Predicting Material Accounting Misstatements*

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Predicting Material Accounting Misstatements

Abstract

We examine 2,190 SEC Accounting and Auditing Enforcement Releases (AAERs) issued between 1982 and 2005. We obtain 677 firms that are alleged to have misstated their quarterly or annual financial statements. We examine the characteristics of misstating firms along five dimensions: accrual quality; financial performance; non-financial measures; off-balance sheet activities; and market-based measures. We compare misstating firms to themselves during non-misstatement years and misstating firms to the broader population of all publicly listed firms. The results reveal that during misstatement years, accruals and cash and credit sales are unusually high, while earnings and the number of employees are declining. In addition, misstating firms finance more of their assets through operating leases. We find that market pressures appear to affect incentives to misstate. Misstating firms are raising new financing, have higher market-to-book ratios, and strong prior stock price performance. We develop a model to predict accounting misstatements. The output of this model is a scaled logistic probability that we term the *F-Score*, where values greater than one suggest a greater likelihood of a misstatement.

1. INTRODUCTION

What causes managers to misstate their financial statements? How best can investors, auditors, financial analysts and regulators detect misstatements? Addressing these questions is of critical importance to the efficient functioning of capital markets. For an investor it can lead to improved returns, for an auditor it can mean avoiding costly litigation, for an analyst it can mean avoiding a damaged reputation, and for a regulator it can lead to enhanced investor protection and fewer investment debacles. The objective of our research is two-fold. First, we develop a comprehensive database of financial misstatements. Our objective is to describe this database and make it broadly available to other researchers to promote research on earnings misstatements. Second, we analyze the financial characteristics of misstating firms and develop a model to predict misstatements. The output of this analysis is a scaled probability (*F-Score*) that can be used as a red flag or signal of the likelihood of misstatement.

We compile our database through a detailed examination of firms that have been subject to enforcement actions by the Securities and Exchange Commission (SEC) for allegedly misstating their financial statements. Since 1982, the SEC has issued *Accounting and Auditing Enforcement Releases* (AAERs) during or at the conclusion of an investigation against a company, an auditor, or an officer for alleged accounting and/or auditing misconduct. These releases provide varying degrees of detail on the nature of the misconduct, the individuals and entities involved and the effect on the financial statements. We examine the 2,190 AAERs released between 1982 and 2005. Our examination identifies 677 unique firms that have misstated at least one of their quarterly or annual financial statements.

We adopt a financial statement analysis perspective when identifying the characteristics of misstating firms since such information is readily available to auditors, investors and regulators.

We analyze (i) accrual quality; (ii) financial performance; (iii) non-financial measures; (iv) off-balance sheet activities; and (v) market-based measures. We provide time-series analysis of these variables for misstating firms and cross-sectional analysis comparing misstating firms to the broader population of firms.

Accruals are commonly used by researchers to examine issues concerning earnings quality. We examine several measures of accruals to determine which measure appears most powerful at identifying misstatements in our sample. We use composite measures of working capital accruals (as reported in Sloan (1996)) and broader measures of accruals that incorporate long-term operating assets and liabilities (as reported in Richardson, Sloan, Soliman and Tuna (2005)). We examine various models of discretionary accruals developed in prior accounting research. We measure discretionary accruals using the cross-sectional modified Jones model (see Dechow, Sloan, and Sweeney (1995) and DeFond and Jiambalvo (1994)) and the performance matched discretionary accruals model promoted by Kothari, Leone, and Wasley (2005)). In addition, we examine measures of earnings quality developed in Dechow and Dichev (2002). Finally, we provide an analysis of two specific accruals: change in receivables and inventory since these accounts are likely to reflect common ways earnings are misstated.

We find that all measures of accruals are unusually high during misstatement periods. The broad measure of total accruals developed by Richardson et al. (2005) has the highest statistical association with misstatements. We also find that including periods after the misstatements in these tests provides additional explanatory power. This result arises because the subsequent reversal of overstated accruals makes the overstated accruals more obvious. Note that while subsequent accruals are not available for those interested in predicting misstatements, they are available to researchers and regulators who seek to determine whether a misstatement existed after the fact.

We next examine whether performance is declining at the time of misstatement. We find that earnings are generally declining but contrary to our initial expectations, we find that cash sales are increasing during misstatement periods. We failed to anticipate this result because we expected firms to boost sales through the misstatement of credit sales. There are, however, two explanations for this result. First, misstating firms tend to be growing their capital bases and increasing the scale of their business operations. The greater scale of operations should lead to increases in both cash and credit sales. Second, an inspection of the AAERs reveals that many firms misstate sales through transaction management - for example, by encouraging sales to customers with return provisions that violate the definition of a "sale," selling goods to related parties, or forcing goods onto customers at the end of the quarter. All of these misstatement techniques can boost *cash* sales and so accrual-based measures of earnings quality are unlikely to detect such misstatements.

We find that two non-financial measures are useful in detecting misstatements. The first is a decline in order backlog. A decline in order backlog suggests a weakening demand for the firm's product and deteriorating operating performance (Lev and Thiagarajan 1993). This decline could lead managers to overstate earnings in order to hide deteriorating performance from investors. The second non-financial measure is new to the literature and is abnormal reductions in the number of employees. Reductions in the number of employees are also likely to occur when there is declining demand for the firm's product. In addition, cutting employees directly improves short-run earnings performance by lowering wage expenses.

Our examination of off-balance sheet information focuses on the existence and use of operating leases and the expected return assumption on plan assets for defined benefit pension plans. Operating leases can be used to front-load earnings and reduce reported debt. Therefore, operating leases can be used as 'legal' earnings management and balance sheet management tools. We find that the use of operating leases is unusually high during misstatement years. We also find that misstating firms have higher expected returns on their pension plan assets than other firms. Higher expected return assumptions reduce reported pension expense. The results for leases and pensions suggest that misstating firms might exhaust 'legal' earnings management options before resorting to potentially illegal financial misstatements.

Our final set of variables relates to stock and debt market incentives. Dechow, Sloan, and Sweeney (1995) suggest that market incentives are an important reason for engaging in earnings management. Teoh, Welch, and Wong (1998) and Rangan (1998) provide corroborating evidence that accruals appear to be unusually high during equity issuances. We find that misstating firms tend to be running short of cash and have higher financial leverage. In addition, we find that misstating firms are actively seeking additional financing from capital markets. These findings suggest that misstating firms are attempting to inflate their stock prices in order to raise capital on more favorable terms.

We examine the growth expectations embedded in misstating firms' stock market valuations. We find that price-earnings ratios and market-to-book ratios are unusually high prior to misstatements, suggesting that investors are optimistic about the future growth opportunities of these firms. We also find that the misstating firms have had unusually strong stock price performance in the years prior to misstatement. Thus managers may misstate earnings because they want to avoid disappointing investors and losing their high valuations. They may do this because they own stock options, or because they plan to raise new financing. Either way, strong prior operating performance is likely to create incentives for managers to continue to report strong results to the market, even if it means misstating earnings. A consistent theme among misstating firms appears to be that they have shown strong performance prior to the misstatements and that the misstatements are made to hide deteriorating performance.

Our final tests develop a prediction model that provides a parsimonious approach to evaluating the likelihood of misstatement. The model is built in stages and compares the characteristics of misstating firm-years to other public firms. **Model 1** includes variables that are obtained from the primary financial statements. These variables include accrual quality and firm performance. **Model 2** adds off-balance sheet and non-financial measures such as operating leases and abnormal changes in employees. **Model 3** adds market-related variables such as prior stock price performance and the book-to-market ratio. We find that the bulk of the power of the prediction model is obtained using our simple **Model 1**. The output of these models is a scaled logistic probability for each firm-year that we term the *F-Score*. We show that while only 20 percent of the public firms have an F-Score greater than 1.2, almost fifty percent of misstating firms have F-Scores of 1.2 or higher. In addition, we discuss interpretation issues concerning *Type I* and *Type II* errors, and provide marginal analysis and sensitivity analysis to examine the robustness of the models.

The remainder of the paper is organized as follows. Section 2 reviews previous research on this topic. Section 3 describes database construction and research design. Section 4 presents our analysis of misstatement firms and develops our misstatement-prediction model. Section 5 concludes.

2. PREVIOUS LITERATURE

Describing and predicting the types of firms that will misstate financial statements or commit fraud is an extensive area of research. Many studies have used samples that include firms subject to Accounting and Auditing Enforcement Releases (AAERs). We briefly discuss some of the key findings but do not attempt to document all literature examining characteristics of misstating firms.

Feroz, Park and Pastena (1991) examine 224 AAERs issued between April 1982 and April 1989. Feroz et al provide a detailed description of their sample of 188 firms of which 58 have stock price information. They document that receivables and inventory are most commonly misstated. Two pioneering papers analyzing misstating firms are Beneish (1997 and 1999). Beneish (1997) analyzes 363 AAERs and obtains a sample of 49 firms that violate GAAP. He also collects a sample of 15 firms whose accounting was questioned by the news media between 1987 and 1993. Both sets of firms are classified in the manipulators sample. He creates a separate sample of firms he terms "aggressive accruers" using the modified Jones model to select firms with high accruals. His objective is to distinguish the manipulators from firms that have high accruals and appear to be applying GAAP aggressively. Beneish (1997) finds that accruals, day's sales in receivables and prior performance are important for explaining the differences between the two groups. Beneish (1999) matches the sample of manipulators to 2,332 Compustat non-manipulators by two-digit SIC industry and year for which the financial statement data used in the model were available. For seven of the eight financial statement ratios that he analyzes, he calculates an index. Higher index values indicate a higher likelihood of an earnings overstatement. Beneish shows that the days' sales in receivables index, gross margin index, asset quality index, sales growth index, and accruals (measured as the change in non-cash working capital plus depreciation) are important. He provides a probit model and analyzes the probability cutoffs that minimize the expect costs of misstatements.

Our research supports and extends Beneish (1997, 1999). In addition to financial statement variables, we analyze off-balance sheet, non-financial, and market-related variables. We use a computational algorithm to help in variable selection and create three parsimonious prediction models. We find that measures beyond the financial statement variables are incrementally informative in our models. Similar to Beneish, we find that growth in receivables and revenues are important, and we also find that the change in inventory and earnings are incrementally important. We find that the broader measure of accruals described in Richardson et al (2006) dominates the working capital accrual measure used by Beneish in misstatement detection. Finally, we analyze 2,261 AAERs so our sample is comprehensive and includes recent manipulators.

In concurrent research, Ettredge, Sun, Lee, and Anandarajan (2006) examine 169 AAER firms matched by firm size, industry and whether the firm reported a loss. They find that deferred taxes can be useful for predicting misstatements, along with auditor change, market-to-book, revenue growth and whether the firm is an OTC firm. Brazel, Jones, and Zimbelman (2006) examine whether several non-financial measures (e.g., patents and trademarks) can be used to predict misstatement in 77 AAER firms. They find that growth rates between financial and non-financial variables are significantly different for AAER firms. Bayley and Taylor (2007) study 129 AAER firms and a match sample based on industry, firm size and time period. They find that total accruals are better than various measures of unexpected accruals in identifying material accounting misstatements. In addition, they find that various financial statement ratio indices are incrementally useful. They conclude that future earnings management research should move away from further refinements of discretionary accrual models and instead consider supplementing accruals with other financial statement ratios. The focus of their research differs from ours but complements and is consistent with our findings.

Dechow, Sloan and Sweeney (1996) analyze 436 AAERS released between April 1982 and December 1992. Their final sample after eliminations consists of 92 firms. Each firm is matched in the year prior to misstatement to a control firm in the same three-digit SIC industry and with similar asset values. The authors provide some evidence that accruals appear to be high at the time of misstatement. However, the paper focuses primarily on showing that various corporate governance factors appear to be correlated with misstatement. For example, they find that misstating firms have a higher number of insiders on the board and a CEO who is more powerful and entrenched. They provide matched-pairs logit analysis; however, they do not report how effective their model is at predicting misstatement. Skousen and Wright (2006) analyze 86 misstatement firms matched by industry and sales. Similar to Dechow et al. (1996), they focus on governance variables. They find that misstatement firms tend to have managers with higher stockholdings (greater than five percent), have less effective audit committees, have more powerful CEOs, and are more likely to have recently switched auditors.

We extend the literature on accounting misstatements on three dimensions. First, prior literature examining accounting misstatements has relied on either small samples of accounting misstatements obtained from a limited number of SEC AAERs or larger samples of earnings restatements obtained from the Government Accounting Office or keyword news searches. For this paper we rigorously collect, categorize and code detailed information on all 2,190 SEC AAERs from 1982 through June 2005. This new database enables us to provide a comprehensive analysis of over 600 misstating firms, a sample size far larger than those used in prior research. Availability of this database will encourage research on earnings misstatement and increase knowledge of the determinants and consequences of misstatement. Second, we systematically examine a comprehensive set of prediction variables that relate to accrual quality, performance, and market-related incentives and establish which variables are relatively more important. In addition, we analyze whether off-balance sheet metrics provide useful information over and above measures reported in the financial statements. Although previous literature has analyzed several of the variables we examine in a univariate framework, we extend this research by introducing new variables and confirming their importance in multivariate framework using a larger, more comprehensive sample. Finally, we develop a parsimonious prediction model and an associated *F-score* that is readily amenable to practical implementation and future research. By testing our model in a large population of firms, we are able to provide detailed evidence on the number of *Type I* and *II* errors users of our prediction models will likely encounter. Our analysis of *Type I* and *II* errors provides subsequent researchers with a framework for analyzing the costs and benefits of implementing more extensive models.

3. DATA AND SAMPLE FORMATION

3.1 Data Sample

The objective of our data collection efforts is to construct a comprehensive sample of material and economically significant accounting misstatements involving both GAAP violations and the allegation that the misstatement was made with the intent of misleading investors. The SEC's series of published Accounting and Auditing Enforcement Releases provides the ideal starting point for our sample construction. The SEC takes enforcement actions against firms, managers, auditors and other parties involved in violations of SEC and federal rules. At the completion of a significant investigation involving accounting and auditing issues, the SEC issues an Accounting and Auditing Enforcement Release (AAER). The SEC identifies firms for review through anonymous tips and news reports. Another source is the voluntary restatement of the financial results by the firm itself since restatements are viewed as a red flag by the SEC. The SEC also states that it reviews about one-third of public companies' financial statements each year and checks for compliance with GAAP. If SEC officials believe that reported numbers are inconsistent with GAAP, then the SEC can initiate informal inquiries and solicit additional information. If the SEC is satisfied after such informal inquiries, then it will drop the case. However, if the SEC believes that one or more parties violated securities laws, then the SEC can take further steps, including enforcement actions requiring the firm to change its accounting methods, restate financial statements, and pay damages.

There are a number of conceivable alternative sources for identifying accounting misstatements. They are discussed briefly below, along with our reasons for not pursuing these alternatives.

