV for measures). In addition, we examine whether other types of accounting fraud make analysts more likely to drop coverage or revise recommendations down earlier prior to the public disclosure of the fraud.

IV. SAMPLE SELECTION, VARIABLE DEFINITIONS AND DESCRIPTIVE STATISTICS

The firms for our analyses are the companies that were subject to SEC AAER Numbers 700 through 1700.[4] The SEC filed these enforcement actions between August 1995 and December 2002. We find that 405 individual companies are named in these 1000 AAERs. Of these, 24 are excluded because the AAER is related to the firm's auditor and not due to accounting fraud by the firm. An additional 34 companies are excluded from our analyses because the AAER did not provide detailed information regarding the type of accounting fraud. This leaves 347 companies with detailed fraud information for possible analysis. We term this our 'full' sample of firms for the remainder of this discussion.

We search Compustat and IBES for the data needed for our survival analyses. We find that a total of 111 companies were never listed on Compustat and an additional 58 companies never appeared on IBES.[5] For the remaining 178 companies, in order to perform our survival analysis, we search IBES for analyst recommendations two years prior to the public announcement date of the fraud (t_{-2}). We eliminate an additional 122 companies due to missing IBES data at this time. Therefore, 56 companies remain in the detailed survival analyses. We term this our 'final' sample of firms for the remainder of the discussion. We next determine the first public disclosure of the accounting fraud for our full sample of firms. To identify the first public disclosure dates of the fraud, we search the Factiva database for the period between the end of the accounting fraud and the date of the first SEC AAER. We use the company name and terms such as "fraud", "overstatement", and "accounting" to search for the earliest public disclosure of the accounting problem. The following occurrences were classified as the first public disclosure date: announcement of a SEC investigation, announcement of an auditor resignation, an audit or filing delay due to accounting issues, the announcement of a class action lawsuit related to financial reporting issues, the announcement of a lawsuit by an internal auditor, company announcement indicating accounting irregularities, announcement that the financial statements will be restated, and any public accusations of specific fraudulent accounting activity by a source outside the company, e.g. media or analysts. Table 1 summarizes the sources of the first public disclosure for our full and final sample of firms. The majority of the first public disclosures are company generated, i.e. the companies issue a press release announcing accounting irregularities and restatements. We find that 61 percent of our full sample and 63 percent of our final sample have public disclosures that fall into one of the three firm generated disclosure categories. We provide data on the timeline of disclosure dates in Panel B.

Table 2 provides detail of the types of accounting fraud for our full and final sample of firms. Table 3 provides a summary of firms by SIC Code for our final sample of firms. The majority of our sample firms are in the manufacturing, technology, and wholesale and retail sectors. Table 4 provides descriptive statistics the final sample of 56 firms used in our survival analyses. The final sample consists of 275 analysts who make recommendations for 56 companies. The sample includes 326 observations as some analysts report on multiple companies in the sample. The empirical analyses are based on data gathered from I/B/E/S, Compustat, CRSP and SDC databases. The earliest fraud period in the sample begins in January 1, 1985 and the latest ends September 30, 2002. The first public disclosure dates range from November, 1995 through November, 2002.

The measurement of our dependent and independent variables is described next, along with a discussion of descriptive statistics.

Dependent variables

Days to Revise Recommendations. To determine our set of analyst recommendations for the fraud firms for survival analysis, we move back two years (t_{-2}) from the public disclosure date (t_0) and determine the analysts that have an active recommendation outstanding at this time (t_{-2}). An active recommendation is considered to be one where the analyst has provided at least one earnings forecast for the firm in the one-year period prior to t_{-2}. We then count forward from time t_{-2} and assign the number of days up to the day the analyst first revises his recommendation down. If the analyst does not revise his forecast down by the time of the first public disclosure, the analyst is assigned the maximum value of 731 days (t_0 +1 day). For example if Analyst A actively follows Company B at time t_{-2} and revises his recommendation down one year later, he is assigned 365 days. We also measure revision of recommendation prior to public disclosure with a dummy variable set equal to 1 if the days to revision of recommendation are less than 731. We find that 148 analysts revise their recommendations down prior to the public disclosure of the fraud for the 56 firms.

Days to Dropped Coverage. We use the same set of analysts with active outstanding recommendations at t_{-2} to determine whether the analyst continues to actively forecast up to the date of public disclosure. If an analyst has not provided a forecast for the firm for one year according to the IBES detail file, he is coded as dropping coverage on the date of his last forecast.[6] We then count forward from time t_{-2} and assign the number of days up to the drop day for the analyst. If he does not drop coverage, the analyst is assigned the maximum value of 731 days. We also measure dropped coverage prior to public disclosure with a dummy variable set equal to 1 if the days to dropped coverage are less than 731. We find that 124 analysts drop coverage of a firm prior to the public disclosure of the fraud for the 56 firms.

Independent variables

Fraud type. We classify the types of accounting frauds committed by our sample of companies using the fraud taxonomy developed by Bonner et al (1998). The taxonomy includes twelve categories of fraud: (A) fictitious revenues, (B) premature revenue recognition, (C) misclassifications, (D) fictitious assets and/or reductions of expenses/liabilities, (E) overvalued assets and undervalued expenses/liabilities, (F) omitted or undervalued liabilities (affecting expenses or assets), (G) omitted or improper disclosures, (H) equity frauds, (I) related party transactions, (J) frauds going the “wrong way” (those understating income and/or assets), (K) illegal acts and (L) miscellaneous. We code each fraud type as a dummy variable, 1 if the fraud type is present, 0 otherwise. Table 2 summarizes the fraud types for all fraud firms and our final sample of firms for analysis. The percentages sum to over 100 since most firms commit more than one type of fraud. We find, in concordance with Bonner et al. (1998) that revenue frauds are quite common (TYPE A and TYPE B) as are frauds related to overvalued assets and undervalued expenses/liabilities (TYPE E) and omitted or improper disclosure frauds (TYPE G).

Measures of egregious frauds. We measure the egregiousness of the fraud committed in several ways. Our key measures are fictitious frauds, fraud size and loss to profit frauds. Fictitious frauds (FICT) are considered more egregious due to the nature of the deception. While recognizing revenues prematurely is a violation of GAAP, creating false invoices, for example, seems significantly more flagrant. FICT is coded 1 if the firm has committed fraud types A, D or I1: fictitious revenues, fictitious assets and fictitious sales to related parties.

To measure fraud size, we examine the AAERs, restated financial statements, SEC filings, and other public announcements to determine the total effect of the fraud on the firm's revenues and net income. In Table 4 we show the average total effect of the fraud on revenues (net income) is $246.8 ($455.73) million for our final sample. We then scale the total effect on revenues and net income over the fraud period by the firm's total assets (IMPREV/TA AND IMPNI/TA) to provide relative size variables for use in our survival analyses. We also determine whether the fraud the firm committed moved the firm from a loss to a profit position during any quarter of the fraud. LOSSTPRF is coded 1 in this situation, 0 otherwise. In Panel B of Table 2, we show that 48.1 (37.5) percent of our full (final) sample have committed a fictitious fraud, and that the fraud has impacted revenues for 53.0 (51.8) percent of our full (final) sample and net income for 75.8 (85.7) percent, for our full (final) sample. We find that 34.4 (27.8) percent of our firms committed a fraud that moved the firm from a loss to a profit position.

We also examine length of fraud (LNGTH) defined as the number of quarters the company committed the fraud. Number of frauds (#FRDS) is the total number of frauds committed by the company. There can be multiple frauds within each fraud type. Therefore, this variable may have a total greater than the sum of frauds across types. Number of months from end of fraud to first public disclosure (MNTHSDISC) is the total months between the end of the fraud period and the public announcement of the fraud.