1. The GAO Financial Statement Restatement Database. This database consists of approximately 2309 restatements between January 1997 and September 2005. This database was constructed through a Lexis-Nexis text search of press releases and other media coverage based on variations of the word 'restate.' There is some overlap between the AAER firms and the GAO restatement firms since a) the SEC often requires firms to restate their financials as part of a settlement; and b) restatements often trigger SEC investigations. The GAO database covers a relatively small time period, but consists of a relatively large number of restatements. The reason for the large number of restatements is that the GAO database includes all restatements relating to accounting irregularities regardless of managerial intent, materiality and economic significance. Consequently, it includes a large number of economically insignificant restatements. In addition, the results in Plumlee and Yohn (2008) suggest that many restatements are a consequence of

misinterpreting accounting rules rather than intentional misstatements. Another shortcoming of the GAO database is that it only identifies the year in which the restatement was identified in the press and not the reporting periods that were required to be restated.[1]

2. Stanford Law Database on Shareholder Lawsuits. Shareholder lawsuits typically result from material intentional misstatements. However, shareholder lawsuits can also arise for a number of other reasons that are unrelated to financial misstatements. Shareholder lawsuits alleging misstatements are also very common after a stock has experienced a precipitous stock price decline, even when there is no clear evidence supporting the allegation. In contrast, the SEC only issues an enforcement action when it has established intent or gross negligence on the part of management in making the misstatement.

3.2 Datasets

We catalog all the AAERs from AAER 1 through AAER 2261 spanning May 17th, 1982 through June 10th, 2005. We next identify all firms that are alleged to have violated GAAP by at least one of these AAERs (we describe this procedure in more detail in the next section). We then create three data files: the *Detail, Annual* and *Quarterly files*. The *Detail* file contains all AAER numbers pertaining to each firm, firm identifiers, a description of the reason the AAER was issued, and indicator variables categorizing which balance sheet and income statement accounts were identified in the AAER as being affected by the violation.[2] There is only one observation per firm in the *Detail* file. The *Annual* and *Quarterly* files are compiled from the *Detail* file and are

[1] For example, while Xerox is included in the GAO database in 2002, the restatements in question relate to Xerox's financial statements for 1997, 1998, 1999, 2000 and 2001.
[2] The dataset includes the CIK (central index key) available from the SEC. Cusips and GvKeys are used in this study to link the data to Compustat. However, these identifiers are the property of Compustat and will not be included in the dataset.

formatted by reporting period so that each quarter or year affected by the violation is a separate observation. Appendix 1 lists the variable names and description for each file in the database.

[Appendix 1]

3.3 Data Collection

The original AAERs are the starting point for collecting data. Copies of the AAERs are obtained from the SEC website and the Lexis Nexis database. Each AAER is separately examined to identify whether it involves an alleged GAAP violation. In cases where a GAAP violation is involved, the reporting periods that were alleged to be misstated are identified.

The data coding was completed in three phases. In the first phase, all releases were read in order to obtain the company name and period(s) in which the violation took place. The AAERs are simply listed chronologically based on the progress of SEC investigations. To facilitate our empirical analysis, we record misstatements by firm and link them back to their underlying AAERs in the detail file. Note that multiple AAERs may pertain to a single set of restatements at a single firm. Panel A of Table 1 indicates that of the 2,261 AAERs, we are unable to locate 30 AAERs either because they were missing or not released by the SEC. A further 41 AAERs relate to auditors or other parties and do not mention specific company names. This leaves us with 2,190 AAERs mentioning a company name.

Figure 1 reports that in the 2,190 AAERs, the SEC takes action against 2,614 different parties. Note that one AAER can be issued against multiple parties. In 49.2 percent (1,077) of the cases, the party was an officer of the company (e.g., CEOs or CFOs), in 15.1 percent (331) of the cases both an officer and the company were charged by the SEC, in 14.1 percent (308) of cases the party was the firm itself, in a further 15.9 percent (348) of cases the party was an auditor, in 3.1 percent (68) the party was an combination of various parties (e.g., auditor and officer), and in 2.65

percent (58) cases the party was classified as “other,” which includes consultants and investment bankers.

[Figure 1]

Table 1 Panel B provides the distribution of the 2,190 AAERs across years based on the AAER release date. Relatively few AAERs were released prior to 1990. However, the number of AAERs increased particularly after 2000, when over one hundred AAERs were released per year. The number of AAERs in 2005 falls to 94 because our sample cutoff date is June 10th, 2005 and so our sample does not include the full year. Table 1 Panel C reports that in many cases there are multiple AAERs referring to the same firm. This is because the SEC can take action against multiple officers as well as the firm itself. The number of releases ranges from one per firm (371 firms) to a high of 24 per firm (Enron). From our reading of the AAERs we obtain a list of 895 firms mentioned in the 2,190 releases.

In phase two, we created the Annual and Quarterly files. All releases were reread in order to identify the year and/or quarter-end when the misstatements occurred. Panel D of Table 1 indicates that of the 895 original firms identified, 218 firms involved either wrongdoings that are unrelated to financial misstatements (such as bribes or disclosure related issues) or financial misstatements that were not linked to specific reporting periods. This leaves us with 677 firms with alleged financial misstatements. We lose a further 138 firms because we are unable to obtain a valid Cusip identifier.[3] For each firm that is in the Detail file but excluded from both the Annual or Quarterly files, we create indicator variables in the Detail file to categorize why it was excluded. Panel D of Table 1 indicates that for 539 firms, the misstatement involved one or more quarters.

[3] Further investigation revealed that 33 of these firms were listed on exchanges such at OTC but had no cusips, 12 firms were sanctioned when registering securities under 12 (g), 12 were IPO firms that never went public, a further 13 firms were subsidiaries of parent firms already included in the sample, or private companies that helped a public company commit the misstatement. There was not sufficient detail in 34 AAERs.

We provide the number of firms with assets and share price data since firms can have a Cusip but no data. In 92 firms the misstatement only involved quarterly financial statements and was corrected by the end of the year. Therefore the annual file contains misstatements of annual data for 447 firms. Among these 447 firms, 376 firms have total assets listed on Compustat during the misstatement period.

[Table 1]

For each annual/quarterly period that was misstated, an additional field was added to the Annual/Quarterly file. If an understatement of earnings or revenues occurred during the quarter or year of the violation, we code the *understatement* variable 1. Since most AAERs involve the overstatement of earnings or revenues, this flag is helpful in conducting earnings management and other discretionary accruals tests. The Annual file contains 1,064 firm-year observations, and the Quarterly file contains 4,488 firm-quarter observations.

Phase three involves reading the AAERs a final time in order to obtain additional details on the misstatements. For each firm, we summarize the reason(s) for the enforcement action(s) in one or two sentences in the "*explanation*" column of the Detail file. We then create eleven indicator variables to code the balance sheet and income statement accounts that the AAER identified as being affected by the misstatements. Figure 2 indicates that 1,150 accounts were affected across the 677 misstating firms. Most misstatements relate to revenue recognition, which occur in 52.8 percent of firms. Types of revenue misstatements include the following: front-loading sales from future quarters (e.g. Coca Cola, Computer Associates), creating fictitious sales (e.g., ZZZZ Best), incorrect recognition of barter arrangements (e.g., Qwest), shipping goods without customer authorization (e.g., Florafax International). Revenue misstatements also frequently involve a misstatement of the allowance for doubtful debts. Other accounts frequently affected by misstatements include costs of goods sold and inventory (11.2 percent and 13.0 percent, respectively). Other types of misstatements include capitalizing expenses or creating fictitious assets (e.g., WorldCom). This occurs in about 25.7% of the firms. The AAERs do not provide consistent information on the magnitude of the misstatements. Therefore, there is insufficient detail to provide a consistent analysis of the magnitude of the misstatements.

[Figure 2]

4. EMPIRICAL RESULTS

Our empirical results first discuss the characteristics of misstatement firms. We then develop our logistic model and associated *F-Score*.

4.1 Characteristics of Misstating Firms

Table 2 Panel A presents information on size for misstating firms. To calculate size deciles, we rank firms based on their market capitalization of equity in each fiscal year. We then determine the decile rankings of misstating firms in their first misstatement year. The results in bold identify the size deciles that are overrepresented in the misstatement firm population. The results indicate that 14.7 percent of firms that misstate their earnings are from the top size decile (decile 10). There are several explanations for why larger firms appear to be relatively more likely to misstate their earnings. First, large firms have greater investor recognition and are under more scrutiny by the press and analysts; therefore, when an account appears suspicious there is likely to be more commentary that alerts the SEC to a potential problem (analyst and press reports are potential triggers for an SEC investigation). Second, the SEC is likely to review large firms on a more regular basis than other firms and so misstatements are more likely to be identified. Note also only 5.2 percent of misstating firms are in decile 1. Recall that 138 firms are excluded from our analysis because we could not obtain their firm identifier. The excluded firms are likely to be smaller in size.

Panel B of Table 2 reports the industry distribution of both misstatement firm-years and all available firm-years on Compustat. We follow Frankel, Johnson, and Nelson's (2002) SIC-based industry classification scheme. The bolded results highlight industries that are significantly overrepresented for misstating firms. Over twenty percent of misstating firms are in the computer industry, whereas only 11.1 percent of firms in the general population are in this industry. The computer industry includes software and hardware manufacturers. This industry is relatively new and has exhibited substantial growth. It is also characterized by substantial investment in intangible assets. Valuations in this industry are often dependent on continual sales growth. Misstating firms frequently overstate their sales to meet optimistic business expectations (e.g., Computer Associates), ship goods without authorization (e.g., Information Management Technologies Corp), or create fictitious sales (e.g., Clarent Corporation and AremisSoft Corporation). Retail is also overrepresented among misstating firms (12.9% versus 9.9%). For example, Sunbeam Corporation front-loaded sales and misstated reserves for restructurings. Services are also overrepresented (12.5% versus 10.4%). Service firms include firms such as WorldCom, Qwest, and Waste Management. These firms typically capitalized expenses as assets and misstated sales. Note also, the SEC could systematically review more firms from growth industries and so identify a relatively greater proportion of manipulators in those industries.

Panel C of Table 2 provides the distribution of misstatements over calendar time. Our sample covers misstatements in fiscal years beginning in 1971 and ending in 2003. The years 1999 and 2000 have by far the most misstatements (8.02% and 7.31% respectively). This may be because growth in technology stocks slowed around this time, providing incentives for managers to misstate earnings in order to mask declining growth.

[Table 2]

4. 2 Predictive Variables for Misstatements

Our next set of tests examines observable variables that we hypothesize to be associated with misstatements. This analysis provides the underpinnings for our subsequent development of our prediction model. Since all variables are consistently reported on an annual basis, we focus only on the sample of firms with annual misstatements in these tests. The tests compare misstatement years to non-misstatement years. Misstatement years are separately compared to (i) all non-misstatement years; and (ii) only years prior to the misstatement. Using all firm years provides the most powerful tests, while using only prior firm years sheds light on the predictive ability of the variables with respect to misstatements.

We investigate several different variables that we hypothesize to be associated with misstatements. Each variable is briefly discussed below. More detailed definitions are provided in Table 3. The variables that we analyze are not intended to be exhaustive of all variables correlated with accounting misstatements. Previous literature has identified several corporate governance variables and non-financial performance variables correlated with accounting misstatements that we do not consider in our analysis. Our goal in this analysis is not to identify and analyze all variables correlated with accounting misstatements, but rather to explore variables that are available for the largest set of firms and readily accessible to accounting researchers and practitioners. Focusing on this more limited set of variables allows us to create prediction models that are more general. We leave it to future research whether alternative variables add significantly to the power of our prediction models. The variables we analyze focus on accrual quality, financial performance, non-financial performance, off-balance sheet variables and stock market performance.

Accrual Quality

Starting with Healy (1985) a large body of literature hypothesizes that earnings are primarily misstated via the accrual component of earnings. We therefore investigate whether misstatement years are associated with unusually high accruals. The first measure termed *WC accruals*, focuses on working capital accruals and is described in Sloan (1996). Our next measure is from Richardson, Sloan, Soliman, and Tuna (2006) that we term *RSST accruals*. This measure extends the definition of *WC accruals* to include changes in long-term operating assets and long-term operating liabilities. This measure is equal to the change in non-cash net operating assets. We also look at two accrual components. The first is *change in receivables*. Misstatement of this account improves sales growth, a metric closely followed by investors. The second is *change in inventory*. Misstatement of this account improves gross margin, another metric closely followed by investors.

We also employ several 'discretionary accrual' models commonly used in the accounting literature to isolate accruals that are more likely to be attributable to misstatement. Our comprehensive sample of misstatements provides a unique opportunity to investigate whether these models enhance the ability to detect earnings misstatements. First, we employ the cross-sectional version of the *Modified Jones model discretionary accruals* (see Dechow, Sloan, and Sweeney 1996 for modified Jones model, and Defond and Jiambalvo (1994) for the cross-sectional version). We also investigate the effect of adjusting discretionary accruals for financial performance as suggested in Kothari, Leone, and Wasley (2005). We term this *Performance-matched discretionary accruals*. Finally, we employ two variations of the accrual quality measure described in Dechow and Dichev (2002). The Dechow and Dichev measure is based on the residuals obtained from industry-level regressions of working capital accruals on past, present, and future operating cash flows. Our first variation on this measure takes the absolute value of each residual and subtracts the average absolute value of the residuals for each industry. We term this the *mean-adjusted absolute value of DD residuals*. Our second variation scales each residual by its standard error from the industry-level regression. This measure leaves the sign of the residual intact and provides information on how many standard deviations the residual is above or below the regression line. We term this variable the *Studentized DD residuals*. We predict a positive association between all accrual variables and misstatement years.

Performance

A potential reason for managers to misstate their financial statements is to mask deteriorating financial performance. Our next set of variables gauges the firm's financial performance on various dimensions. The first we analyze is *change in cash sales*. This measure excludes accruals-based sales, such as credit sales, and we use it to evaluate whether sales that are not subject to accruals management are declining. We also analyze *change in cash margin*. Cash margin is equal to cash sales less cash cost of goods sold. This performance measure abstracts from receivable and inventory misstatements. We anticipate that when cash margins decline, managers are more likely to make up for the decline by boosting accruals. *Change in earnings* is also analyzed since managers appear to prefer to show positive growth in earnings (e.g., Burgstahler and Dichev, 1997). Therefore, during misstatement periods managers could be attempting to provide positive increases in earnings. *Change in free cash flows* is a more fundamental measure than earnings since it abstracts from accruals. We predict that managers are more likely to misstate when there is a decrease in free cash flows. We also investigate whether deferred tax expense increases during misstatement periods. Larger accounting income relative to taxable income is reflected in the deferred tax expense and could indicate more misstatement of book income (Phillips, Pincus, and Olhoft-Rego 2003).

Non-financial Measures

Economics teaches us that firms trade-off the marginal cost of labor against the marginal cost of capital to maximize profits. Investments in both labor and capital should lead to increases in future sales and profitability. However, unlike capital expenditures, most expenditure on labor must be expensed as incurred (the primary exception being direct labor that is capitalized in inventory). We therefore conjecture that managers attempting to mask deteriorating financial performance will reduce employee headcount in order to boost the bottom line. Moreover, if managers are overstating assets, then the difference between the change in the number of employees, which is not likely overstated, and the change in assets, which is overstated, might be a useful measure of the underlying economic reality. We measure *abnormal change in employees* as the percentage change in the number of employees less the percentage change in total assets. We predict a negative association between *abnormal change in employees* and misstatements.

Greater order backlog is indicative of higher future sales. When a firm exhibits a decline in order backlog, this suggests a slowing demand and lower future sales. We measure *abnormal change in order backlog* as the percentage change in order backlog less percentage change in sales. We predict a negative association between *abnormal change in order backlog* and misstatements.

Off-Balance Sheet Activities

The most prevalent source of off-balance sheet financing is operating leases. The accounting for operating leases allows firms to record lower expenses early on in the life of the lease (because the interest charge implicit in capital lease accounting is higher earlier on in the life of the lease). Therefore, the use of operating leases (*existence of operating leases*) and unusual increases in operating lease activity (*change in operating lease activity*) could be indicative of managers who are focused on financial statement window-dressing. We predict that *change in operating lease activity* is positively associated with misstatements. *Change in operating lease activity* is measured as the change in the present value of future non-cancelable operating lease obligations following Ge (2006).

Another off-balance sheet activity is the accounting for pension obligations and related plan assets for defined benefit plans. Firms have considerable flexibility on the assumptions that determine pension expense. The expected return on plan assets is an assumption that is relatively easy for managers to adjust. Management can increase the expected return on plan assets and immediately decrease currently reported pension expense. Comprix and Mueller (2006) provide evidence that such income-increasing adjustments are not filtered out of CEO compensation. Therefore, similar to leases, such adjustments could be indicative of managers who are focused on financial statement window-dressing. For the subset of firms that have defined benefit plans we obtain the *expected return on pension plan assets* and calculate *the change in expected return on pension plan assets*. We predict that in misstatement years, firms will assume larger expected returns on their plan assets.

Market-related Incentives

One obvious incentive for misstating earnings is to maintain a high stock price. We investigate whether managers who misstate their financial statements are particularly dependent on a high stock price. We examine two motivations. First, if the firm needs to raise cash to finance its ongoing operations and growth plans, then a high stock price will reduce the cost of raising new equity. High book value, consistent earnings performance and a high stock price will also reduce the cost of issuing new debt. We use various empirical constructs to capture a firm's need to raise additional capital. First, we use an indicator variable identifying whether the firm has issued new debt or equity during the misstatement period (*actual issuance*). Second, we look at the net amount of new financing raised, deflated by total assets (*CFF*). Third, we construct a measure of *ex ante financing need*. Some firms may have wished to raise new capital, but did not because they were unable to secure favorable terms; our ex ante measure of financing need provides a measure of the incentive to raise new capital. Following Dechow, Sloan, and Sweeney (1996) we report an indicator variable that equals one if the firm is estimated to have negative free cash flows over the next two years that exceed its current asset balance. Finally, we examine leverage. We expect that managers of firms with higher leverage will have incentives to boost financial performance both to satisfy financial covenants in existing debt contracts and to raise new debt on more favorable terms.

A second motivation for why managers may be particularly dependent on a high stock price is because a significant portion of management compensation is typically tied to stock price performance. This can cause managers to become overly concerned with maintaining or increasing their firm's stock price, since it affects their wealth. Such managers can become focused on managing 'expectations' rather than managing the business. We expect that managers whose firms have had large run-ups in their stock prices and have high prices relative to fundamentals are more prone to 'expectations' management. Managers of such firms are predicted to be more likely to misstate earnings to hide diminishing performance. We identify firms with optimistic expectations built into their stock prices using *market-adjusted stock return*, *earnings-to-price,* and *book-to-market*.

[Table 3]

4.3 Time-series Analysis of Misstating Firms

Table 4 provides our time-series analysis of misstating firms. Panel A compares misstatement years to all available non-misstatement years. We begin with our various measures of accrual quality and predict that accruals will be larger in misstatement years. The results indicate that *RSST accruals* has a slightly larger t-statistic than the *WC accruals* measure, suggesting that the more comprehensive RSST measure of accruals is more effective at detecting misstatements. *Change in receivables* has the highest t-statistic of all accrual variables, 6.76, probably because half of the misstating firms are alleged to have misstated sales. The next set of accrual variables relates to various models of 'discretionary' accruals. The objective of these models is to provide more powerful measures of earnings management by eliminating 'nondiscretionary' accruals that are required under GAAP. However, such modeling comes at the cost of unintentionally removing some of the 'discretionary' accruals. The t-statistic on *Jones discretionary accrual* is lower than that on either the *WC accruals* or *RSST accruals*, suggesting that this model could suffer from this problem. Interestingly, *performance-matching* has little effect on the results. The signed *Studentized DD residuals* appears to be the most powerful discretionary accrual model.

We next examine various measures of financial performance. We predict that misstatements are often made to mask deteriorating financial performance. Our first measure is *change in cash sales*. Contrary to our expectations, cash sales significantly increase (rather than decline) during misstatement years. A reading of the AAERs helps to explain why. We find that many firms engage in transactions-based earnings management. That is, they front-load their sales and engage in unusual transactions at the end of the quarter (e.g., Coca Cola, Sunbeam, Computer

Associates). Cash sales increase with this type of misstatement, providing an explanation for the finding. Cash margins, however, are declining but the difference is not statistically significant. Earnings are also declining at the time of misstatement, suggesting that accruals are being used to mask the extent of decline. *Change in free cash flows* is not significantly different across misstatement and non-misstatement years. *Deferred tax expense* is also not significantly different. For a small sample of 27 firms subject to SEC enforcement actions, Erickson, Hanlon, and Maydew (2004) show that firms pay substantial taxes on overstated earnings. For example, misstating cash sales boosts both accounting and tax income. If their findings are generalizable, then this could explain why deferred taxes are not unusually high during misstatement years.

We next turn to the non-financial variables, *abnormal change in employees* and *abnormal change in order backlog*. Both variables show significant declines during misstatement years. For our off-balance sheet variables, we find an increase in both the magnitude of operating lease commitments and the percentage of firms that use operating leases during misstatement years. It appears that misstating firms are quick to exploit the financial reporting flexibility afforded by operating leases. For defined benefit pension plans we have only a small sample size. We find that the *expected return on pension plan assets* is not significant but that the *change in expected return on pension plan assets* is significantly greater in misstatement years.

The final set of variables captures market-related incentives. As predicted, we find that *ex ante need for financing* is significantly greater in misstating years (18.9%) than in non-misstating years (11.2%). More firms are issuing either debt or equity (92.8% versus 88.5%) and cash from financing more than doubles during misstating years (20.4% versus 7.9%). We argue that incentives to misstate are higher during issuing periods. In addition, the SEC is probably more likely to perform a review when a firm is raising capital, and hence detect the misstatement.

Leverage is also significantly higher for misstatement years (19.6% versus 18.5%). *Market-adjusted stock return* is higher during misstatement years (18.3% versus 7.3%). We analyze this finding in more detail in Figure 3 discussed next. *Book to market* ratios are not significantly different while *earnings to price* ratios are lower in misstating periods, consistent with our prediction that misstating firms have optimistic future earnings growth expectations built into their prices.

Panel B replicates the analysis in Panel A but uses only years prior to the misstatement as non-misstatement years. We provide Panel B to identify variables that are most likely to be useful in predicting misstatements. For example, misstating firms typically report deteriorating future performance. But while deteriorating future performance may be associated with misstatements, it cannot be used to predict misstatements. Thus, Panel A sheds light on the overall characteristics of misstatement years, while Panel B focuses on characteristics that are most useful in predicting misstatements. The results are generally consistent with those in Panel A, but there are a few points to note. First, the significance of the accrual variables declines. For example, the difference between misstating years and non-misstating years declines by more than half for *RSST accruals* (0.085 to 0.041). This suggests that the inclusion of the subsequent accrual reversal boosts the power of these tests (e.g., the subsequent receivable inventory write-off). Note that the modified Jones Model pools across years to calculate the industry coefficients, and the Dechow and Dichev models use future cash flows, so these models would not be completely implementable for financial statement users. The power of both models is relatively unchanged across the two panels, but they involve an implicit hindsight bias. The results for the performance variables, off-balance sheet variables and market-related variables are similar across panels A and B. Book-to-market is now significant and in the predicted direction. Prior to the misstatement, these firms had relatively high market valuations relative to earnings or book value. Thus one reason managers may have misstated earnings was to maintain the current stock price at artificially high levels.

[Table 4]

Figure 3 provides a graphical timeline of (a) annual raw stock returns; and (b) annual market-adjusted stock returns for misstating firms before and after the misstatement years. For the firms misstating for multiple years, we take the average of their stock returns during the misstatement period. Both graphs reveal that returns are increasing in the three years leading up to the misstatement. In the misstatement years, on average, the firms are able to maintain positive stock returns. However, in the first year after the misstatement years, the stock prices decline and returns are negative. The negative returns likely result from the revelation of the misstatement (Feroz, Park and Pastena (1991) and Karpoff, Lee and Martin 2007).

[Figure 3]

4.4 Cross-sectional Analysis of Misstating Years

Our next test compares misstating firm-years to all firms listed on the Compustat Annual File between 1979 and 2002. We limit the sample to these years since the first AAER release occurred in 1982, and very few firms are identified as misstating prior to 1979. Using the AAER database, we identify 372 firms with 665 firm-year observations for our large cross-sectional sample. These tests identify unusual characteristics of misstating firms relative to the general population. We make this comparison since it is helpful to auditors and investors to make both time-series and cross-sectional comparisons.

Table 5 replicates the analysis in table 4, but compares misstating years to all firm-years available on Compustat. We exclude the performance matched discretionary accruals, since this adjustment is redundant when using the entire population. The results for the accrual quality related variables are very similar to those reported in Table 4. The accruals of misstating firms are unusually high relative to the population. For example, in misstating years the *RSST accrual* measure is 12.5 percent of assets; whereas, for the population, this measure is 2.9 percent of assets. Similarly, *change in receivables* is 5.9 percent for misstating firms and only 2.1 percent for the population. The *studentized DD* measure indicates that misstating firms' residuals are on average 0.41 deviations from the regression line in the positive direction.

For the performance variables, *change in cash sales* for misstating firms is about twice as large as for the population (0.495 versus 0.211). However, on other dimensions, performance for misstating firms is poor relative to the population. The *change in earnings* is significantly lower for misstating firms. The results for non-financial variables and off-balance sheet variables are all in the predicted direction. One difference from Table 4 is that misstating firms assume significantly higher expected returns on their plan assets than other firms (8.06% versus 7.17%). However, the change in expected returns is no longer significantly different.

Finally, for the market-related variables, the results indicate that demand for external financing is higher for misstating firms than for the average firm in the population. We report market-adjusted stock returns in the misstatement year and the prior year. Compared to the average firm, misstating firms have significantly greater returns in both years. In addition, misstating firms have high valuations relative to fundamentals when compared to the Compustat population. Similar to the results in Table 4 Panel B, both book-to-market and earnings-to-price are significantly lower for misstating firms (i.e., they have high valuations relative to fundamentals). The results in Table 5 confirm that the variables identified as unusual in time-series analysis also tend to be unusual in cross-sectional analysis.

[Table 5]

4.5 Prediction Analysis and Development of the *F-Score*

In this section we provide multivariate analysis of variables identified in Tables 4 and 5. Misstatements resulting in SEC Enforcement Actions are rare events. Our misstatement sample represents less than half of one percent of the firm-years available on Compustat. However, misstatements are extremely costly to the auditor (in terms of lawsuits), to investors (in terms of negative stock returns), to regulators like FASB and SEC (in terms of reputation for quality and enforcement of accounting rules), and to capital markets (in terms of lost investor confidence and reduced liquidity). Therefore, even though misstatements are rare, a model that can help identify misstatements is useful.

Table 6 provides our logistic models for the determinants of misstatements. Our dependent variable is equal to one for firm-years involving a misstatement, and zero otherwise. We estimate logistic regressions to determine whether the variables we have examined in univariate tests are jointly significant in predicting misstatement firm-years. We build three models for predicting misstatement. **Model 1** includes only financial statement variables as predictors; **Model 2** adds non-financial statement and off-balance sheet variables; and **Model 3** incorporates market-based measures. We form our models in this way so we can see the incremental benefit from including information beyond the financial statements for predicting misstatement. We use a backward elimination technique to arrive at our prediction models. The backward elimination technique begins with all of our selected variables.[4] We then use the computational algorithm of Lawless and Singhal (1978) to compute a first-order approximation of the remaining slope estimates for

[4] We exclude from the selection process discretionary accrual measures because we want variables that can be relatively easily calculated from the financial statements; variables calculated using the statement of cash flows (CFF and Ex ante financing need) because these variables would restrict our analysis to observations after 1987; variables that are not significantly different in Table 5; and order backlog and pension variables since these are available for a limited set of firms.

subsequent variable eliminations. Variables are removed based on these approximations. We set the significance level for elimination at the 15% level.[5]

Model 1 begins with our accruals quality measures, the performance measures, and the market-related measures that are computed from variables in the financial statements. After performing backward elimination, we retain the following variables: *RSST accruals, change in receivables, change in inventory, change in cash sales, change in earnings, and actual issuance*. For **Model 2**, we retain the variables from **Model 1** and add the non-financial variables and off-balance sheet variables. After backward elimination, we retain *abnormal change in employees* and *existence of operating leases*. For **Model 3**, we add our market-based variables (our two return measures and *book to market*). From which, *book to market* and *lagged market-adjusted stock return* are retained in the model after backward elimination. Table 6 Panel A provides the resulting coefficient estimates for the models. The coefficients are all in the predicted direction.

To examine the quality of our models, we analyze the predicted probabilities that the model assigns to each observation. Predicted values are obtained by plugging each firm's individual characteristics into the model and using the estimated coefficients to determine the predicted value. The predicted probability is derived as:

$$Probability = \frac{e^{(PredictedValue)}}{(1+e^{(PredictedValue)})}$$

We then divide the probability by the unconditional expectation of misstatement to calculate our *F-Score*. The unconditional expectation is equal to the number of misstatement firms divided by the total number of firms. Below is an example of how this is done for **Model 1** for Enron.

[5] We run the logistic procedure in SAS, with the model selection equal to BACKWARD and FAST. Other model selection procedures produce similar results.

Enron in 2000
Predicted Value:
=-6.789+.817 x (rsst_acc)+3.230 x (ch_rec)+2.436 x (ch_inv)+.122 x (ch_cs)+-.992 x (ch_earn)+.972 x (issue)
Predicted Value:
=-6.789+.817 x (.01659)+3.230 x (.17641)+2.436 x (.00718)+.122 x (1.3333)+-.992 x (-.01285)+.972 x (1)
Predicted Value=-5.041
Probability =$e^{(-5.041)} / (1+e^{(-5.041)})$
e= 2.71828183
Probability =0.00643
Unconditional probability = 498/(143,490 + 498) = 0.00345
F-Score = 0.0064/0.0035
F-Score for Enron = 1.86

An *F-Score* of 1.00 indicates that the firm has the same probability of misstatement as the unconditional expectation. *F-Scores* less than one indicate a lower probability of misstatement. *F-Scores* greater than one indicate higher probabilities of misstatement than the unconditional expectation. Enron has an *F-Score* of 1.86. This suggests that Enron has almost twice the probability of having misstated compared to a randomly selected firm from the population.