We expect that there is a range of management capability in the commitment of fraud. We attempt to control for this by using various aspects of the fraud to infer management capability. We might expect that a manager who is more capable may have a longer lag between the end of the fraud period and 'getting caught,' as proxied by the first public announcement.

Panel C of Table 2 provides descriptive statistics for our additional continuous measure of egregious fraud. We show that the mean (median) length of the fraud for our final sample is 9.48 (8) quarters and the mean (median) number of fraud types committed is 3.32 (3) frauds. We also show that the mean (median number of months between the end of the accounting fraud and the first public disclosure of the fraud is 5.68 (3.50) months.

Additional Variables

Analyst measures. We expect that more experienced analysts are likely to detect the presence of fraudulent accounting information at an earlier date. Prior research indicates that analyst ability to forecast earnings accurately is increasing in certain analyst characteristics (Clement 1999; Jacob et al. 1997; Mikhail et al. 1997; Sinha et al. 1997; Stickel 1992). In particular, Clement (1999) finds that forecast accuracy is positively associated with measures for analyst ability, skill and resources available, and negatively associated with measures of task complexity. Mikhail et al. (1999) find that turnover is related to analyst ability and Mikhail et al. (2003) find that analysts who have more firm-specific forecasting experience are more accurate forecasters and positively affect the degree of information reflected in a firm's market price. We measure firm specific experience (FIRMEXP) as the number of quarters an analyst has forecast for the fraud firm on the IBES detail tape.[7] Table 4 provides descriptive statistics for our analyst measures. We find that the mean (median) firm specific experience for the analysts in our final sample is 11.98 (9) quarters.

There is also evidence that an analyst whose brokerage house is affiliated with the firm tend to report higher recommendations, are slower to downgrade and faster to upgrade recommendations, and are less likely to drop coverage (O'Brien et al. 2005; Lin and McNichols 1998). To control for possible differences in incentives, we also include a measure of affiliation in our regression models. Affiliated (AFFL) is a dummy variable that equals 1 if the analyst's brokerage house was an underwriter for equity or debt issuances from 12 months prior to t_{-2} to 6 months after $t_{0,}$ and 0 otherwise. An affiliated brokerage house employed fourteen of the 275 analysts over this time period. We find that 14 analysts' brokerage houses had an investment banking relationship with the followed firm over the specified period.

Turnover (TURNOVR) is measured by examining the analyst/broker codes on the IBES detail tape for the period t_{-2} to t_0. If the analyst changed brokerage house prior to the public disclosure, he receives a 1; if there is no change in brokerage house, he receives a 0. In this two-year period, 37 percent of the 275 analysts changed brokerage houses. Including this variable in our regressions controls for the observation of dropped coverage that is solely due to a change in brokerage house and not a signal of bad news associated with accounting fraud.

Finally, we control for the analysts beginning recommendation at time t_{-2} (BEGREC), as this constrains future revisions and may indicate whether an analyst is closer to dropping coverage of a firm. The average beginning recommendation is 1.76, with a range from 1 (strong buy) to 5 (strong sell).

Firm measures. We control for firm size (SIZE), market adjusted returns (ADJRET), number of analysts following (ANFOL) and whether the firm is delisted prior to the first public disclosure of the fraud (DLST). SIZE is measured by the log of total assets. As reported in Table 4, average assets for our firms are $10,595 million. ANFOL is measured by the number of analysts actively following the firm according to the IBES database. Average number of analysts following each firm in our final sample is 9.3. These are both measured at time $t_{-2.}$ Adjusted return (ADJRET) is measured as the firm returns over the two year period prior to the public disclosure minus the market rate of return. As expected, the average adjusted return for our firms is negative and 52 percent. DLST is a dummy variable equal to 1 when the *firm* is delisted prior to the first public disclosure, otherwise 0. Four of our sample firms were delisted prior to the public disclosure of the fraud.

Table 5 shows Pearson and Spearman Rank correlations between the variables capturing egregious frauds, analyst measures, and firm measures that we include in our multivariate analysis. The majority of our measures capturing fraud egregiousness are highly positively correlated (FICT, LOSSTPRF, IMPREV/TA, IMPNI/TA, #FRDS). With the exception of #FRDS, these variables are significantly negatively associated with firm size (SIZE), market adjusted performance (ADJRET), and analyst following (ANFOL). These correlations suggest that smaller, poorly performing firms are more likely to commit frauds that involve fictitious transactions and have a greater effect on revenues and net income. We also see that firm specific experience (FIRMEXP) is positively correlated with firm size (SIZE), market adjusted performance (ADJRET) and analyst following (ANFOL) indicating that more experienced analysts appear to choose to follow larger firms with higher returns.

V. EMPIRICAL RESULTS

Univariate Results

Univariate regression results for our variables are reported in Tables 6 and 7. We estimate Cox proportional hazard models of time to drop coverage and revise recommendations down for our fraud types and egregious fraud measures. In Table 6, we examine the likelihood of analysts dropping coverage earlier in the period prior to the public disclosure of the fraud. In Panel A, we see that analysts are significantly more likely to drop coverage earlier prior to the public announcement for firms that have committed fictitious revenue frauds (TYPE A), firms whose frauds moved net income from a loss to profit (LOSSTPRF), and firms who have larger relative revenue frauds (IMPREV/TA). Analysts are less likely to drop coverage earlier in the period for firms that have committed equity frauds (TYPE H). Contrary to expectations, many of our additional egregious measures, FICT, IMPNI/TA, LNGTH, and #FRDS, show no significant difference in the timing of dropped coverage over our study period. One analyst variable is significantly related to the timing of dropped coverage—analysts who change brokerage houses (TURNOVR) are more likely to stop covering a firm earlier in the period, as we would expect. However, none of our individual measures of analyst ability reflect differences in the timing of dropping coverage of the fraud firms. Finally, we see that the more negative the prior year returns (ADJRET), the more quickly an analyst will drop coverage and the DLST variable shows, as expected, that analysts are more likely to drop coverage earlier when a firm has been delisted prior to the public disclosure.

Table 7 reports the results of the Cox proportional hazard models for the likelihood of revising down a recommendation prior to the public disclosure of the fraud. The percentage change in odds indicates the size and direction of the effect of the independent variable on the probability of dropping coverage or revising down at an earlier date in the period prior to public disclosure. For fraud types, the results show that analysts are significantly more likely to revise down sooner for wrong way frauds (TYPE J) but no more or less likely to revise down earlier for the remaining fraud types. Again, contrary to expectations, no egregious measure is individually related to the timing of the revision of recommendation. We do find differences in two of the analyst ability variables--the higher the analyst's firm specific and general experience (FIRMEXP and GENEXP), the later the analyst will revise down prior to public disclosure. These results may indicate that more experienced analysts choose to drop coverage versus revising recommendations downward when fraud is detected. We explore this possibility further in our multivariate results. We see that the more firms an analyst follows (FRMSFOL), a measure of task complexity, the later he will revise down his recommendation and that the negative relationship with BEGREC confirms that the lower an analysts beginning recommendation, the lower the odds of revising down prior to the disclosure of the fraud. It is also interesting to note that ADJRET does not significantly affect the timing of revisions in recommendations for our sample of analyst firms. This may reflect the notion that if a firm is showing a significant decline in returns, the analyst would prefer to drop the firm versus revise recommendations down, consistent with McNichols and O'Brien (1997).