We begin our analysis of the *F-Score* in Table 6 Panel B by ranking firm-years into five portfolios based on the magnitude of their *F-Score*. We report the frequency with which misstating and non-misstating firms fall into each quintile and the minimum *F-Score* required to be included in each quintile. If our models do a good job in identifying misstatement firms, then we expect misstatement firms to be clustered in the fifth portfolio. The results for **Model 1** that include only financial statement variables indicate that 47.79 percent of misstatement firms are in Quintile 5, compared to the expected level of 20 percent. The cut-off to be included in Quintile 5 (i.e., the minimum value) is 1.217 and so Enron's score for 2000 of 1.86 easily places it in Quintile 5. **Model 2** that includes non-financial and off-balance sheet variables indicates that 47.24 percent of misstatement firms are in Quintile 5, while for **Model 3** that includes market-related variables 43.80% are included in Quintile 5.

We graphically examine the relative *F-Scores* for each of the models in Figure 4. Figure 4 provides the cumulative distribution of *F-Scores* for (a) misstating firm-years and (b) all publicly listed firms. The Panel at the bottom of Figure 4 provides the percentage of publicly listed firms and the percentage of misstating firms for various *F-Score* levels. The Panel indicates that 65.9% of misstating firms have *F-Scores* greater than 1 while only 35% of public firms have *F-Scores* greater than 1. As a rule of thumb, an *F-Score* greater than 1 can therefore be considered "above normal risk." Moving to higher *F-Scores*, we see that only five percent of public firms have an *F-Score* of 2.125 or greater, whereas 18.9% of misstating firms have this *F-Score* or higher. We label an *F-Score* greater than 2.125 as "high risk".

Figure 4 provides the distribution of *F-Scores* in the population and also insights into the likelihoods of *Type I* and *Type II* errors. A *Type I* error occurs when our model <u>incorrectly classifies a non-misstating firm</u> as a misstating firm. A *Type II* error occurs when our model <u>incorrectly classifies a misstating firm</u> as a non-misstating firm. The cost of these errors is not likely the same. From an auditor's perspective a *Type II* error is by far the more costly. When a misstatement goes undetected (and is later revealed), the auditor is likely to be sued by investors and sanctioned by regulatory bodies such as the SEC and the PCAOB. A *Type I* error (a non-misstating firm is suspected of misstatement) is not costless and may result in lost fees, as the auditor may choose to drop the client. Since *Type II* errors are more costly to the auditor, an auditor is likely to prefer a model that makes more *Type I* errors than *Type II* errors. This trade-off will determine the *F-score* cut-off that minimizes the auditor's costs. In Panel C of Table 6, we evaluate type I and type II error rates for an F-score cut-off of 1.00. The results for **Model 1** indicate that we correctly classify 328 of the 498 firms (65.9%). The *Type I* error rate (false classification of a regular firm) is 35% (as reflected in Figure 4). For **Model 2** and **Model 3** there is a slight decline in the sensitivity ratio (correct classification of misstating firms) to 65.78% and 63.36%, respectively.[6]

[Figure 4 and Table 6]

Figure 5 provides further insights into how to make the trade-off between *Type I* versus *Type II* errors. Figure 5A provides the error rates for **Model 1** in Table 6. At an *F-Score* of 0.000 all firms are classified as misstating firms, so the *Type I* error rate is 100% and the *Type II* error rate is 0%. As higher *F-Scores* are selected the *Type I* error rate declines, while the *Type II* error rate increases. At an *F-Score* cut-off of 1.00, the *Type I* error rate is 34.97% while the *Type II* error rate is 34.14% (as shown in Panel C of Table 6). Figure 5B reports the relative cost of errors ratio calculated as the number of *Type I* errors (incorrect classification of a non-misstatement firm) divided by the sensitivity (the number of correctly classified misstating firms) for each *F-score* cut-off. Assume that the cost of investigating a firm for misstatement is $1 and that all firms investigated that have misstated are detected. When the cost of missing a misstatement firm is over $290, then Figure 5B indicates that an *F-Score* of 0.000 should be used and all firms are investigated. At the other extreme, if the cost of missing a misstatement firm is less than $50 then no firms should be investigated (i.e., just pay the lawsuit costs as they occur). If the cost of a missed misstating firm is 153 times that of a non-misstating firm, then the *F-Score* cut-off should be 1.00. Here 50,185 of the 143,490 non-misstating firms have *F-Scores* greater than 1.00, while 328 of the 498 misstating firms have *F-Scores* greater than 1.00. At this point the costs are 50,185

[6] In Table 6 we include all observations with available data for the calculation of variables included in model selection. This results in the number of observations declining across models and makes direct comparisons across the models difficult. We reran **Model 1** and **2** using only observations available for **Model 3** and find that variable selection does not change (not tabulated). When we set an F-score cut-off of 1.00 we find that with a consistent set of observations **Model 3** correctly classifies as above, 63.36% (230/363) firms but that the correct classification for Model **1** declines to 58.40% (212/363) and for **Model 2** to 62.53% (227/363). This suggests that when considering only firms with stock price information, **Model 3** provides a slight improvement over **Model 2** and greater improvement over **Model 1.**

x \$1 and 328 x \$153 = \$50,184 and are approximately equal. The cost ratio of 153 is calculated as 50,185/170.

[Figure 5]

4.6 Marginal Analysis and Robustness Tests of F-Score Models

In this section we evaluate the relative importance of variables in the models for determining the magnitude of *F-Scores* (marginal effect analysis). We then examine the sensitivities of models to different time periods and industry clustering.

Table 7 provides our marginal effect analysis. In this test we: (i) calculate the value of the *F-Score* when all variables are held at their mean values; (ii) recalculate the *F-Score* after moving one independent variable to its lower quartile value, holding all other variables at their mean value; (iii) recalculate the *F-Score* moving the independent variable to its upper quartile value; (iv) calculate the change in the *F-Score* across the inter-quartile range for that variable (for indicator variables such as *actual issuance* the marginal impact is the difference in *F-Score* when the variable equals one versus zero); (v) repeat steps (ii) through (iv) for the next independent variable.

Table 7 Panel A reports the mean, upper and lower quartile values of the variables included in the models. Panel B provides the marginal effect analysis for **Model 1** through **3**. The first thing to note is that the average *F-Score* for **Model 1** is 0.835.[7] When *RSST* accruals are at their lower quartile value and all other variables are at their mean values, the *F-Score* changes from 0.835 to 0.796. Moving *RSST* accruals to their upper quartile value changes the *F-Score* to 0.879, giving an inter-quartile range of 0.083. The results for **Model 1** indicate that issuing securities (*issue*) has the greatest marginal impact of 0.620 on the *F-Score*. Since 81.4 percent of the sample

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[7] The mean *F-Score* differs from 1.00 (the unconditional expectation) because predicted values are determined using the exponential function that gives different weights than those obtained using a linear estimation technique such as ordinary least squares regressions (see the Enron example included in the text).

issue securities in a given year, a firm that does not issue has a far lower risk of being a misstating firm. Among the other variables, *change in receivables* (*ch_rec*) has the largest marginal effect of 0.153 on the *F-Score*. The joint marginal effect (when moving all independent variables in the predicted direction between the 1st and 3rd quartiles or between zero and one for indicator variables) increases the *F-Score* from 0.299 to 1.213. For **Model 2**, *existence of operating leases* (*leasedum*) has a relatively large marginal impact on the *F-Score* (0.430), note that 61.3 percent of firms have leases. *Actual issuance* (*issue*) and *change in receivables* (*ch_rec*) continue to have large marginal effects. For **Model 3**, in addition to the above variables, *RSST accrual (rsst_acc)* has a marginal impact of 0.095, while the interquartile change for *book to market* (*bm*) increases the *F-Score* by 0.077. Overall, the results in Table 7 suggest that all variables in the models contribute to the *F-Score*.

[Table 7]

We next investigate the sensitivity of our models to the time period examined. In Table 6 we develop our prediction model and evaluate its effectiveness using the same sample. Therefore the models suffer from a hindsight bias and could over-represent our predictive ability. To evaluate the importance of this concern we test the sensitivity of variable selection by estimating models using the backward elimination technique during the 1979 to 1998 time period. We follow a similar procedure of first including only financial statement variables, then adding off-balance sheet variables to **Model 2** and market-related variables to **Model 3**. We find that all and only the original variables load in **Model 1** in the earlier time period. The only change that occurs for **Model 2** and **Model 3** is that *abnormal change in employees* no longer loads. We report the results for **1979-1998 Model 3** in Table 8 Panel A Column (1). We use the new estimates from this model to predict the *F-Scores* for a hold-out sample of firm-years from 1999 to 2002. We rank the hold-out sample firms into quintiles and report the frequency and mean probabilities for misstating and non-misstating firms by quintiles. The results are reported in Table 8 Panel B. Compared to the results in Table 6 Panel B, the model shows a slight improvement in the percent of misstating firms classified in Quintile 5 (47.75% versus 43.80% in Table 6). In Panel C of Table 8 we find that using an F-Score cut-off of 1, the **1979-1998 Model 3** classifies 63.06% of misstating firms correctly (versus 63.36% in Table 6).

Another concern is that the internet boom years (1998 to 2000) represent a large proportion of misstatements and so could unduly effect variable selection. We therefore rerun our backward elimination technique for **Model 1** excluding these years. We find that *WC accruals* now loads as an incremental variable in **Model 1** and **Model 2**. However, when we add the market-related variables for **Model 3** we find that *WC accrual*s still loads but *change in receivables* and *change in inventory* are no longer included in the model and neither is *book-to-market.* This suggests that *change in receivables* and *change in inventory* were particularly important for identifying misstatement during boom years as was low *book-to-marke*t. However, it is an open question as to whether these variables will be important for predicting future misstatements. Note also that *change in receivables* and *change in inventory* are included in and highly correlated with *WC accruals* and so what the boom year results suggest is that it may be better in the future to give these variables the same weight of 2.461 rather than different weights of 2.173 and 2.676 as documented in **Model 3** of Table 6.

Table 2 Panel B documents that the computer, retail and service industries appear to be over-represented in the population of misstating firms. In addition, since leasing is used extensively in retail, another concern is that our leasing results could be due to the over-representation of retail firms in our sample. Our next test investigates whether our models are just identifying industry characteristics rather than firm characteristics. We create industry dummies and an interactive dummy (*retail* x *existence of operating leases*) and add these variables to the estimation of **Model 3** in Table 6. The results in Table 8 Panel A column (3) indicate that only the service industry is significant. Table 8 Panel B indicates that one additional firm is classified in Quintile 5 (160 versus 159 in Table 6) when we include industries as determinants. However using a cut-off *F-Score* of 1.00 we find that one less firm is correctly classified (229 versus 230 in Table 6). Therefore the models do not appear to be unduly driven by the computer, retail, or service industries.

[Table 8]

5. CONCLUSION

This paper provides a comprehensive sample of firms investigated by the SEC for misstating earnings. We conduct a detailed analysis of 2,190 Accounting and Auditing Enforcement Releases available between 1982 and 2005 and identify 677 firms with misstated quarterly or annual earnings. We document the most common types of misstatements and find that the overstatement of revenues and reserves are the most frequent types of misstatements. We also identify the industries and time periods in which misstatements are most common.

We investigate the characteristics of misstating firms on various dimensions, including accrual quality, financial performance, non-financial performance, off-balance sheet activities, and market-related variables. We find that at the time of misstatements, accrual quality is low and both financial and non-financial measures of performance are deteriorating. We also find that financing activities and related off-balance sheet activities are much more likely during misstatement periods. Finally, we find that managers of misstating firms appear to be very sensitive to their firm's stock price. These firms have experienced strong recent earnings and price performance and trade at high valuations relative to fundamentals. The misstatements appear to be made with the objective of covering up a slowdown in financial performance in order to maintain high stock market valuations.

Based on the above findings, we develop a logistic model to determine the probability of misstatements. The output of this model is an *F-Score* – a scaled probability that a firm has engaged in an earnings misstatement. We show that our models have power to detect misstatements both within sample and using a holdout sample. Using a cut-off *F-Score* of 1.00, we find that our models correctly identify over 60 percent of misstating firm-years. We suggest that the *F-Score* can be used as a first-pass screening device for detecting possible misstatements.

We emphasize that one unavoidable issue in developing models to detect misstatement is that the revelation of a misstatement is a rare event. Thus, similar to bankruptcy prediction models, our models generate a high frequency of false positives (i.e., many firms that do not have enforcement actions against them are predicted to have misstated their earnings). Another limitation of our analysis is that we can only identify misstatements that were actually identified by the SEC. There are likely many cases where a misstatement goes undetected, or is at least not subject to an SEC enforcement action. An interesting avenue for future research would be to investigate other high *F-Score* firms. For example, do high *F-score* firms engage in earnings management, within the realms of GAAP? Do they experience declines in subsequent financial performance? Are they more likely to record future asset write-offs or write-downs? In addition, can models be improved by considering corporate governance arrangements, top executive characteristics, or industry specific characteristics?

Our paper provides useful insights into research on earnings management. Prior research has generally focused on measures of discretionary accruals as proxies for incentives to engage in earnings management. Our results suggest that researchers could also consider using an *F-Score* as an alternative proxy for detecting the likelihood of earnings management. In addition, we find that growth in cash sales is unusually high during misstatement years. An important avenue for future research is to better understand the role of real transaction or cash flow management.

Finally, our analysis should provide useful insights to auditors, regulators, investors, and other financial statement users about the characteristics of misstating firms. By better understanding these characteristics, financial statement users should be in a better position to identify and curtail misstatement activity in the future. The efficient functioning of capital markets depends crucially on the quality of the financial information provided to capital market participants. Curtailing misstatement activity should lead to improved financial information and hence improved returns for investors and more efficient allocation of capital.

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Appendix 1: Variable Definitions of the Enforcement Releases Datasets

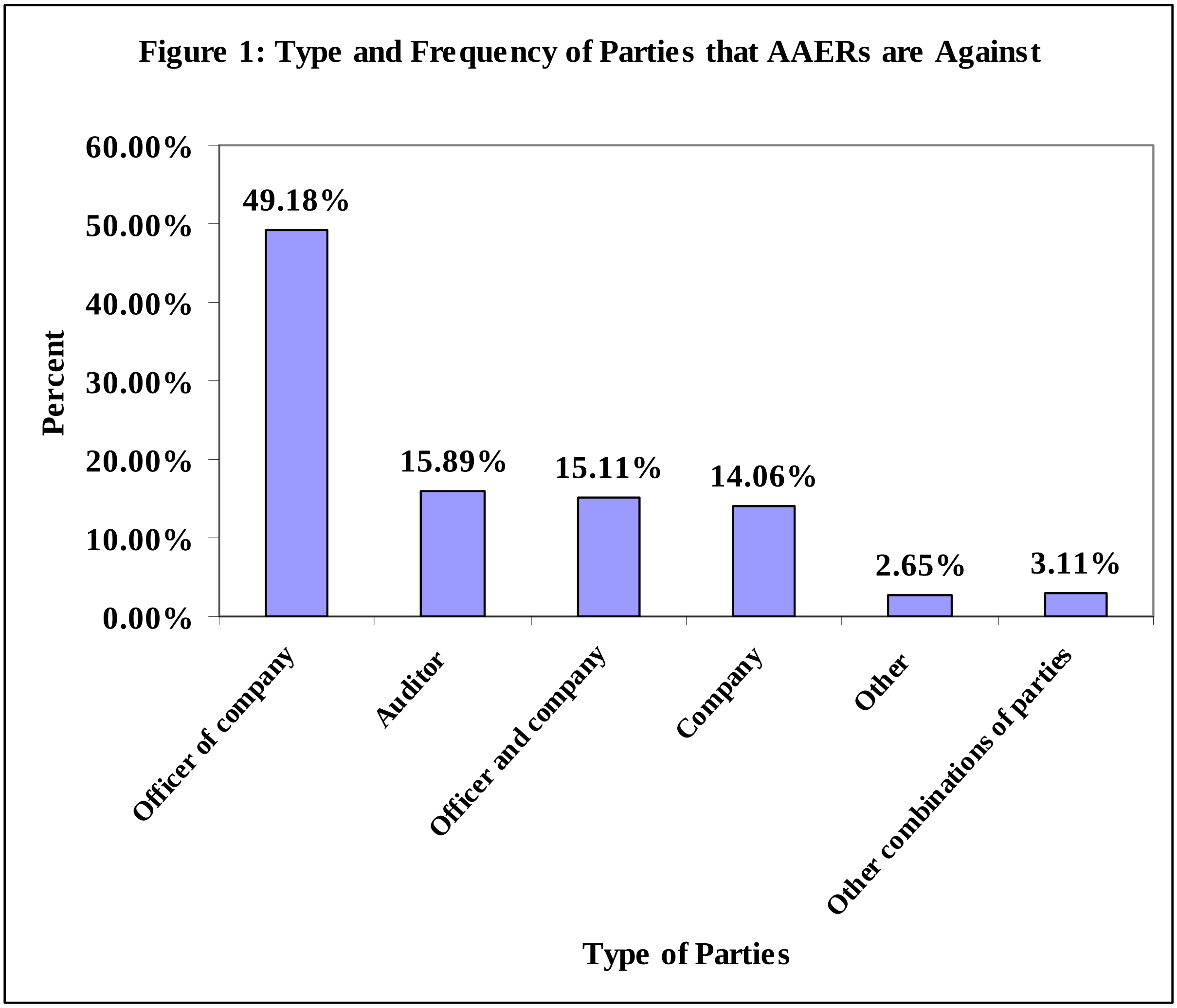
Panel A: DETAIL FILE	**detail.sas7bdat**
Variable Name	**Description**
coname	Name from AAER
CIK	Central Index Key
cnum	6-digit Cusip (not available in the public dataset)
ticker	Compustat ticker (not available in the public dataset)
gvkey	Compustat Gvkey (not available in the public dataset)
permno	CRSP Permno
iticker	IBES Ticker (not available in the public dataset)
eticker	Exchange Ticker
explanation	Two sentence explanation of the violation
Indicator variables (file inclusion):	
annual	Equals 1 if the firm is in the Annual file, 0 otherwise
quarter	Equals 1 if the firm is in the Quarterly file, 0 otherwise
reason	Reason why firm is not included in Annual or Quarterly files
Indicator variables (exclusion from Annual or quarterly files):	
audit	Equals 1 if the AAER was brought against the auditor and there was no misstatement, 0 otherwise
bribes	Equals 1 if the AAER was for bribe charges, 0 otherwise
disclosure	Equals 1 if related to disclosure issue only and not earnings misstatement, 0 otherwise
Nodates	Equals 1 if the time period of the financial misstatements cannot be determined from the AAER, 0 otherwise
Other	Equals 1 if related to other issues not listed above, 0 otherwise
Indicator variable (Accounts affected):	
Rev	Equals 1 if misstatement affected Revenues, 0 otherwise
rec	Equals 1 if misstatement affected Accounts Receivables, 0 otherwise
Cogs	Equals 1 if misstatement affected Cost of Goods Sold, 0 otherwise
Inv	Equals 1 if misstatement affected Inventory, 0 otherwise
Res	Equals 1 if misstatement affected reserves accounts, 0 otherwise
Debt	Equals 1 if misstatement affected bad debts, 0 otherwise
mkt_sec	Equals 1 if misstatement affected Marketable Securities, 0 otherwise
Pay	Equals 1 if misstatement affected Accounts Payable, 0 otherwise
Asset	Equals 1 if misstatement affected an asset account but could not be classified in an asset account above, 0 otherwise
Liab	Equals 1 if misstatement affected liabilities, 0 otherwise
inc_exp_se	Equals 1 if misstatement could not be classified in an income, expense or equity account above, 0 otherwise
Figure	Equals 1 if the actual amount of the misstatement can potentially be obtained from the AAER, 0 otherwise
AAER columns	There are 24 columns that identify all AAERs related to the firm
Total AAERs	Total number of AAERs for the firm
Reason for no Cnum	0 if firm has a cusip or a number that identifies why the firm has no Cusip

Appendix 1: (continued)

Panel B: ANNUAL FILE	**ann.sas7bdat**
Variable Name	**Description**
coname	Name from AAER
CIK	Central Index Key
permno	CRSP Permno
yeara	Compustat convention year
fyr	Fiscal month end
date	Actual misstatement date collected from AAER (DD/MM/YYYY)
p_aaer	Primary AAER used to collect data
understatement	Equals 1 if earnings/revenues were understated in the year, 0 otherwise

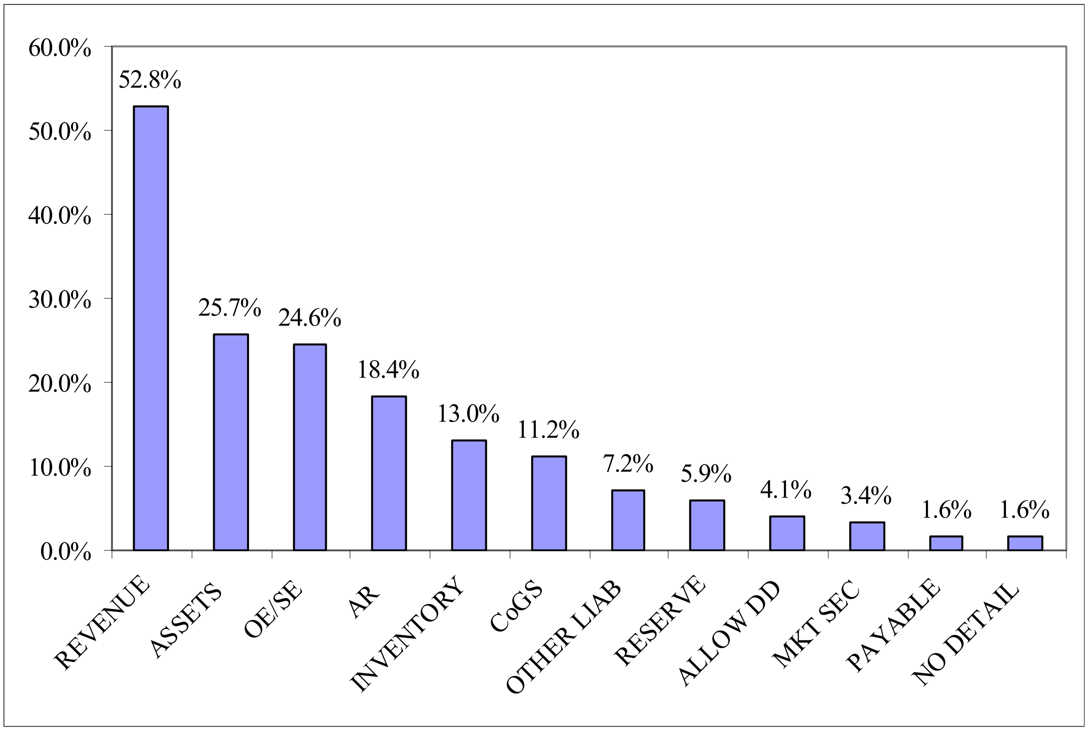
Panel C: QUARTERLY FILE	**qtr.sas7bdat**
Variable Name	**Description**
coname	Name from AAER
CIK	Central Index Key
permno	CRSP Permno
yeara	Compustat convention year
fyr	Fiscal month end
qtr	Quarter (1, 2, 3 or 4)
date	Actual date collected from AAER (DD/MM/YYYY)
p_aaer	Primary AAER used to collect data
understatement	Equals 1 if earnings/revenues were understated in the quarter, 0 otherwise

Figure 1
Percent of the 2,190 AAERs that are against various parties.



Notes: Categories add up to 2190 AAERs (100%).

Figure 2
Type of misstatements mentioned in the AAERs for 677 firms included in either the quarterly or annual file.

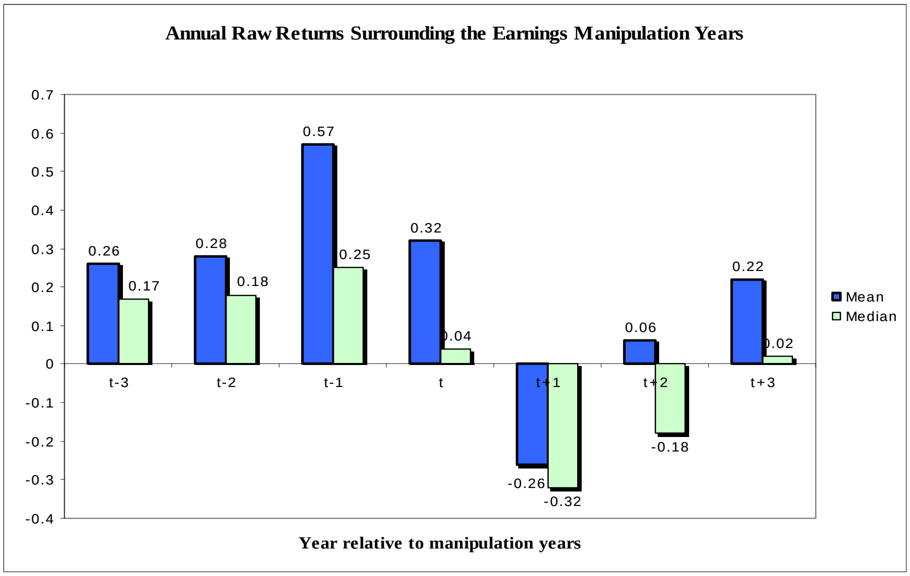


Notes:
There are 1150 misstatements mentioned in the AAERs for 677 firms so percentages add to more than 100 percent.

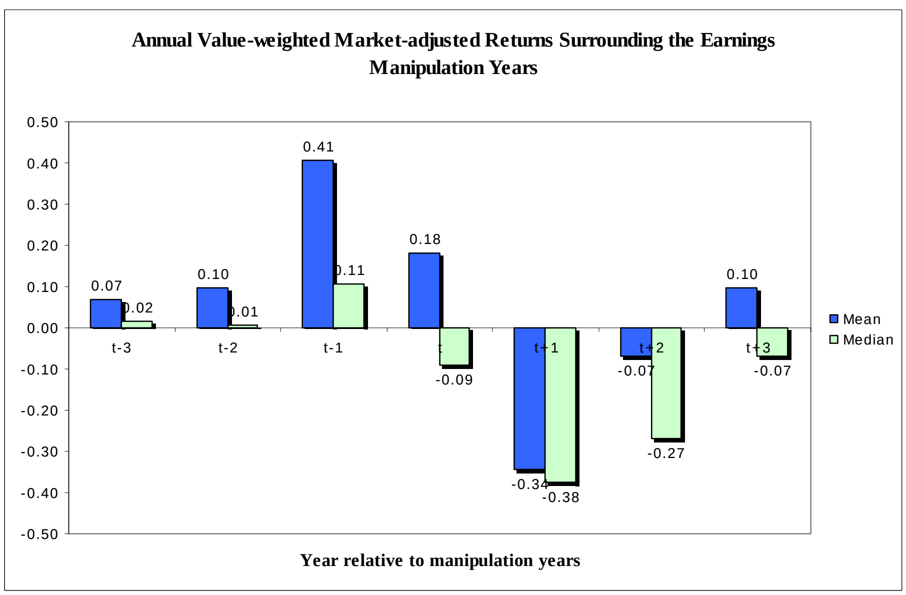
REVENUE	=	Misstated revenue
ASSETS	=	Capitalized costs as assets
OE/SE	=	Misstatement of other expense/shareholder equity account
AR	=	Misstated accounts receivable
INVENTORY	=	Misstated inventory
CoGS	=	Misstated cost of goods sold
OTHR LIAB	=	Misstated liabilities
RESERVE	=	Misstated a reserve account
ALLOW DD	=	Misstated allowance for bad debt
MKT SEC	=	Misstated marketable securities
PAYABLE	=	Misstated payables
NO DETAIL	=	No disclosure on how misstatement occurred

Figure 3
Stock price performance surrounding misstatement years

(a) Annual raw stock returns surrounding misstatement years.



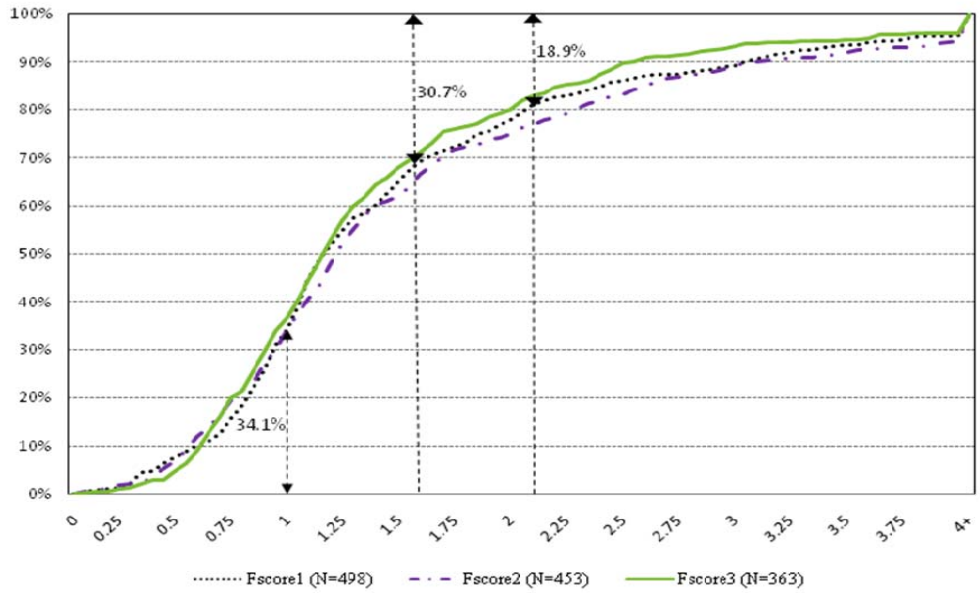
(b) Annual market-adjusted stock returns surrounding misstatement years.