Multivariate results

Table 8 presents the results for our multivariate tests of the duration of coverage using the Cox proportional hazard models for our survival analyses.[8] Recall that the percentage change in odds indicates the size and direction of the effect of the independent variable on the probability of dropping coverage or revising down at an earlier date in the period prior to public disclosure. The Cox regression with all fraud types (Model 1) provides evidence that analysts are more likely to drop coverage sooner for firms with frauds with overvalued assets (TYPE E), less likely to drop coverage sooner for firms with equity frauds (TYPE H) and no more or less likely to drop earlier for other fraud types. For Model 2, we find that FICT fraud does not significantly change the odds of dropping coverage earlier in the study period versus firms with no FICT fraud. Model 3 shows that whether the firm fraud moved net income from a loss to a profit in any quarter (LOSSTPRF) does increase the odds of dropping coverage as does the relative size of the fraud (Models 4 and 5). There is a significant and positive relationship between dropping coverage earlier prior to the public disclosure and both size measures (IMPREV/TA and IMPNI/TA). The control variables TURNOVR and DLST are also significant across all models, indicating that analysts who change brokerage houses and firms that are delisted prior to the public disclosure are significantly more likely to be dropped earlier in the period as expected. We also find that ADJRET is significant and negative in Models 1 – 3 indicating that analysts are more likely to drop coverage earlier prior to public disclosure for decreasing returns and that this effect goes away when fraud size is included in the models.

In Table 9 we examine the models for revising recommendation prior to fraud disclosure. Model 1 provides evidence that analysts are more likely to revise down sooner in the period for wrong way frauds (TYPE J) and less likely to revise down sooner for overvalued asset frauds (TYPE E) and related party transaction frauds (TYPE I). In Model 2, we see that again, the FICT measure of egregious frauds is not significant indicating that analysts are no more likely to revise recommendations down earlier in the study period for firms who committed fictitious versus non-fictitious frauds. For the egregious measure LOSSTPRF (Model 3), we find evidence that analysts are more likely to revise down sooner for firms whose fraud moves net income from a loss to a profit. In Models 4 and 5, we show that analysts are not more or less likely to revise down earlier when the total impact on revenues or net income, scaled by assets, (IMPREV/TA and IMPNI/TA) is larger i.e. the relative size of the fraud does not affect the timing of the revision. For the control variables, we see that analysts are less likely to revise down sooner the closer their BEGREC is to sell, as expected, and less likely to revise down sooner the higher the ADJRET. In Models 1 – 4, we see that analysts are also more likely to revise down sooner for each additional analyst that follows the firm (ANFOL). This is indicative of a richer information environment associated with higher analyst following. We see that many of our additional variables do not appear to influence the decision to revise down earlier in the period including firm affiliation (AFFL), firm specific experience (FIRMEXP), analyst turnover (TURNOVR), firm size (SIZE) and our delisting dummy variable (DLST).[9]

Our results provide some interesting insights into analyst reactions to different types of frauds. Taken together, we find that analysts are more likely to drop coverage of firms with overvalued asset frauds (TYPE E) earlier in the study period versus those firms without TYPE E fraud, and less likely to revise their forecasts down for such firms. This provides some evidence that analysts choose different methods of communicating bad news about a company and these choices may be influenced by economic incentives. Conversely, we find that analysts are more likely to revise recommendations down earlier for firms with frauds that go the wrong way (increase assets/income) but not more or less likely to drop these firms (TYPE J). We also find that analysts are less likely to revise down for firms with related party transactions (TYPE I) but not more or less likely to drop these firms and less likely to drop firms with equity frauds (TYPE H) but not more or less likely to revise down. Our measures of egregious frauds show that analysts are more likely to drop coverage of firms with larger frauds in revenues and assets but not more or less likely to revise recommendations down, also indicating the possible presence of economic incentives in analyst decision making. These results are consistent with those reported by McNichols et al. (1997) suggesting a censored distribution of analyst recommendations due to dropping coverage. Further, there is some evidence that our sample of analysts may be fooled by fictitious frauds (FICT) as we find no evidence that they drop coverage or revise down earlier for these fraud types. Interestingly, we do not show that analysts are more or less likely to revise or drop earlier for either type of revenue fraud (TYPE A and TYPE B). Given that these frauds are the most common type of fraud, we should expect analysts to be more sensitive to their occurrence. As expected, we find that analysts are more likely to drop coverage earlier for firms that are experiencing poorer market adjusted performance (ADJRET), although the significance of market returns goes away when fraud size (IMPREV/TA and IMPNI/TA) is included in the models, also consistent with economic incentives of analysts. The evidence regarding analysts' opening recommendations indicates that their beginning recommendation (BEGREC) is a constraint on revising down during the two year period prior to the public disclosure. Greater analyst following (ANFOL) is significantly associated with earlier downward recommendation revisions in most models but not dropping coverage, indicating a richer information environment may increase market efficiency.

VI. CONCLUSIONS AND LIMITATIONS

Analysts are considered important information intermediaries between management and investors (Schipper 1991). In this paper, we examine a situation where the contribution of analysts for investors would be considered particularly important. We study whether sell-side equity analysts anticipate accounting fraud and reveal this negative information by revising their recommendations down or dropping coverage of the firm prior to the public disclosure of the fraud. The results of our analyses indicate some evidence that analysts anticipate fraud and use different signals to inform investors about different fraud types. However, these results also point to the possibility that analysts' decisions may be more closely aligned with their own economic incentives and reputation concerns than client protection.

We find that firms that commit larger frauds are significantly more likely to have analysts drop coverage earlier in the period preceding the public announcement, but are not significantly more likely to show downward revisions in recommendations. We also find that analysts are more likely to drop coverage of firms who commit frauds involving overvalued assets and less likely to revise their recommendations down for these same firms prior to the disclosure of the fraud. We also show that analysts appear to be fooled by fictitious frauds – they are no more likely to drop coverage or revise down prior to disclosure for firms that commit these frauds versus non-fictitious frauds. However, analysts are more likely to both revise recommendations down and to drop coverage of firms whose fraud moves them from a loss to profit position than for firms whose frauds do not change their loss/profit position. Interestingly, we find that for firms that commit revenue frauds, whether fictitious or premature, analysts are no more likely to drop coverage or revise recommendations downward prior to public disclosure despite the fact that these frauds have been found to be the most commonly occurring frauds both in our sample and in prior literature (Bonner et al. 1998). In addition, we find no evidence that analyst experience is related to coverage and recommendation choices.

While acknowledging the limits of our sample size, our analysis contributes to the literature in several ways. We use a unique data set to examine how analysts react to various accounting fraud types using survival analyses and also provide evidence on analysts' decision-making abilities and coverage decisions. We describe the types of fraud committed by firms covered by analysts over our sample of firms and the types of issues that lead to public disclosure of these frauds. As discussed by Richardson (2003), we would not expect analysts to react identically to different types of corrective disclosure and likewise, to different types of accounting frauds, which have different effects on firm value. Finally, our results show that the decision and timing of dropping coverage is not correlated with the decision and timing of the revision of forecasts, indicating that analysts consider different variables for the two decisions.

[1] See Bonner et al. (1998) for a detailed explanation of the development of the taxonomy.

[2] Various incentives may discourage analysts from revealing this private information to the capital market. These incentives would then bias against finding evidence of analysts detecting accounting fraud. We discuss this further in the next section.

[3] Dechow et al. (1996) also examines the reasons managers commit fraud. They find that obtaining external financing at a low cost and to avoiding debt covenant restrictions are key motivations for earnings manipulation. Dechow et al. also note that several corporate governance issues are related to the firms found guilty of fraud, including: the firms were more likely to have a CEO who is the chairman of the board of directors, a board of directors dominated by management and are less likely to have an audit committee.

[4] We choose to examine the AAERs after August 1995 because analyst forecasts on IBES become more "complete" during the mid-1990's. Prior to this, few analysts/brokers reported to IBES. More importantly, recommendations only became available on IBES in 1993.

[5] A random sample of these companies shows that the SEC enforcement release was usually related to a company's initial registration statements or the company was traded on over-the-counter exchanges. An analysis of these companies that were on Compustat but not on IBES shows that 37 (64%) were not traded on a major exchange (e.g. pink sheets or over-the-counter).

[6] We recognize that investors may only observe dropped coverage with a lag. While there are examples of analysts' reports that state they are dropping coverage, this information is not accurately reported to IBES.

[7] We also test additional measures for analyst experience and ability that have been used in previous research (e.g. Clement 1997). General experience (GENEXP) is measured as the number of quarters an analyst has forecast for any firm on the IBES detail tape. Task complexity is measured by the number of firms and industries followed by analyst (FRMSFOL and INDFOL). Resources available is measured by the size of the analysts' brokerage house (BRKRSZE). Each of these variables is measured as of the quarter two years prior to the public disclosure of the fraud. We include descriptive univariate statistics for these variables in our tables, but choose one, FIRMEXP to include in our multivariate results. Inclusion of other measures of experience does not affect the interpretation of these results.

[8]The Cox estimation does not impose a parametric structure to the baseline hazard $h_0(t)$ and has test statistics for all coefficients that are based on heteroskedasticity-consistent standard errors clustered on firms.

[9]Additional tests using a dependent variable that measures the range of change in an analyst's recommendation for the firm over the two years prior to the first public disclosure of the fraud yields similar results. The range of revisions ranged from 0 (no revision) to 4 (revision from strong buy to strong sell).

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Table 1
Source of the public disclosure that reveals to the market that the firm has engaged in accounting fraud: 347 firms subject to enforcement actions by the SEC between 1995 and 2002.

Panel A: Source of the first public disclosure

	# of Companies in sample with disclosure source		Percentage of sample with disclosure source	
	N=347	**N=56**	**N=347**	**N=56**
Company announces restatement	73	15	21.0	26.8
Company discloses accounting irregularities have been discovered	59	16	17.0	28.5
Company discloses delay in filing financial statements	19	4	5.5	7.1
SEC investigation disclosed	69	11	19.9	19.6
Lawsuit related to financial reporting issues	24	3	6.9	5.4
Fraud accusations by analysts or media	21	2	6.1	3.6
Auditor resigns	14	3	4.0	5.4
Other (Action by a regulatory authority, fraud raised by whistleblower, company officers and directors resign	12	1	3.5	1.8
No specific disclosure date identified – date of AAER used as the disclosure date	56	1	16.1	1.8
Total	347	56	100	100

Panel B: Calendar year of first public disclosure

Year	Pre92	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
	18	21	23	36	33	38	36	40	27	41	13	21

Table 2
Classification of accounting frauds: 347 firms subject to enforcement actions by the SEC between 1995 and 2002 and final sample of 56 firms

	# of Companies in sample with fraud type		Percentage of sample with fraud type	
Panel A: Fraud Categories	**N=347**	**N=56**	**N=347**	**N=56**
Type A - Fictitious Revenues	127	19	36.6	33.9
Type B - Premature Revenue Recognition	121	25	34.9	44.6
Type C - Misclassifications	34	8	9.8	14.3
Type D - Fictitious Assets and/or Reductions of Expenses/Liabilities	53	6	15.3	10.7
Type E - Overvalued Assets and Undervalued Expenses/Liabilities	141	27	40.6	48.2
Type F - Omitted or Undervalued Liabilities	44	13	12.7	23.2
Type G - Omitted or Improper Disclosures	143	19	41.2	33.9
Type H - Equity Frauds	29	3	8.1	5.4
Type I - Related Party Transactions	49	5	14.1	8.9
Type J - "Wrong Way" Frauds	12	4	3.5	7.1
Type K - Illegal Acts	49	9	14.1	16.1
Panel B: Categorical measures of egregious frauds				
Fictitious Transaction Frauds: Categories A, D & I1†	167	21	48.1	37.5
Fraud impacted revenues	134	29	53.0	51.8
Fraud impacted net income	182	48	75.8	85.7
Fraud changed reported net income to a profit from a loss in any quarter	87	15	34.4	26.8
Panel C: Continuous measures of egregious frauds	Mean		Median	
Number of quarters over which fraud is committed	8.28	9.48	7.00	8.00
Number of fraud types committed	3.00	3.32	3.00	3.00
Number of months between end of fraud and first public disclosure	10.02	5.68	4.00	3.50

Notes:† I1 is fictitious sales to related parties.

Table 3
S.I.C. Industry Breakdown of Final Sample

Industry[a]	*SIC Code*	*Number Of Firms*	%
Agriculture, mining & construction	0-1999	1	1.8
Manufacturing	2000-3999	15	26.8
Technology	3570-3579 and 7370-7379	11	19.6
Transportation	4000-4799	0	0
Communication	4800-4899	3	5.4
Utilities	4900-4999	4	7.1
Wholesale and retail	5000-5999	11	19.6
Financial services	6000-6999	5	8.9
Services	7000-8999	3	5.4
Other	9000-9999	3	5.4
Total		56	100

Table 4
Descriptive statistics for 56 firms subject to enforcement actions by the SEC and 275 analysts providing recommendations.

PANEL A: 56 firms subject to enforcement actions by the SEC					
Variable[a]	*Mean*	*Median*	*Std. Dev.*	*Min.*	*Max.*
ASSETS (MM$)	10,595	445	29,884	4	185,794
SALES (MM$)	1,231	159	2,414	1	10,973
NETINC (MM$)	76	4	296	-711	1,257
ADJRET	-0.519	-0.668	0.601	-1.368	1.487
ANFOL	9.30	7	7.84	1	35
IMPACTREV (MM$)	246.80	3.60	881.59	0	4,703
IMPACTNI (MM$)	455.73	11.69	1602.88	-0.60	11,000
	Yes	*No*			
DLST	4	52			
PANEL B: 275 sample analysts following the firms					
Variable[a]	*Mean*	*Median*	*Std. Dev.*	*Min.*	*Max.*
FIRMEXP	11.98	9	10.39	1	54
GENEXP	28.59	26	17.97	1	75
BKRSZE	49.38	43	41.08	1	241
FRMSFOL	15.72	13	11.01	1	95
INDFOL	3.50	3	2.75	1	18
BEGREC	1.76	2	0.82	1	5
	Yes	*No*			
AFFL	14	261			
TURNOVER	103	172			

Notes:
ASSETS = Total assets, in millions; measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).
SALES = Total sales, in millions; measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).
NETINC = Net income, in millions; measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).

ADJRET = Firm returns over the two years prior to the public disclosure of the fraud, adjusted by the market rate of return over the same period (t_{-2} to t_0).
ANFOL = number of non-stale forecasts in analyst consensus, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}); where a forecast is considered non-stale if the analyst forecasted within the last year.
IMPACTNI = total impact of the fraud on net income, in millions; measured over the entire fraud period.
IMPACTREV = total impact of the fraud on revenues, in millions; measured over the entire fraud period.
DLST = yes if the firm was delisted prior to the public disclosure, otherwise no.
FIRMEXP = number of quarters that the analyst reported an earnings forecast for the fraud firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
GENEXP = number of quarters that the analyst reported an earnings forecast for any firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
BKRSZE = number of analysts issuing forecasts for the brokerage house, measured two years prior to the public disclosure of the fraud (t_{-2}).
FRMSFOL = number of firms followed by the analyst, measured two years prior to the public disclosure of the fraud (t_{-2}).
INDFOL = number of industries followed by the analyst, measured two years prior to the public disclosure of the fraud (t_{-2}).
BEGREC = IBES recommendation code two years prior to the public disclosure of the fraud (t_{-2}); where 1 = strong buy and 5 = strong sell.
AFFL = yes if the analyst is employed by a brokerage house that is affiliated with the fraud firm, otherwise no; measured from 12 months prior to t_{-2} through 6 months after t_0.
TURNOVR = yes if the analyst left the brokerage house prior to the public disclosure of the fraud, otherwise no.