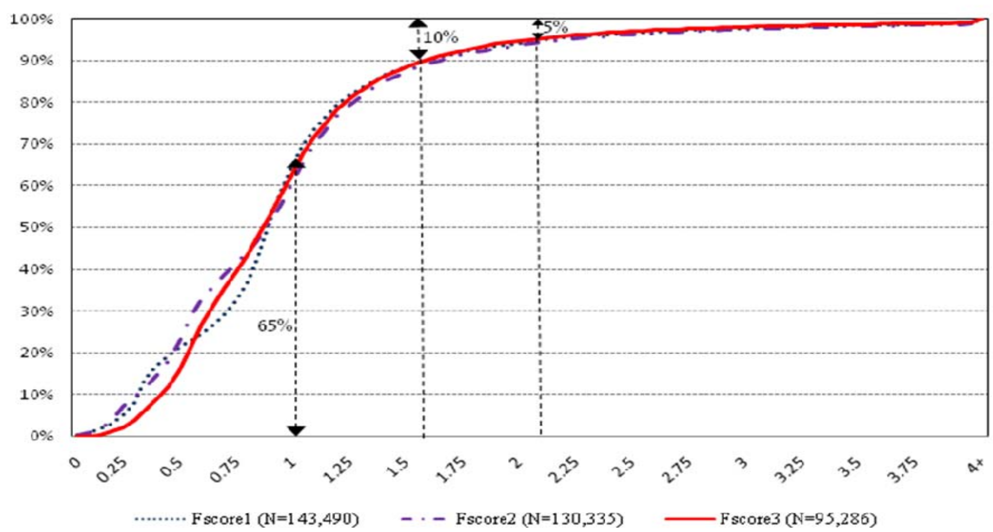
Note: For all firm-years with available returns data on CRSP. Returns include delisting returns. For year t-3 n=154, for year t-2 n=185, for year t-1 n=210, for year t n=510, for year t+1 n=213, for year t+2 n=182, for year t+3 n=141. Year t is the average return for all misstatement firms. Market-adjusted returns are calculated as the difference between annual raw returns and value-weighted market returns.

Figure 4: Evaluating the likelihood of a given F-score

- Figure 4A: Cumulative Distribution of F-scores for Misstating Firms



- Figure 4B: Cumulative Distribution of F-scores for All Firms Listed on NYSE, AMEX, and NASDAQ from 1979 to 2002 (Excluding Misstating Firms)



Interpreting F-score1 (Similar interpretation for F-score2 and F-score3)			
F-score1 greater than 2.125	5% of All Firms	18.9% of Misstating Firms	High Risk
F-score1 greater than 1.593	10% of All Firms	30.7% of Misstating Firms	Substantial Risk
F-score1 greater than 1	35% of All Firms	65.9% of Misstating Firms	Above Normal Risk
F-score1 less than 1	65% of All Firms	34.1% of Misstating Firms	Normal or Low Risk

Figure 5:
Analysis of error rates for Model 1 reported in Table 6 for F-Scores ranging from 0 to 3.00.

Figure 5A

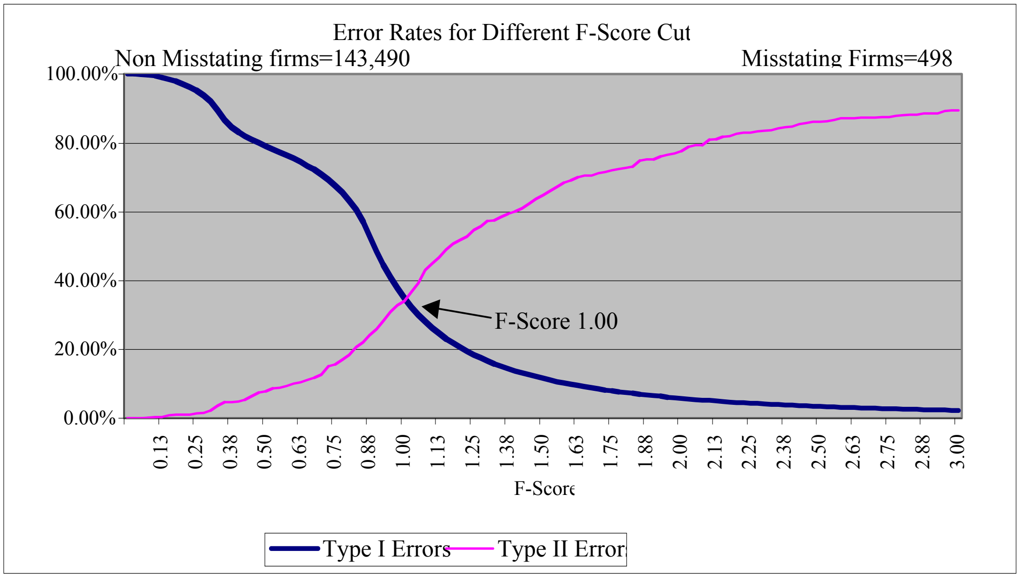
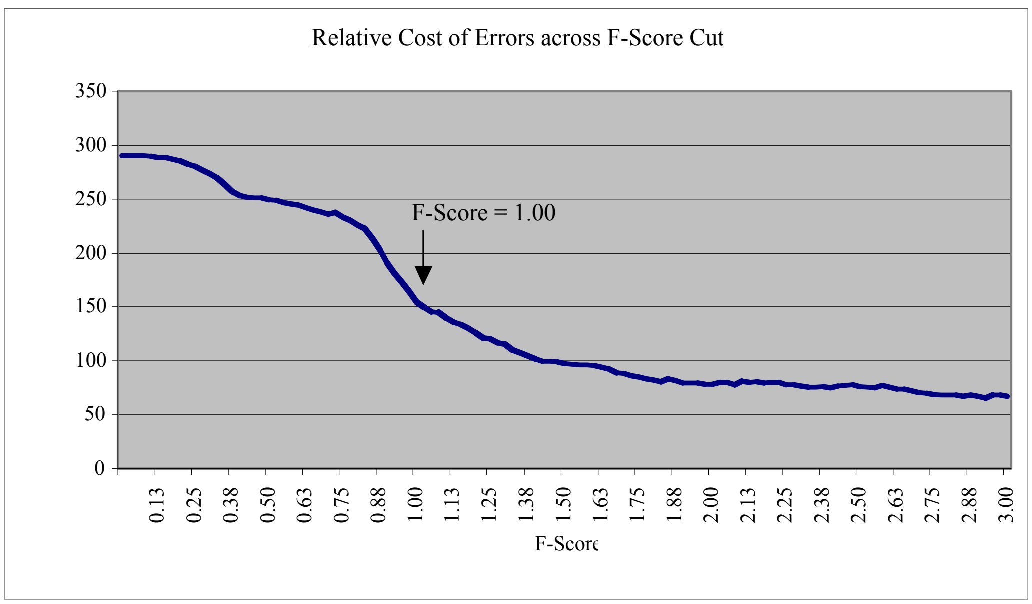


Figure 5B



Note: Figure 5A reports the Type I and Type II error rates for a given F-Score based on Model 1 in Table 6.
Type I errors = misclassified non-misstating firm; Type II errors = misclassified misstating firm.
Figure 5B reports the number of Type I errors divided by the sensitivity for each F-score cut-off. For example at an F-Score cut-off of 1.00, the total number of non-misstating firms is 143,490 of which 93,305 have F-Scores less than 1.00, the remaining 50,185 firms (Type I error firms) have F-Scores greater than 1.00. At an F-Score cut-off of 1.00, 328 of the 498 misstating firms have F-Scores greater than 1.00 (sensitivity firms or correctly classified misstating firms is 328), while 170 (type II error firms) have F-scores less than 1.00. At this F-Score cut-off the relative cost ratio is 153 (50,185/328). If the cost of investigating a non-misstating firm is less than 153 times the cost of missing a misstating firm, then investigating all firms with F-Scores of 1.00 or higher would reduce overall costs to the audit firm.

Table 1
Sample description

Panel A: Sample selection of AAERs

Number of AAERs	Number
AAER No. 1- No. 2261 from May 1982 to June 2005	2261
Less: missing AAERs	(30)
Less: AAERs that do not involve specific company names	(41)
Total	**2190**

Note: Among 30 missing AAERs, eleven AAERs are intentionally omitted and nineteen AAERs are missing.

Panel B: Frequency of AAERs by year

AAER release date	Number of AAERs	Percentage
1982	2	0.1%
1983	16	0.7%
1984	28	1.3%
1985	35	1.6%
1986	39	1.8%
1987	51	2.3%
1988	37	1.7%
1989	38	1.7%
1990	35	1.6%
1991	61	2.8%
1992	78	3.6%
1993	76	3.5%
1994	120	5.5%
1995	107	4.9%
1996	121	5.5%
1997	134	6.1%
1998	85	3.9%
1999	111	5.1%
2000	142	6.5%
2001	125	5.7%
2002	209	9.5%
2003	237	10.8%
2004	209	9.5%
2005	94	4.3%
Total	**2190**	100.0%

Table 1 (continued)

Panel C: Frequency of the number of AAERs by firm

Number of AAERs for each firm	Number of firms	Percent of firms	Total AAERs
1	371	41.5%	371
2	235	26.3%	470
3	106	11.8%	318
4	69	7.7%	276
5	40	4.5%	200
6	33	3.7%	198
7	15	1.7%	105
8	9	1.0%	72
9	3	0.3%	27
10	6	0.7%	60
11	2	0.2%	22
12	2	0.2%	24
13	1	0.1%	13
15	1	0.1%	15
20	1	0.1%	20
24	1	0.1%	24
Total	895	100.0%	2215

Note: There are 24 (2215 less 2191) AAERs involving multiple companies.

Panel D: Number of distinct firms

Number of distinct companies mentioned in the AAERs		Number
AAER No. 1- No. 2261 from May 1982 to June 2005		**895**
Less: Enforcements which are unrelated to earnings misstatement (e.g., bribes, disclosure etc.) or firms with misstatements that cannot be linked to specific reporting periods		218
Earnings misstatement firms		**677**
Less: firms without CUSIP		138
Firms with at least one quarter of misstated numbers		**539**
Firms with total assets on Compustat:	446	
Firms with stock price data on Compustat:	422	
Less: firms with quarterly misstatements corrected by the end of the fiscal year		92
Firms with at least one annual misstated number		**447**
Firms with total assets on Compustat:	376	
Firms with stock price data on Compustat:	350	

Table 2
Frequency of misstating firms by size, industry and calendar year
(both annual and quarterly misstatements)

Panel A: Frequency of the misstating firms by firm size (market capitalization) deciles

Decile rank of market value of Compustat population	Frequency	Percentage
1	22	5.2%
2	33	7.8%
3	35	8.3%
4	43	10.2%
5	37	8.8%
6	52	**12.3%**
7	47	11.1%
8	53	**12.6%**
9	38	9.0%
10	62	**14.7%**
Total	422	100.0%

Panel B: Frequency of the misstating firms by industry

Industry	Misstating Firms	Compustat Population
Agriculture	0.2%	0.4%
Mining & Construction	2.7%	3.0%
Food & Tobacco	2.5%	2.1%
Textile and Apparel	2.7%	1.7%
Lumber, Furniture, & Printing	2.3%	3.1%
Chemicals	2.3%	2.0%
Refining & Extractive	1.0%	4.7%
Durable Manufacturers	19.3%	18.9%
Computers	**20.5%**	**11.1%**
Transportation	4.4%	5.8%
Utilities	1.7%	3.2%
Retail	**12.9%**	**9.9%**
Services	**12.5%**	**10.4%**
Banks & Insurance	12.2%	20.8%
Pharmaceuticals	2.9%	3.2%
Total	100.0%	100.0%

Note: There are 422 misstating firms in the annual and quarterly files that have data to calculate market value and 482 misstating firms that have SIC codes. Industries are based on the following SIC codes: Mining: 1000–1299, 1400–1999; Food: 2000–2199; Textiles: 2200–2799; Drugs: 2830–2839, 3840–3851; Chemicals: 2800–2829, 2840–2899; Refining: 1300–1399, 2900–2999; Rubber: 3000–3499; Industrial: 3500–3569, 3580–3659; Electrical: 3660–3669, 3680–3699; Miscellaneous Equipment: 3800–3839, 3852–3999; Computers: 3570–3579, 3670–3679, 7370–7379; Transportation: 4000–4899; Utilities: 4900–4999; Retail: 5000–5999; Banks: 6000–6999; Services: 7000–7369, 7380–8999.

Table 2 (continued)

Panel C: Distribution of misstating firm-years

Year	Firm-years	Percentage
1971	1	0.12%
1972	1	0.12%
1973	1	0.12%
1974	2	0.24%
1975	2	0.24%
1976	1	0.12%
1977	1	0.12%
1978	4	0.48%
1979	10	1.20%
1980	15	1.80%
1981	20	2.40%
1982	32	3.83%
1983	24	2.87%
1984	25	2.99%
1985	17	2.04%
1986	30	3.59%
1987	25	2.99%
1988	27	3.23%
1989	40	4.79%
1990	32	3.83%
1991	46	5.51%
1992	48	5.75%
1993	42	5.03%
1994	35	4.19%
1995	36	4.31%
1996	39	4.67%
1997	43	5.15%
1998	52	6.23%
1999	**67**	**8.02%**
2000	**61**	**7.31%**
2001	39	4.67%
2002	14	1.68%
2003	3	0.36%
Total	835	100.00%

Note: This table is calculated based on the sample of 447 misstating firms (as shown in Table 1 Panel D) with at least one misstated annual financial statement.

Table 3: Variable definitions

	Variable	Abbrevia-tion	Pred Sign*	Calculation
	Misstatement flag	*misstate*	N/A	Indicator variable equal to 1 for misstatement firm-years and 0 otherwise
Accruals quality related variables	*WC accruals*	*WC_acc*	+	[[ΔCurrent Assets (DATA 4) – ΔCash and Short-term Investments (DATA 1)]– [ΔCurrent Liabilities (DATA 5) – ΔDebt in Current Liabilities (DATA 34) – ΔTaxes Payable (DATA 71)] – Depreciation (DATA 14)]/Average total assets; following Sloan (1996)
	RSST accruals	*rsst_acc*	+	(ΔWC + ΔNCO + ΔFIN)/Average total assets, where WC = [Current Assets (DATA 4) – Cash and Short-term Investments (DATA 1)] – [Current Liabilities (DATA 5) – Debt in Current Liabilities (DATA 34)]; NCO = [Total Assets (DATA 6) – Current Assets (DATA 4) - Investments and Advances (DATA 32)] – [Total Liabilities (DATA 181) – Current Liabilities (DATA 5) – Long-term Debt (DATA 9)]; FIN = [Short-term Investments (DATA 193) + Long-term Investments (DATA 32)] – [Long-term Debt (DATA 9) + Debt in Current Liabilities (DATA 34) + Preferred Stock (DATA 130)]; following Richardson et al. (2006)
	Change in receivables	*ch_rec*	+	ΔAccounts Receivables (DATA 2)/Average total assets
	Change in inventory	*ch_inv*	+	ΔInventory (DATA 3)/Average total assets
	Modified Jones model discretionary accruals	*da*	+	The modified Jones model discretionary accrual is estimated cross-sectionally each year using all firm-year observations in the same two-digit SIC code: *WC Accruals* = $\alpha + \beta(1/\text{Beginning assets}) + \gamma(\Delta \text{Sales}-\Delta \text{Rec})/\text{Beginning assets} + \rho\Delta \text{PPE}/\text{Beginning assets} + \varepsilon$. The residuals are used as the modified Jones model discretionary accruals.
	Performance-matched discretionary accruals	*dadif*	+	The difference between the modified Jones discretionary accruals for firm i in year t and the modified Jones discretionary accruals for the matched firm in year t, following Kothari et al (2005); each firm-year observation is matched with another firm from the same two-digit SIC code and year with the closest return on assets.
	Mean-adjusted absolute value of DD residuals	*resid*	+	The following regression is estimated for each two-digit SIC industry: $\Delta WC = b_0 + b_1{*}CFO_{t-1} + b_2{*}CFO_t + b_3{*}CFO_{t+1} + \varepsilon$. The mean absolute value of the residual is calculated for each industry and is then subtracted from the absolute value of each firm's observed residual.
	Studentized DD residuals	*sresid*	+	The scaled residuals are calculated as $\frac{\hat{e}_i}{\hat{\sigma}\sqrt{1-h_{ii}}}$ where h_{ii} is the *ii* element of the hat matrix, $X(X^TX)^{-1}X^T$ and $\hat{\sigma} = \sqrt{\frac{1}{n-m}\sum_{j=1}^{m}\hat{\varepsilon}^2_j}$ where m is the number of parameters in the model and n is the number of observations. SAS can output the scaled residuals using the following code: proc reg data= dataset; model Y=X; output data=temp student=studentresidual;