Table 5

Pearson and Spearman Rank correlations between variables capturing egregious frauds, analyst measures, and firm measures that are included in our multivariate models. The Pearson (Spearman) correlation is above (below) the diagonal. Two-tailed probability values are in parentheses.

	FICT	LOSSTPRF	IMPREV/TA	IMPNI/TA	LNGTH	#FRDS	MTHSDISC	BEGREC	AFFL	FIRMEXP	TURNOVR	SIZE	ADJRET	ANFOL	DLST
FICT		.524	.461	.323	-.002	.580	-.106	-.044	-.005	-.092	-.017	-.231	-.287	-.238	.118
		(.000)	(.000)	(.000)	(.971)	(.000)	(.057)	(.433)	(.934)	(.098)	(.756)	(.000)	(.000)	(.000)	(.033)
LOSSTPRF	.524		.197	.160	.012	.434	-.175	-.197	.070	-.090	-.045	-.117	-.225	-.287	-.030
	(.000)		(.001)	(.008)	(.824)	(.000)	(.002)	(.081)	(.207)	(.104)	(.416)	(.034)	(.000)	(.000)	(.595)
IMPREV/TA	.475	.379		.710	.028	.374	-.115	-.106	.117	-.161	.041	-.287	-.307	-.139	-.015
	(.000)	(.000)		(.000)	(.647)	(.000)	(.057)	(.081)	(.052)	(.008)	(.503)	(.000)	(.000)	(.022)	(.810)
IMPNI/TA	.581	.689	.630		.020	.143	-.098	-.116	.211	-.120	-.018	-.173	.087	-.137	-.024
	(.000)	(.000)	(.000)		(.740)	(.017)	(.105)	(.055)	(.000)	(.047)	(.769)	(.004)	(.148)	(.023)	(.693)
LNGTH	.110	.142	.035	.219		.146	-.156	-.097	.152	.023	-.107	.194	.142	.067	-.030
	(.047)	(.011)	(.561)	(.000)		(.009)	(.005)	(.079)	(.006)	(.681)	(.053)	(.000)	(.010)	(.229)	(.588)
#FRDS	.552	.437	.291	.381	.261		-.260	-.044	.081	.013	.009	.194	-.140	-.037	-.051
	(.000)	(.000)	(.000)	(.000)	(.000)		(.000)	(.433)	(.146)	(.815)	(.867)	(.000)	(.011)	(.510)	(.363)
MTHSDISC	.019	-.079	-.316	-.279	-.174	-.259		-.015	-.079	-.082	.090	-.177	.018	-.050	-.105
	(.732)	(.156)	(.000)	(.000)	(.002)	(.000)		(.785)	(.157)	(.139)	(.103)	(.001)	(.750)	(.368)	(.058)
BEGREC	-.029	-.079	-.132	-.115	-.102	-.024	-.079		-.132	.202	.145	.190	.057	.038	-.069
	(.604)	(.157)	(.029)	(.057)	(.065)	(.667)	(.156)		(.017)	(.000)	(.009)	(.001)	(.305)	(.498)	(.213)
AFFL	-.005	.070	.151	.158	.185	.082	-.148	-.132		-.013	-.037	.021	.040	-.077	-.024
	(.934)	(.207)	(.013)	(.008)	(.001)	(.140)	(.007)	(.017)		(.812)	(.507)	(.700)	(.472)	(.167)	(.660)
FIRMEXP	-.100	-.100	-.173	-.113	.064	.062	-.181	.185	.028		.052	.333	.216	.068	-.099
	(.071)	(.073)	(.004)	(.061)	(.252)	(.264)	(.001)	(.001)	(.610)		(.349)	(.000)	(.000)	(.222)	(.074)
TURNOVR	-0.017	-.045	-.042	-.059	-.090	.010	.065	.159	-.037	.016		.053	-.003	.045	.036
	(.756)	(.416)	(.493)	(.329)	(.105)	(.859)	(.243)	(.004)	(.507)	(.776)		(.342)	(.953)	(.420)	(.518)
SIZE	-.235	-.136	-.443	-.329	.305	.248	-.287	.207	.007	.358	.060		.268	.558	-.148
	(.000)	(.014)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.903)	(.000)	(.280)		(.000)	(.000)	(.007)
ADJRET	-.260	-.210	-.498	-.181	.017	-.006	-.074	.094	-.030	.233	-.014	.327		.211	-.105
	(.000)	(.000)	(.000)	(.002)	(.757)	(.916)	(.180)	(.090)	(.584)	(.000)	(.806)	(.000)		(.000)	(.057)
ANFOL	-.226	-.260	-.265	-.385	.239	.027	-.071	.058	-.067	.118	.039	.612	.150		-.137
	(.000)	(.000)	(.000)	(.000)	(.000)	(.631)	(.202)	(.298)	(.228)	(.034)	(.479)	(.000)	(.007)		(.013)
DLST	.118	-.030	.007	.030	-.012	-.044	.152	-.070	-.024	-.132	.036	-.156	-.134	-.158	
	(.033)	(.595)	(.912)	(.623)	(.825)	(.434)	(.006)	(.209)	(.660)	(.017)	(.518)	(.005)	(.015)	(.004)	

Notes:

FICT = one if fraud includes a fictitious transaction fraud: categories A, D; scheme I1; otherwise zero.

LOSSTPRF = one if the fraud changed reported net income to a profit from a loss in any quarter.

IMPREV/TA = total impact of the fraud on revenues, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
IMPNI/TA = total impact of the fraud on net income, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
LNGTH = number of quarters over which the fraud is committed.
#FRDS = number of fraud types committed.
MTHSDISC = number of months between the end of the fraud and the public disclosure.
BEGREC = IBES recommendation code two years prior to the public disclosure of the fraud (t_{-2}); where 1 = strong buy and 5 = strong sell.
AFFL = 1 if the analyst is employed by a brokerage house that is affiliated with the fraud firm, otherwise 0; measured from 12 months prior to t_{-2} through 6months after t_0.
FIRMEXP = number of quarters that the analyst has reported an earnings forecast for the fraud firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
TURNOVR = 1 if analyst changed brokerage houses prior to the public disclosure of the fraud, 0 otherwise.
SIZE = log of total assets, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).
ADJRET = firm returns over the two years prior to the public disclosure of the fraud, adjusted by the market rate of return over the same period (t_{-2} to t_0).
ANFOL = number of non-stale forecasts in analyst consensus, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}); where a forecast is considered non-stale if the analyst forecasted within the last year.
DLST = 1 if firm was delisted prior to the public disclosure of the fraud, 0 otherwise.

Table 6
Univariate regression results for Cox proportional hazard model. Duration of analyst coverage for two years, until the public disclosure of the fraud.