Performance variables	*Change in cash sales*	*ch_cs*	-	Percentage change in cash sales [Sales(DATA 12)-ΔAccounts Receivables (DATA 2)]
	Change in cash margin	*ch_cm*	-	Percentage change in cash margin, where cash margin is measured as [(Cost of Good sold (DATA 41) - ΔInventory (DATA 3)+ ΔAccounts payable (DATA70))/(Sales(DATA 12)- ΔAccounts Receivable(DATA 2))]
	Change in earnings	*ch_earn*	?	[Earnings_t (DATA 18)/Average total assets_t]- [Earnings_{t-1}/Average total assets_{t-1}]
	Change in free cash flows	*ch_fcf*	-	Δ[Earnings (DATA 18)-RSST Accruals] /Average total assets
	Deferred tax expense	*tax*	+	Deferred tax expense for year t (DATA 50) / total assets for year t-1 (DATA 6)
Non-financial variables	*Abnormal change in employees*	*ch_emp*	-	Percentage change in the number of employees (DATA 29) - percentage change in assets (DATA 6)
	Abnormal change in order backlog	*ch_backlog*	-	Percentage change in order backlog (DATA 98) - percentage change in sales(DATA 12)
Off-balance-sheet variables	*Existence of operating leases*	*leasedum*	+	An indicator variable coded 1 if future operating lease obligations are greater than zero
	Change in operating lease activity	*oplease*	+	The change in the present value of future non-cancelable operating lease obligations (DATA 96, 164, 165, 166 and 167) deflated by average total assets following Ge (2006)
	Expected return on pension plan assets (%)	*pension*	+	Expected return on pension plan assets (DATA 336)
	Change in Expected return on pension plan assets (%)	*ch_pension*	+	ΔExpected return on pension plan assets [DATA 336 at t) - (DATA 336 at t-1)]
Market Incentives	*Ex ante financing need*	*exfin*	+	An indicator variable coded 1 if [(CFO-past three year average capital expenditures)/Current assets]<-0.5
	Actual issuance	*issue*	+	An indicator variable coded 1 if the firm issued securities during year t (i.e., an indicator variable coded 1 if DATA 108>0 or DATA111>0)
	CFF	*cff*	+	Level of finance raised (DATA 313/Average total assets)
	Leverage	*leverage*	+	Long-term debt (DATA 9)/ Total assets (DATA 6)
	Market-adjusted Stock return	ret_t	+	Annual buy-and-hold return inclusive of delisting returns minus the annual buy-and-hold value-weighted market return
	Lagged market-adjusted Stock return	ret_{t-1}	+	Previous years annual buy-and-hold return inclusive of delisting returns minus the annual buy-and-hold value-weighted market return
	Book to market	*bm*	-	Equity (DATA 60)/ Market value (DATA 25 x DATA 199)
	Earnings to price	*ep*	-	Earnings (DATA 18)/ Market Value (DATA 25 x DATA 199)

*Predicted Sign shows the expected direction of the relations between various firm-year characteristics and misstatements

Table 4 Panel A
Descriptive statistics of misstatement years versus non-misstatement years for AAER firms.

	Misstatement years			Non-misstatement years				Misstate - Non-misstate		
Variable	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**Predicted sign**	**Diff. in Mean**	***One tailed P-value***	**t-statistics**
Accruals quality variables										
WC accruals	586	**0.018**	-0.004	4433	**-0.023**	-0.023	+	**0.041**	*0.001*	4.89
RSST accruals	592	**0.123**	0.063	4478	**0.038**	0.032	+	**0.085**	*0.001*	5.89
Change in receivables	605	**0.060**	0.032	4736	**0.025**	0.015	+	**0.035**	*0.001*	6.76
Change in inventory	594	**0.038**	0.005	4612	**0.020**	0.004	+	**0.018**	*0.001*	4.46
Modified Jones model discretionary accruals	550	**0.049**	0.022	3796	**0.003**	0.001	+	**0.046**	*0.001*	3.34
Performance-matched discretionary accruals	549	**0.048**	0.024	3796	**0.002**	0.002	+	**0.046**	*0.001*	3.33
Mean-adjusted absolute value of DD residuals	344	**0.017**	-0.012	2098	**0.000**	-0.022	+	**0.017**	*0.001*	3.00
Studentized DD residuals	344	**0.407**	0.270	2098	**0.061**	0.028	+	**0.346**	*0.001*	5.34
Performance variables										
Change in cash sales	526	**0.472**	0.203	4298	**0.194**	0.101	-	**0.278**	*0.001*	6.57
Change in cash margin	510	**-0.010**	0.002	4058	**0.010**	0.001	-	**-0.020**	*0.200*	-0.84
Change in earnings	549	**-0.023**	-0.011	4567	**-0.009**	0.000	+	**-0.014**	*0.066*	-1.51
Change in free cash flows	530	**0.028**	0.006	4114	**0.011**	0.004	-	**0.017**	*0.152*	1.03
Deferred tax expense	609	**0.001**	0.000	4659	**0.002**	0.000	+	**-0.001**	*0.260*	-0.64
Non-financial variables										
Abnormal change in employees	533	**-0.235**	-0.096	4400	**-0.097**	-0.052	-	**-0.139**	*0.001*	-3.72
Abnormal change in order backlog	152	**-0.028**	-0.075	1104	**0.069**	-0.027	-	**-0.097**	*0.069*	-1.49
Off-balance sheet variables										
Change in operating lease activity	612	**0.016**	0.002	4932	**0.007**	0.000	+	**0.008**	*0.001*	4.62
Existence of operating leases	659	**0.781**	1.000	5295	**0.623**	1.000	+	**0.158**	*0.001*	9.07
Expected return on pension plan assets (%)	76	**8.095**	9.000	651	**7.730**	8.500	+	**0.365**	*0.147*	1.05
Change in expected return on plan assets (%)	63	**-0.159**	0.000	562	**-9.345**	0.000	+	**9.186**	*0.027*	1.94
Market-related variables										
Ex ante financing need	433	**0.189**	0.000	2521	**0.112**	0.000	+	**0.077**	*0.001*	3.88
Actual issuance	637	**0.928**	1.000	4375	**0.885**	1.000	+	**0.043**	*0.001*	3.81
CFF	449	**0.204**	0.099	2644	**0.079**	0.004	+	**0.124**	*0.001*	7.57
Leverage	659	**0.196**	0.158	5295	**0.185**	0.133	+	**0.011**	*0.087*	1.36
Market-adjusted stock return	510	**0.183**	-0.091	3664	**0.073**	-0.027	+	**0.110**	*0.054*	1.61
Book to market	601	**0.555**	0.369	4389	**0.545**	0.471	-	**0.009**	*0.393*	0.27
Earnings to price	380	**0.070**	0.046	3393	**0.084**	0.065	-	**-0.014**	*0.001*	-3.63

All variables are defined in Table 3. Each of the continuous variables (except stock return variables) is winsorized at 1% and 99% to mitigate outliers.

Table 4 Panel B
Descriptive statistics on misstatement years versus YEARS PRIOR TO MISSTATEMENT YEARS for AAER firms

	Misstatement years			Early years				Misstate – Early Years		
Variable	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**Predicted Sign**	**Diff. in Mean**	***One tailed P-value***	**t-statisics**
Accruals quality variables										
WC accruals	586	**0.018**	-0.004	2602	**0.002**	-0.012	+	**0.016**	*0.028*	1.92
RSST accruals	592	**0.123**	0.063	2636	**0.081**	0.046	+	**0.041**	*0.003*	2.85
Change in receivables	605	**0.060**	0.032	2806	**0.043**	0.024	+	**0.018**	*0.001*	3.34
Change in inventory	594	**0.038**	0.005	2706	**0.034**	0.013	+	**0.004**	*0.170*	0.96
Modified Jones model discretionary accruals	550	**0.049**	0.022	2164	**0.012**	0.003	+	**0.037**	*0.004*	2.67
Performance-matched discretionary accruals	549	**0.048**	0.024	2164	**0.013**	0.007	+	**0.035**	*0.007*	2.50
Mean-adjusted absolute value of DD residuals	344	**0.017**	-0.012	768	**-0.001**	-0.017	+	**0.018**	*0.002*	2.94
Studentized DD residuals	344	**0.407**	0.270	768	**0.202**	0.129	+	**0.206**	*0.002*	2.92
Performance variables										
Change in cash sales	526	**0.472**	0.203	2449	**0.246**	0.135	-	**0.226**	*0.001*	5.24
Change in cash margin	510	**-0.010**	0.002	2301	**0.009**	0.001	-	**-0.019**	*0.213*	-0.80
Change in earnings	549	**-0.023**	-0.011	2648	**0.001**	0.000	+	**-0.024**	*0.003*	-2.74
Change in free cash flows	530	**0.028**	0.006	2337	**0.009**	0.003	-	**0.019**	*0.133*	1.11
Deferred tax expense	609	**0.001**	0.000	2690	**0.003**	0.000	+	**-0.002**	*0.036*	-1.80
Non-financial variables										
Abnormal change in employees	533	**-0.235**	-0.096	2599	**-0.125**	-0.070	-	**-0.110**	*0.002*	-2.91
Abnormal change in order backlog	152	**-0.028**	-0.075	580	**0.067**	-0.043	-	**-0.095**	*0.105*	-1.26
Off-balance sheet variables										
Change in operating lease activity	612	**0.016**	0.002	2955	**0.010**	0.000	+	**0.005**	*0.002*	2.85
Existence of operating leases	659	**0.781**	1.000	3282	**0.516**	1.000	+	**0.265**	*0.001*	14.47
Expected return on pension plan assets (%)	76	**8.095**	9.000	184	**8.770**	9.000	+	**-0.675**	*0.023*	2.03
Change in expected return on plan assets (%)	63	**-0.159**	0.000	145	**-6.517**	0.000	+	**6.359**	*0.092*	1.33
Market-related variables										
Ex ante financing need	433	**0.189**	0.000	943	**0.115**	0.000	+	**0.075**	*0.001*	3.48
Actual issuance	637	**0.928**	1.000	2498	**0.906**	1.000	+	**0.022**	*0.032*	1.85
CFF	449	**0.204**	0.099	989	**0.125**	0.026	+	**0.079**	*0.001*	4.32
Leverage	659	**0.196**	0.158	3282	**0.185**	0.142	+	**0.011**	*0.094*	1.32
Market-adjusted stock return	510	**0.183**	-0.091	2267	**0.105**	0.009	+	**0.077**	*0.052*	1.63
Book to market	601	**0.555**	0.369	2508	**0.657**	0.507	-	**-0.102**	*0.002*	-2.95
Earnings to price	380	**0.070**	0.046	2266	**0.084**	0.068	-	**-0.014**	*0.001*	-3.39

All variables are defined in Table 3. Each of the continuous variables (except stock return variables) is winsorized at 1% and 99% to mitigate outliers.

Table 5
Descriptive statistics on misstatement firm-years versus Compustat firm-years for the sample from 1979 to 2002.

	Misstatement firm-years			Compustat firm-years				Misstate – Compustat		
Variable	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**Predicted sign**	**Diff. in Mean**	***One-tailed P-value***	**t-statistics**
Accruals quality variables										
WC accruals	574	**0.015**	-0.002	169234	**-0.042**	-0.037	+	**0.057**	*0.001*	7.00
RSST accruals	580	**0.125**	0.068	173927	**0.029**	0.020	+	**0.096**	*0.001*	6.62
Change in receivables	592	**0.059**	0.033	177096	**0.021**	0.009	+	**0.039**	*0.001*	8.00
Change in inventory	582	**0.038**	0.006	178567	**0.010**	0.000	+	**0.028**	*0.001*	7.36
Modified Jones model discretionary accruals	522	**0.055**	0.025	150599	**0.000**	0.001	+	**0.056**	*0.001*	4.11
Mean-adjusted absolute value of DD residuals	343	**0.017**	-0.012	91303	**0.000**	-0.019	+	**0.017**	*0.001*	3.13
Studentized DD residuals	343	**0.408**	0.269	91303	**0.002**	0.014	+	**0.406**	*0.001*	6.58
Performance variables										
Change in cash sales	515	**0.495**	0.207	153140	**0.211**	0.077	-	$\boxed{\textbf{0.284}}$	*0.001*	5.99
Change in cash margin	499	**-0.006**	0.001	146520	**0.026**	0.003	-	**-0.032**	*0.141*	-1.07
Change in earnings	537	**-0.023**	-0.011	166354	**-0.009**	-0.001	+	$\boxed{\textbf{-0.014}}$	*0.060*	-1.56
Change in free cash flows	519	**0.031**	0.006	156452	**0.019**	0.004	-	**0.012**	*0.258*	0.65
Deferred tax expense	599	**0.001**	0.000	183631	**0.001**	0.000	+	**0.000**	*0.456*	0.11
Non-financial variables										
Abnormal change in employees	492	**-0.164**	-0.095	145802	**-0.063**	-0.048	-	**-0.101**	*0.001*	-3.39
Abnormal change in order backlog	143	**-0.008**	-0.062	36495	**0.087**	-0.041	-	**-0.095**	*0.091*	-1.33
Off-balance sheet variables										
Change in operating lease activity	599	**0.016**	0.002	183754	**0.007**	0.000	+	**0.008**	*0.001*	4.58
Existence of operating leases	599	**0.803**	1.000	183754	**0.658**	1.000	+	**0.145**	*0.001*	8.90
Expected return on pension plan assets	74	**8.057**	9.000	26272	**7.168**	8.500	+	**0.889**	*0.003*	2.83
Change in expected return on plan assets	63	**-0.159**	0.000	22248	**-4.234**	0.000	+	**4.076**	*0.177*	0.91
Market-related variables										
Ex ante finance need	432	**0.190**	0.000	110870	**0.163**	0.000	+	**0.026**	*0.081*	1.40
Actual issuance	582	**0.933**	1.000	171171	**0.816**	1.000	+	**0.117**	*0.001*	11.23
CFF	448	**0.207**	0.100	116048	**0.134**	0.006	+	**0.073**	*0.001*	4.51
Leverage	599	**0.200**	0.158	183612	**0.192**	0.128	+	**0.008**	*0.157*	1.01
Mkt-adj return	506	**0.185**	-0.089	168255	**0.045**	-0.060	+	**0.140**	*0.018*	2.10
Lagged mkt-adj return	437	**0.291**	0.021	154079	**0.054**	-0.055	+	**0.237**	*0.001*	3.33
Book-to-market	571	**0.534**	0.368	158384	**0.663**	0.573	-	**-0.129**	*0.001*	-4.28
Earnings-to-price	361	**0.067**	0.046	104697	**0.087**	0.069	-	**-0.019**	*0.001*	-4.86

All variables are defined in Table 3. Each of the continuous variables (except stock return variables) is winsorized at 1% and 99% to mitigate outliers. Note that even though we restrict our sample to 1979-2002 in the cross-sectional analysis, for some variables, the number of observations appears to be slight larger in Table 5. This is because in the time-series analysis, we eliminate those observations with available data only in either misstatement period or non-misstatement period to make the comparison meaningful.