					Average days to drop (!)		
Variable	Coef.	% change in odds of dropping	z-Stat.	N	Absent	Present	Difference
Panel A: Fraud variables							
Type A	0.581	78.8	2.43**	326	663	628	35
Type B	0.150	16.2	0.58	326	656	653	3
Type C	0.222	24.9	0.87	326	659	628	31
Type D	-0.013	-1.2	0.02	326	654	660	-6
Type E	0.299	34.8	1.11	326	658	649	9
Type F	0.145	15.6	0.49	326	659	651	8
Type G	-0.011	-1.1	0.04	326	658	649	9
Type H	-1.300	-72.7	-5.51***	326	652	695	-43
Type I	-0.339	-28.7	-1.04	326	655	653	2
Type J	0.307	35.9	0.65	326	656	634	22
Type K	-0.276	-24.1	-0.58	326	654	655	-1
FICT	0.467	59.6	1.84	326	662	634	28
LOSSTPRF	0.514	67.1	2.02*	325	662	643	19
IMPREV/TA	1.250	2.5	3.98***	274	n/a	n/a	n/a
IMPNI/TA	0.190	0.2	0.89	276	n/a	n/a	n/a
LNGTH	-0.023	-2.3	-1.30	326	n/a	n/a	n/a
#FRDS	0.085	8.9	1.45	326	n/a	n/a	n/a
MTHSDISC	0.010	1.0	1.23	326	n/a	n/a	n/a
Panel B: Analyst variables							
BEGREC	-0.124	-0.1	-1.18	326	n/a	n/a	n/a
AFFL	0.112	11.9	0.30	326	656	626	30
TURNOVR	1.091	197.6	6.06***	326	689	588	101
FIRMEXP	-0.013	-1.3	-1.28	326	n/a	n/a	n/a
GENEXP	-0.004	-0.4	-0.94	326	n/a	n/a	n/a
BKRSZE	-0.001	-0.1	-0.36	326	n/a	n/a	n/a
FRMSFOL	0.002	0.2	0.21	326	n/a	n/a	n/a
INDFOL	-0.014	-1.4	-0.28	326	n/a	n/a	n/a
Panel C: Company variables							
DLST	2.386	987.2	4.51***	326	657	424	233
SIZE	-0.050	-4.8	-0.84	326	n/a	n/a	n/a
ADJRET	-0.565	-43.2	-3.40***	326	n/a	n/a	n/a
ANFOL	-0.012	-1.2	-0.55	326	n/a	n/a	n/a

Notes:
* Significant at the 0.10 level, ** significant at the 0.05 level, *** significant at the 0.01 level.
! largest observed analysis time is censored, mean is underestimated
DYSDRP = number of days from two years prior to the first public disclosure of the fraud (t_{-2}) until the analyst dropped coverage of the firm, censored at the date of the disclosure (t_0) for analysts that did not drop coverage.
TYPE A = one if fraud includes recognition of fictitious revenues, otherwise zero.
TYPE B = one if fraud includes premature revenue recognition, otherwise zero.
TYPE C = one if fraud includes a misclassification, otherwise zero.
TYPE D = one if fraud includes fictitious assets and/or reductions of expenses/liabilities, otherwise zero.

TYPE E = one if fraud includes overvalued assets and undervalued expenses/liabilities, otherwise zero.
TYPE F = one if fraud includes omitted or undervalued liabilities, otherwise zero.
TYPE G = one if fraud includes omitted or improper disclosures, otherwise zero.
TYPE H = one if fraud includes an equity fraud, otherwise zero.
TYPE I = one if fraud includes related party transactions, otherwise zero.
TYPE J = one if fraud includes a fraud going the "wrong way", otherwise zero.
TYPE K = one if fraud includes an illegal Act, otherwise zero.
TYPE L = one if fraud includes a miscellaneous fraud, otherwise zero.
FICT = one if fraud includes a fictitious transaction fraud: categories A, D; scheme I1; otherwise zero.
LOSSTPRF = one if the fraud changed reported net income to a profit from a loss in any quarter.
IMPREV/TA = total impact of the fraud on revenues, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
IMPNI/TA = total impact of the fraud on net income, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
LNGTH = number of quarters over which the fraud is committed.
#FRDS = number of fraud types committed.
MTHSDISC = number of months between the end of the fraud and the public disclosure.
BEGREC = IBES recommendation code two years prior to the public disclosure of the fraud (t_{-2}); where 1 = strong buy and 5 = strong sell.
AFFL = 1 if the analyst is employed by a brokerage house that is affiliated with the fraud firm, otherwise 0; measured from 12 months prior to t_{-2} through 6 months after t_0.
TURNOVR = 1 if analyst changed brokerage houses prior to the public disclosure of the fraud, 0 otherwise.
FIRMEXP = number of quarters that the analyst reported an earnings forecast for the fraud firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
GENEXP = number of quarters that the analyst reported an earnings forecast for any firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
BKRSZE = number of analysts issuing forecasts for the brokerage house, measured two years prior to the public disclosure of the fraud (t_{-2}).
FRMSFOL = number of firms followed by the analyst, measured two years prior to the public disclosure of the fraud (t_{-2}).
INDFOL = number of industries followed by the analyst, measured two years prior to the public disclosure of the fraud (t_{-2}).
DLST = 1 if firm was delisted prior to the public disclosure of the fraud, 0 otherwise.
SIZE = log of total assets, measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
ADJRET = firm returns over the two years prior to the first public disclosure of the fraud, adjusted by the market rate of return over the same period (t_{-2} to t_0).
ANFOL = number of non-stale forecasts in analyst consensus, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}); where a forecast is considered non-stale if the analyst forecasted within the last year.

Table 7
Univariate regression results for Cox proportional hazard model. Duration of time to analyst recommendation revision for two years, until the public disclosure of the fraud.

					Average days to revise down (!)		
Variable	Coef.	% change in odds of rev. down	z-Stat.	N	Absent	Present	Difference
Panel A: Fraud variables							
Type A	-0.182	-16.7	-0.60	326	545	573	-28
Type B	0. 023	2.3	0.09	326	542	565	-23
Type C	0.207	23.0	0.64	326	553	545	8
Type D	-0.668	-48.7	-1.69	326	545	654	-109
Type E	-0.029	-2.8	-0.11	326	546	552	-6
Type F	-0.266	-23.4	-0.78	326	538	586	-48
Type G	-0.227	-20.3	-0.82	326	530	590	-60
Type H	-0.339	-28.7	-0.86	326	547	634	-87
Type I	-0.604	-45.3	-1.50	326	537	659	-122
Type J	0.884	142.2	3.54***	326	560	422	138
Type K	0.246	27.8	0.63	326	565	497	68
FICT	-0.253	-22.4	-0.87	326	539	583	-44
LOSSTPRF	0.255	29.0	0.93	325	557	540	17
IMPREV/TA	0.442	0.6	1.16	274	n/a	n/a	n/a
IMPNI/TA	0.119	0.1	0.79	276	n/a	n/a	n/a
LNGTH	0.008	0.8	0.81	326	n/a	n/a	n/a
#FRDS	-0.055	-5.3	-0.79	326	n/a	n/a	n/a
MTHSDISC	0.004	0.4	0.33	326	n/a	n/a	n/a
Panel B: Analyst variables							
BEGREC	-0.984	-0.6	-7.62***	326	n/a	n/a	n/a
AFFL	0.256	29.2	0.75	326	550	581	-31
TURNOVR	-0.130	-12.2	-0.73	326	559	537	22
FIRMEXP	-0.030	-2.9	-2.37**	326	n/a	n/a	n/a
GENEXP	-0.016	-1.6	-2.84***	326	n/a	n/a	n/a
BKRSZE	0.001	0.1	0.66	326	n/a	n/a	n/a
FRMSFOL	-0.034	-3.3	-4.01***	326	n/a	n/a	n/a
INDFOL	-0.027	-2.7	-0.68	326	n/a	n/a	n/a
Panel C: Company variables							
DLST	-0.631	-46.8	-0.63	326	551	562	-11
SIZE	-0.085	-8.2	-1.62	326	n/a	n/a	n/a
ADJRET	-0.358	-30.1	-1.44	326	n/a	n/a	n/a
ANFOL	0.010	1.0	0.46	326	n/a	n/a	n/a

Notes:
* Significant at the 0.10 level, ** significant at the 0.05 level, *** significant at the 0.01 level.
! largest observed analysis time is censored, mean is underestimated
DYSRVDN = number of days from two years prior to the first public disclosure of the fraud (t_{-2}) until the analyst revised his recommendation for the firm down, censored at the date of the disclosure (t_0) for analysts that did not revise down prior to then.
TYPE A = one if fraud includes recognition of fictitious revenues, otherwise zero.
TYPE B = one if fraud includes premature revenue recognition, otherwise zero.
TYPE C = one if fraud includes a misclassification, otherwise zero.

TYPE D = one if fraud includes fictitious assets and/or reductions of expenses/liabilities, otherwise zero.
TYPE E = one if fraud includes overvalued assets and undervalued expenses/liabilities, otherwise zero.
TYPE F = one if fraud includes omitted or undervalued liabilities, otherwise zero.
TYPE G = one if fraud includes omitted or improper disclosures, otherwise zero.
TYPE H = one if fraud includes an equity fraud, otherwise zero.
TYPE I = one if fraud includes related party transactions, otherwise zero.
TYPE J = one if fraud includes a fraud going the "wrong way", otherwise zero.
TYPE K = one if fraud includes an illegal Act, otherwise zero.
TYPE L = one if fraud includes a miscellaneous fraud, otherwise zero.
FICT = one if fraud includes a fictitious transaction fraud: categories A, D; scheme I1; otherwise zero.
LOSSTPRF = one if the fraud changed reported net income to a profit from a loss in any quarter.
IMPREV/TA = total impact of the fraud on revenues, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
IMPNI/TA = total impact of the fraud on net income, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
LNGTH = number of quarters over which the fraud is committed.
#FRDS = number of fraud types committed.
MTHSDISC = number of months between the end of the fraud and the public disclosure.
BEGREC = IBES recommendation code two years prior to the public disclosure of the fraud (t_{-2}); where 1 = strong buy and 5 = strong sell.
AFFL = 1 if the analyst is employed by a brokerage house that is affiliated with the fraud firm, otherwise 0; measured from 12 months prior to t_{-2} through 6months after t_0.
TURNOVR = 1 if analyst changed brokerage houses prior to the public disclosure of the fraud, 0 otherwise.
FIRMEXP = number of quarters that the analyst reported an earnings forecast for the fraud firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
GENEXP = number of quarters that the analyst reported an earnings forecast for any firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
BKRSZE = number of analysts issuing forecasts for the brokerage house, measured two years prior to the public disclosure of the fraud (t_{-2}).
FRMSFOL = number of firms followed by the analyst, measured two years prior to the public disclosure of the fraud (t_{-2}).
INDFOL = number of industries followed by the analyst, measured two years prior to the public disclosure of the fraud (t_{-2}).
DLST = 1 if firm was delisted prior to the public disclosure of the fraud, 0 otherwise.
SIZE = log of total assets, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).
ADJRET = firm returns over the two years prior to the public disclosure of the fraud, adjusted by the market rate of return over the same period (t_{-2} to t_0).
ANFOL = number of non-stale forecasts, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}); where a forecast is considered non-stale if the analyst forecasted within the last one year.

Table 8
Multivariate regression results for Cox proportional hazard models. Duration of analyst coverage for two years, until the public disclosure of the fraud.

	Dependent var. = DYSDRP Percentage change in odds of dropping coverage and z-statistics				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
LNGTH	-1.3 (-0.31)	-1.8 (-0.76)	-2.1 (-0.77)	-1.4 (-0.51)	-1.5 (-0.52)
#FRDS	8.5 (1.05)	9.6 (1.38)	6.0 (0.93)	11.4 (1.97)**	10.5 (1.49)
MTHSDISC	0.5 (0.65)	1.0 (1.28)	1.1 (1.39)	1.2 (1.65)*	0.8 (1.14)*
BEGREC	-12.2 (-1.17)	-19.1 (-1.90)*	-16.9 (-1.63)	-17.7 (-1.53)	-22.3 (-2.11)**
AFFL	39.4 (0.83)	48.4 (1.04)	48.6 (0.96)	31.9 (0.82)	13.8 (0.34)
FIRMEXP	0.0 (0.01)	-0.4 (-0.43)	-0.2 (-0.29)	0.3 (0.30)	-0.4 (-0.41)
TURNOVR	206.1 (5.77)***	221.4 (6.12)***	218.8 (6.12)***	247.3 (5.07)***	223.9 (5.09)***
SIZE	-4.1 (-0.46)	1.3 (0.15)	0.5 (0.06)	-7.8 (-1.04)	1.8 (0.17)
ADJRET	-48.0 (-2.32)**	-38.7 (-2.25)**	-36.3 (-2.43)***	-22.0 (-0.87)	-37.4 (-1.55)
ANFOL	1.6 (0.57)	0.1 (0.04)	1.1 (0.42)	1.4 (0.50)	0.0 (-0.01)
DLST	401.8 (2.48)**	416.8 (3.07)***	591.1 (3.93)***	2281 (9.14)***	484.0 (3.50)***
FICT	-	9.8 (0.38)	-	-	-
LOSSTPRF	-	-	60.9 (1.68)*	-	-
IMPREV/TA	-	-	-	118.7 (3.40)***	-
IMPNI/TA	-	-	-	-	24.6 (2.53)**
TYPE A Fictitious revenues	29.2 (0.68)	-	-	-	-
TYPE B Premature revenues	-26.4 (-1.16)	-	-	-	-
TYPE C Misclassifications	-13.8 (-0.07)	-	-	-	-
TYPE D Fictitious assets	15.4 (0.34)	-	-	-	-
TYPE E Overvalued assets	69.6 (2.03)**	-	-	-	-
TYPE F Omitted liabilities	9.6 (0.29)	-	-	-	-
TYPE G Omitted disclosures	15.3 (0.48)	-	-	-	-
TYPE H Equity	-84.7 (-2.43)**	-	-	-	-
TYPE I Related party trans.	32.1 (0.48)	-	-	-	-

TYPE J Wrong way	-16.2 (-0.52)	-	-	-	-
TYPE K Illegal acts	-11.3 (-0.21)	-	-	-	-
Log pseudo-likelihood	-655.00	-661.65	-654.25	-515.77	-573.74
Wald chi2	315.65***	157.12***	152.78***	161.13***	166.99***
N	326	326	325	274	276