Table 6 Panel A: Logistic regressions (dependent variable is equal to one if the firm-year misstated earnings, zero otherwise) examining the determinants of misstatements.

Variable	**Model 1** **Financial Statement Variables**	**Model 2** **Add Off-balance sheet and Non-financial Variables**	**Model 3** **Add Stock Market-based Variables**
	Coefficient Estimate (Wald Chi-square) (P-value)	Coefficient Estimate (Wald Chi-square) (P-value)	Coefficient Estimate (Wald Chi-square) (P-value)
Intercept	**-6.789**	**-7.184**	**-6.591**
	1460.9	1099.2	717.1
	0.000	*0.000*	*0.000*
RSST accruals	**0.817**	**0.702**	**1.019**
	25.5	14.2	16.5
	0.000	*0.000*	*0.000*
Change in receivables	**3.230**	**3.035**	**2.173**
	46.3	35.6	11.5
	0.000	*0.000*	*0.001*
Change in inventory	**2.436**	**2.678**	**2.676**
	15.9	18.0	12.3
	0.000	*0.000*	*0.001*
Change in cash sales	**0.122**	**0.105**	**0.097**
	10.5	5.9	2.7
	0.001	*0.015*	*0.098*
Change in earnings	**-0.992**	**-1.124**	**-1.412**
	22.8	24.9	22.2
	0.000	*0.000*	*0.000*
Actual issuance	**0.972**	**0.839**	**0.478**
	28.0	18.2	5.0
	0.000	*0.000*	*0.025*
Abnormal change in employees		**-0.199**	**-0.209**
		5.1	3.5
		0.023	*0.063*
Existence of operating leases		**0.615**	**0.516**
		19.3	10.9
		0.000	*0.001*
Book to market			**-0.134**
			3.6
			0.058
Lagged market-adjusted stock return			**0.068**
			5.2
			0.023
Misstating Firm-years:	498	453	363
Non-misstating Firm-years:	143,490	130,335	95,286

Table 6 Panel B: Examination of the detection rates of misstating and non-misstating firms for each Model reported in Panel A.

	Model 1			Model 2			Model 3		
	N	**Minimum *F-Score***	**% of Total**	**N**	**Minimum *F-Score***	**% of Total**	**N**	**Minimum *F-Score***	**% of Total**
Quintile 1									
Misstate Firms	37	0.060	7.43%	29	0.073	6.40%	22	0.093	6.06%
No-Misstate Firms	28,760	0.013	20.04%	26,128	0.010	20.05%	19,107	0.012	20.05%
Quintile 2									
Misstate Firms	66	0.481	13.25%	54	0.487	11.92%	52	0.544	14.33%
No-Misstate Firms	28,732	0.476	20.02%	26,104	0.477	20.03%	19,078	0.541	20.02%
Quintile 3									
Misstate Firms	55	0.831	11.04%	70	0.732	15.45%	55	0.774	15.15%
No-Misstate Firms	28,743	0.831	20.03%	26,088	0.728	20.02%	19,075	0.759	20.02%
Quintile 4									
Misstate Firms	**102**	**0.961**	**20.48%**	**86**	**0.997**	**18.98%**	**75**	**0.973**	**20.66%**
No-Misstate Firms	28,696	0.959	20.00%	26,072	0.993	20.00%	19,055	0.969	20.00%
Quintile 5									
Misstate Firms	**238**	**1.217**	**47.79%**	**214**	**1.273**	**47.24%**	**159**	**1.238**	**43.80%**
No-Misstate Firms	28,559	1.216	19.90%	25,943	1.269	19.90%	18,971	1.236	19.91%

Note: All observations are ranked based on their predicted probabilities (*F-Scores*) and sorted into Quintiles. Minimum *F-Score* is the minimum scaled predicted probability based on estimates in Panel A to enter each quintile.

Panel C: *F-Score* cut-off set at 1.00

	Model 1 Predicted			Model 2 Predicted			Model 3 Predicted		
Observed	Manip.	No-Manip.		Manip.	No-Manip.		Manip.	No-Manip.	
Misstate	**328**	170	498	**298**	155	453	**230**	133	363
No-Misstate	50,185	**93,305**	143,490	51,013	**79,322**	130,335	35,087	**60,199**	95,286
	50,513	93,475	**143,988**	51,311	79,477	**130,788**	35,317	60,332	**95,649**
Misstate	**65.86%**	34.14%	0.3%	**65.78%**	34.22%	0.3%	**63.36%**	36.6%	0.4%
No-Misstate	34.97%	**65.03%**	99.7%	39.14%	**60.86%**	99.7%	36.82%	**63.18%**	99.6%

	Model 1		Model 2	Model 3
Correct classification	**65.03%**	(1)	**60.88%**	**63.18%**
Sensitivity	65.86%	(2)	65.78%	63.36%
Type I errors	34.97%	(3)	39.14%	36.82%
Type II errors	34.14%	(4)	34.22%	36.64%

Notes:

(1) Correct classification is calculated as (328+93,305/143,988)

(2) Sensitivity is calculated as (328/498)

(3) *Type I* errors are calculated as (50,185/143,490)

(4) *Type II* errors are calculated as (170/498)

All variables are defined in Table 3. Each of the continuous variables (except stock return variables) is winsorized at 1% and 99% to mitigate outliers.

Table 7 Marginal effect analysis on *F-Scores* for each model

Panel A: Descriptive statistics

	rsst_acc	*ch_rec*	*ch_inv*	*ch_cs*	*ch_ earn*	*issue*	*ch_emp*	*Lease dum*	*bm*	ret_t	ret_{t-1}
Mean	0.030	0.022	0.011	0.205	-0.005	0.814	-0.068	0.613	0.712	0.046	0.055
Std Dev	0.288	0.090	0.066	0.860	0.204	0.389	0.403	0.487	1.048	0.921	0.929
Lower Quartile	-0.029	-0.008	-0.002	-0.048	-0.030	1.000	-0.159	0.000	0.297	-0.337	-0.323
Median	0.024	0.010	0.000	0.088	0.000	1.000	-0.051	1.000	0.594	-0.060	-0.055
Upper Quartile	0.092	0.049	0.022	0.252	0.022	1.000	0.054	1.000	1.037	0.237	0.238
1%	-1.234	-0.299	-0.238	-1.726	-0.981	0.000	-2.146	0.000	-4.941	-0.982	-0.943
99%	1.221	0.385	0.291	6.024	0.945	1.000	1.490	1.000	4.649	2.821	2.826

Panel B: *F-Score* when one variable is at the lower and upper quartile while all other variables at set at their mean values (except indicator variables that are set at 0 or 1)

Model 1	*rsst_acc*	*ch_rec*	*ch_inv*	*ch_cs*	*ch_earn*	*issue*
Coefficient estimate	0.817	3.23	2.436	0.122	-0.992	0.972
F-Score at upper quartile[b]	0.879	0.911	0.857	0.840	0.856	0.999
F-Score at lower quartile[a]	0.796	0.758	0.808	0.810	0.813	0.379
Inter-quartile marginal change in *F-Score* [c]	0.083	**0.153**	0.049	0.030	0.043	**0.620**

F-Score when all variables are at their: mean values (0.835); lower quartile (0.299); upper quartile (1.213). Change in *F-Score* for joint interquartile marginal effect (moving all variables from the lower to the upper quartile) (0.914)

Model 2	*rsst_ acc*	*ch_rec*	*ch_inv*	*ch_cs*	*ch_earn*	*issue*	*ch_ emp*	*Lease dum*
Coefficient estimate	0.702	3.035	2.678	0.105	-1.124	0.839	-0.199	0.615
F-Score at upper quartile	0.773	0.802	0.762	0.743	0.760	0.864	0.753	0.938
F-Score at lower quartile	0.710	0.675	0.713	0.720	0.717	0.374	0.722	0.508
Inter-quartile marginal change in *F-Score*	0.063	**0.127**	0.049	0.023	0.043	**0.490**	0.031	**0.430**

F-Score when all variables are at their: mean values (0.740); lower quartile (0.200); upper quartile (1.343). Change in *F-Score* for joint interquartile marginal effect (1.143).

Model 3	*rsst_ acc*	*ch_ rec*	*ch_ inv*	*ch_cs*	*ch_ earn*	*issue*	*ch_ emp*	*Lease dum*	*bm*	ret_{t-1}
Coefficient estimate	1.019	2.173	2.676	0.097	-1.412	0.478	-0.209	0.516	-0.134	0.068
F-Score at upper quartile	0.825	0.821	0.797	0.778	0.802	0.846	0.789	0.945	0.819	0.784
F-Score at lower quartile	0.730	0.725	0.747	0.756	0.745	0.525	0.755	0.565	0.742	0.755
Inter-quartile marginal	**0.095**	**0.096**	0.050	0.022	0.057	**0.321**	0.034	**0.380**	**0.077**	0.029

F-Score when all variables are at their: mean values (0.775); lower quartile (0.278); upper quartile (1.360). Change in *F-Score* for joint interquartile marginal effect (1.082).

[a] For indicator variables such as *issue*, we calculated *F-Score* when the indicator variable = 0 for lower quartile and 1 for upper quartile. Therefore, for *Actual issuance*, the marginal effect on *F-Score* reflects changing *issue* from 0 to 1.

[b] For variables with negative coefficient estimates (e.g., *ch_earn, ch_emp, bm)*, *F-Score* at lower quartile reflects the upper quartile values of these variables and *F-Score* at upper quartile reflects the lower quartile values.

[c] Inter-quartile marginal change in *F-Score* reflects the difference in F-Score for interquartile change in the predicted direction for each variable when holding other variables at their mean values.

All variables are defined in Table 3. Each of the continuous variables is winsorized at 1% and 99% to mitigate outliers.

Table 8 Panel A: Logistic regressions (dependent variable is equal to one if the firm-year misstated earnings, zero otherwise) examining the determinants of misstatements estimated for Model 3 (including stock market-based variables).

Variable	**(1) Variables selected for Model 3 1979-1998 period**	**(2) Variables selected for Model 3 excluding boom years (1998-2000)**	**(3) Adding industry variables to Model 3 in Table 6**
	Coefficient Estimate (P-value)	Coefficient Estimate (P-value)	Coefficient Estimate (P-value)
Intercept	**-6.547**	**-6.478**	**-6.652**
	0.000	*0.000*	*0.000*
RSST accruals	**1.083**	**0.805**	**1.016**
	0.000	*0.000*	*0.000*
Change in receivables	**1.658**		**1.128**
	0.025		*0.001*
Change in inventory	**2.874**		**2.591**
	0.001		*0.001*
Change in cash sales	**0.110**	**0.159**	**0.096**
	0.081	0.013	0.104
Change in earnings	**-1.126**	**-1.534**	**-1.408**
	0.003	*0.001*	*0.001*
Actual issuance	**0.394**	**0.383**	**0.484**
	0.081	*0.082*	*0.024*
WC accruals		**2.461**	
		0.000	
Abnormal change in employees		**-0.310**	**-0.215**
		0.023	*0.055*
Existence of operating leases	**0.505**	**0.431**	**0.481**
	0.003	*0.010*	*0.003*
Book to market	**-0.187**		**-0.137**
	0.026		*0.052*
Lagged market-adjusted stock return	**0.089**	**0.091**	**0.069**
	0.003	*0.001*	*0.021*
Computer			**0.256**
			0.187
Retail			**0.697**
			0.244
Services			**0.308**
			0.065
Retail X Existence of operating leases			**-0.446**
			0.471
Misstating Firm-years:	274	273	363
Non-misstating Firm-years:	80,825	80,979	95,286

Table 8 Panel B: Examination of detection rates for each model reported in Panel A

	Out-of-sample test - using a hold-out sample for the time period 1999-2002			Excluding boom years (1998-2000)			Adding industry variables to Model 3 in Table 6		
	N	**Minimum *F-Score***	**% of Total**	**N**	**Minimum *F-Score***	**% of Total**	**N**	**Minimum *F-Score***	**% of Total**
Quintile 1									
Misstate Firms	7	0.284	6.31%	31	0.137	11.36%	22	0.093	6.06%
No-Misstate Firms	4,075	0.025	20.07%	16,219	0.007	20.03%	19,107	0.012	20.05%
Quintile 2									
Misstate Firms	16	0.577	14.41%	25	0.626	9.16%	51	0.543	14.05%
No-Misstate Firms	4,066	0.560	20.03%	16,226	0.602	20.04%	19,079	0.536	20.02%
Quintile 3									
Misstate Firms	17	0.776	15.32%	37	0.788	13.55%	50	0.788	13.77%
No-Misstate Firms	4,066	0.774	20.03%	16,213	0.785	20.02%	19,080	0.754	20.02%
Quintile 4									
Misstate Firms	**18**	**0.997**	**16.22%**	**63**	**0.974**	**23.08%**	**80**	**0.963**	**22.04%**
No-Misstate Firms	4,064	0.974	20.02%	16,188	0.971	19.99%	19,050	0.962	19.99%
Quintile 5									
Misstate Firms	**53**	**1.275**	**47.75%**	**117**	**1.210**	**42.86%**	**160**	**1.254**	**44.08%**
No-Misstate Firms	4,029	1.232	19.85%	16,133	1.209	19.92%	18,970	1.246	19.91%

Note: All observations are ranked based on their predicted probabilities (*F-Scores*) and sorted into Quintiles. Minimum *F-Score* is the minimum scaled predicted probability based on estimates in Panel A to enter each quintile.

Panel C: *F-Score* cut-off set at 1.00

	Out-of-sample test Predicted			**Excluding boom years (1998-2000) Predicted**			**Add industry variables Predicted**		
Observed	Manip.	No-Manip.		Manip.	No-Manip.		Manip.	No-Manip.	
Misstate	**70**	41	111	**174**	99	273	**229**	134	363
No-Misstate	7,525	**12,775**	20,300	29,843	**51,136**	80,979	34,659	**60,627**	95,286
	7,595	12,816	**20,411**	30,017	51,235	**81,252**	34,888	60,761	**95,649**
Misstate	**63.06%**	36.9%	0.5%	**63.74%**	36.3%	0.3%	**63.09%**	36.9%	0.4%
No-Misstate	37.07%	**62.93%**	99.5%	36.85%	**63.15%**	99.7%	36.37%	**63.63%**	99.6%

Correct classification	**62.93%**	(1)	**63.15%**	**63.62%**
Sensitivity	63.06%	(2)	63.74%	63.09%
Type I errors	37.07%	(3)	36.85%	36.37%
Type II errors	36.94%	(4)	36.26%	36.91%

Notes:

(1) Correct classification is calculated as (70+12,775/20,411)

(2) Sensitivity is calculated as (70/111)

(3) *Type I* errors are calculated as (7,525/20,300)

(4) *Type II* errors are calculated as (41/111)

All variables are defined in Table 3. Each of the continuous variables (except stock return variables) is winsorized at 1% and 99% to mitigate outliers.