Notes:
* Significant at the 0.10 level, based on a two-tailed test; ** significant at the 0.05 level, based on a two-tailed test; *** significant at the 0.01 level, based on a two-tailed test.
DYSDRP = number of days from two years prior to the first public disclosure of the fraud (t-2) until the analyst dropped coverage of the firm, censored at the date of the disclosure (t0) for analysts that did not drop coverage prior to then.
TYPE A = one if fraud includes recognition of fictitious revenues, otherwise zero.
TYPE B = one if fraud includes premature revenue recognition, otherwise zero.
TYPE C = one if fraud includes a misclassification, otherwise zero.
TYPE D = one if fraud includes fictitious assets and/or reductions of expenses/liabilities, otherwise zero.
TYPE E = one if fraud includes overvalued assets and undervalued expenses/liabilities, otherwise zero.
TYPE F = one if fraud includes omitted or undervalued liabilities, otherwise zero.
TYPE G = one if fraud includes omitted or improper disclosures, otherwise zero.
TYPE H = one if fraud includes an equity fraud, otherwise zero.
TYPE I = one if fraud includes related party transactions, otherwise zero.
TYPE J = one if fraud includes a fraud going the "wrong way", otherwise zero.
TYPE K = one if fraud includes an illegal Act, otherwise zero.
TYPE L = one if fraud includes a miscellaneous fraud, otherwise zero.
FICT = one if fraud includes a fictitious transaction fraud: categories A, D; scheme I1; otherwise zero.
LOSSTPRF = one if the fraud changed reported net income to a profit from a loss in any quarter.
IMPREV/TA = total impact of the fraud on revenues, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
IMPNI/TA = total impact of the fraud on net income, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
LNGTH = number of quarters over which the fraud is committed.
#FRDS = number of fraud types committed.
MTHSDISC = number of months between the end of the fraud and the public disclosure.
BEGREC = IBES recommendation code two years prior to the public disclosure of the fraud (t_{-2}); where 1 = strong buy and 5 = strong sell.
AFFL = 1 if the analyst is employed by a brokerage house that is affiliated with the fraud firm, otherwise 0; measured from 12 months prior to t_{-2} through 6months after t_0.
FIRMEXP = number of quarters that the analyst reported an earnings forecast for the fraud firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
TURNOVR = 1 if analyst changed brokerage houses prior to the public disclosure of the fraud, 0 otherwise.
SIZE = log of total assets, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).
ADJRET = firm returns over the two years prior to the public disclosure of the fraud, adjusted by the market rate of return over the same period ($t\text{-}_2$ to t_0).
ANFOL = number of non-stale forecasts in analyst consensus, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}); where a forecast is considered non-stale if the analyst forecasted within the last year.
DLST = 1 if firm was delisted prior to the public disclosure of the fraud, 0 otherwise.

Table 9
Multivariate results for Cox proportional hazard models. Duration of time to analyst recommendation revision for two years, until the public disclosure of the fraud.

	Dependent var. = DYSRVDN Percentage change in odds of dropping coverage and z-statistics				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
LNGTH	0.8 (0.48)	1.0 (1.29)	1.2 (1.48)	1.2 (2.13)**	1.0 (1.12)
#FRDS	-0.5 (-0.04)	-5.0 (-0.77)	-13.4 (-2.84)***	-5.0 (-0.96)	-6.6 (-1.22)
MTHSDISC	0.6 (0.56)	0.4 (0.44)	1.0 (0.85)	0.7 (0.66)	0.9 (0.82)
BEGREC	-63.3 (-7.94)***	-62.5 (-7.99)***	-63.5 (-8.22)***	-65.9 (-7.35)***	-64.1 (-7.25)***
AFFL	52.9 (1.30)	2.9 (0.08)	8.7 (0.30)	23.2 (0.66)	18.6 (0.52)
FIRMEXP	-1.7 (-1.41)	-1.2 (-1.05)	-1.3 (-1.09)	-0.9 (-1.62)	-0.4 (-0.32)
TURNOVR	25.0 (0.92)	22.3 (0.89)	26.7 (1.04)	21.2 (0.79)	12.3 (0.48)
SIZE	-2.9 (-0.43)	-7.9 (-1.22)	-6.4 (-1.24)	-11.5 (-1.64)	-7.7 (-0.97)
ADJRET	-17.0 (-0.65)	-31.7 (-2.13)**	-28.1 (-2.12)**	-19.3 (-0.74)	-32.6 (-1.29)
ANFOL	2.9 (1.61)	3.4 (1.75)*	4.2 (2.28)**	4.0 (1.87)*	3.5 (1.81)*
DLST	-74.2 (-0.90)	-71.9 (-0.90)	-73.9 (-1.00)	-74.5 (-0.99)	-70.9 (-0.91)
FICT	-	-22.8 (-0.83)	-	-	-
LOSSTPRF	-	-	63.6 (2.08)**	-	-
IMPREV/TA	-	-	-	-14.7 (-0.55)	-
IMPNI/TA	-	-	-	-	2.4 (0.16)
TYPE A Fictitious revenues	-19.2 (-0.44)	-	-	-	-
TYPE B Premature revenues	-23.6 (0.96)	-	-	-	-
TYPE C Misclassifications	15.7 (0.23)	-	-	-	-
TYPE D Fictitious assets	13.2 (0.28)	-	-	-	-
TYPE E Overvalued assets	-37.9 (-1.87)*	-	-	-	-
TYPE F Omitted liabilities	-10.4 (-0.35)	-	-	-	-
TYPE G Omitted disclosures	-19.7 (-0.69)	-	-	-	-
TYPE H Equity	77.9 (0.78)	-	-	-	-
TYPE I Related party trans.	-58.7 (-1.95)*	-	-	-	-

TYPE J Wrong way	194.2 (2.91)***	-	-	-	-
TYPE K Illegal acts	-17.3 (-0.40)	-	-	-	-
Log pseudo-likelihood	-762.94	-769.49	-765.83	-640.03	-660.74
Wald chi2	176.95***	101.94***	133.98***	167.82***	100.98***
N	326	326	325	274	276

Notes:
* Significant at the 0.10 level, based on a two-tailed test; ** significant at the 0.05 level, based on a two-tailed test; *** significant at the 0.01 level, based on a two-tailed test.
DYSRVDN = number of days from two years prior to the first public disclosure of the fraud (t-2) until the analyst revised his recommendation for the firm down, censored at the date of the disclosure (t0) for analysts that did not revise down prior to then.
TYPE A = one if fraud includes recognition of fictitious revenues, otherwise zero.
TYPE B = one if fraud includes premature revenue recognition, otherwise zero.
TYPE C = one if fraud includes a misclassification, otherwise zero.
TYPE D = one if fraud includes fictitious assets and/or reductions of expenses/liabilities, otherwise zero.
TYPE E = one if fraud includes overvalued assets and undervalued expenses/liabilities, otherwise zero.
TYPE F = one if fraud includes omitted or undervalued liabilities, otherwise zero.
TYPE G = one if fraud includes omitted or improper disclosures, otherwise zero.
TYPE H = one if fraud includes an equity fraud, otherwise zero.
TYPE I = one if fraud includes related party transactions, otherwise zero.
TYPE J = one if fraud includes a fraud going the "wrong way", otherwise zero.
TYPE K = one if fraud includes an illegal Act, otherwise zero.
TYPE L = one if fraud includes a miscellaneous fraud, otherwise zero.
FICT = one if fraud includes a fictitious transaction fraud: categories A, D; scheme I1; otherwise zero.
LOSSTPRF = one if the fraud changed reported net income to a profit from a loss in any quarter.
IMPREV/TA = total impact of the fraud on revenues, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
IMPNI/TA = total impact of the fraud on net income, scaled by total assets measured in the quarter two years prior to the first public disclosure of the fraud (t_{-2}).
LNGTH = number of quarters over which the fraud is committed.
#FRDS = number of fraud types committed.
MTHSDISC = number of months between the end of the fraud and the public disclosure.
BEGREC = IBES recommendation code two years prior to the public disclosure of the fraud (t_{-2}); where 1 = strong buy and 5 = strong sell.
AFFL = 1 if the analyst is employed by a brokerage house that is affiliated with the fraud firm, otherwise 0; measured from 12 months prior to t_{-2} through 6months after t_0.
FIRMEXP = number of quarters that the analyst has reported an earnings forecast for the fraud firm, measured two years prior to the public disclosure of the fraud (t_{-2}).
TURNOVR = 1 if analyst changed brokerage houses prior to the public disclosure of the fraud, 0 otherwise.
SIZE = log of total assets, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}).
ADJRET = firm returns over the two years prior to the public disclosure of the fraud, adjusted by the market rate of return over the same period ($t\text{-}_2$ to t_0).
ANFOL = number of non-stale forecasts in analyst consensus, measured in the quarter two years prior to the public disclosure of the fraud (t_{-2}); where a forecast is considered non-stale if the analyst forecasted within the last year.
DLST = 1 if firm was delisted prior to the public disclosure of the fraud, 0 otherwise.