



Contemporary Accounting Research (CAR), the premier research journal of the Canadian Academic Accounting Association, publishes leading-edge research that contributes to our collective understanding of accounting's role in organizations, markets or society.

Predicting Material Accounting Misstatements

DECHOW, P. M., GE, W., LARSON, C. R. and SLOAN, R. G. (2011), *Predicting Material Accounting Misstatements. Contemporary Accounting Research*, 28: 17–82. doi: 10.1111/j.1911-3846.2010.01041.x

The Canadian Academic Accounting Association (CAAA) is the copyright holder of the above article and retains the rights to publish, republish, transmit, sell, distribute and otherwise use the article in whole or in part in electronic and print editions of *CAR* and in derivative works throughout the world, in all languages and in all media of expression now known or later developed, and to license or permit others to do so.

Further reproduction, posting, transmission or other distribution of this article is not permitted. For more information, please email car@caaa.ca.

Wiley Online Library

Predicting Material Accounting Misstatements*

PATRICIA M. DECHOW, *University of California, Berkeley*

WEILI GE, *University of Washington*

CHAD R. LARSON, *Washington University in St. Louis*

RICHARD G. SLOAN, *University of California, Berkeley*

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. Our research has two objectives. 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.¹ Second, we analyze the financial characteristics of misstating firms and develop a model to predict misstatements. The output of this analysis is

* Accepted by Michael Welker. We appreciate the comments of the workshop participants at the University of Michigan, the UBCOW Conference at the University of Washington, New York University 2007 Summer Camp, University of California, Irvine and University of Colorado at Boulder, Columbia University, University of Oregon, the Penn State 2008 Conference, University of California, Davis 2008 Conference, American Accounting Association meetings 2007, FARS 2008 meetings, the University of NSW Ball and Brown Conference in Sydney 2008, and the 2009 George Mason University Conference on Corporate Governance and Fraud Prevention. We thank Michael Welker (associate editor) and two anonymous referees for their helpful comments. We thank Ray Ball, Sid Balachandran, Sandra Chamberlain, Ilia Dichev, Bjorn Jorgensen, Bill Kinney, Carol Marquardt, Mort Pincus, and Charles Shi for their comments and Seungmin Chee for research assistance. We would like to thank the Research Advisory Board established by Deloitte & Touche USA LLP, Ernst & Young LLP, KPMG LLP and PricewaterhouseCoopers LLP for the funding for this project. However, the views expressed in this article and its content are ours alone and not those of Deloitte & Touche USA LLP, Ernst & Young LLP, KPMG LLP, or PricewaterhouseCoopers LLP. Special thanks go to Roslyn Hooten for administering the funding relationship. This paper is dedicated to the memory of our colleague, friend, and research team member, Nader Hafzalla, who was a joy to all who knew him.

1. For more information on the data, please e-mail CFRMdata@haas.berkeley.edu.

a scaled probability (*F*-score) that can be used as a red flag or signal of the likelihood of earnings management or misstatement.

We compile our database through a detailed examination of firms that have been subject to enforcement actions by the U.S. 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 676 unique firms that have misstated at least one of their quarterly or annual financial statements.²

Using AAERs as a source to investigate characteristics of firms that manipulate financial statements has both advantages and disadvantages. The SEC has a limited budget, so it selects firms for enforcement action where there is strong evidence of manipulation. Firms selected often have already admitted a “mistake” by restating earnings or having large write-offs (e.g., Enron or Xerox); other firms have already been identified by the press or analysts as having misstated earnings (see Miller 2006); in addition, insider whistleblowers often reveal problems directly to the SEC. Therefore, one advantage of the AAER sample is that researchers can have a high level of confidence that the SEC has identified manipulating firms (the Type I error rate is low). However, one disadvantage is that many firms that manipulate earnings are likely to go unidentified, and a second disadvantage is that there could be selection biases in cases pursued by the SEC. For example, the SEC may be more likely to pursue cases where stock performance declines rapidly after the manipulation is revealed, because the identifiable losses to investors are greater. Selection biases may limit the generalizability of our results to other settings. It is worth noting, however, that problems with selection bias exist for other samples of manipulators identified by an external source — for example, shareholder litigation firms, Sarbanes-Oxley Act (SOX) internal control violation firms, or restatement firms.³ Bias concerns also exist for discretionary accrual measures (Dechow, Sloan, and Sweeney 1995). Thus selection bias is a general concern when analyzing the determinants of earnings manipulation and is not unique to AAER firms.

2. Throughout the paper we use the terms *earnings management*, *manipulation*, and *misstatement* interchangeably. Although fraud is often implied by the SEC's allegations, we use the term *misstatement* because firms and managers typically do not admit or deny guilt with respect to the SEC allegations.

3. Shareholder lawsuit firms are biased toward firms that have had large stock price declines; SOX internal violation firms are biased toward younger firms with less developed accounting systems; and restatement firms are biased toward firms that have made a mistake that is not necessarily intentional.

In our tests we focus on variables that can be easily measured from the financial statements because we want our analysis to be applicable in most settings facing investors, regulators, or auditors. Our tests focus only on AAER firm-years that have overstated earnings. We examine (i) accrual quality, (ii) financial performance, (iii) nonfinancial measures, (iv) off-balance-sheet activities, and (v) market-based measures for identifying misstatements.

We investigate several measures of *accrual quality*. We examine working capital accruals and the broader measure of accruals that incorporates long-term net operating assets (Richardson, Sloan, Soliman, and Tuna 2005). We provide an analysis of two specific accruals, changes in receivables and inventory. These accounts have direct links to revenue recognition and cost of goods sold, both of which impact gross profit, a key performance metric. We measure the percentage of “soft” assets on the balance sheet (defined as the percentage of assets that are neither cash nor property, plant, and equipment (PP&E)). We predict that the more assets on the balance sheet that are subject to changes in assumptions and forecasts, the greater the manager’s flexibility to manage short-term earnings (e.g., Barton and Simko 2002; Richardson et al. 2005). We find that all measures of accrual quality are unusually high in misstating years relative to the broad population of firms. We also find that the percentage of soft assets is high, which suggests that manipulating firms have more ability to change and adjust assumptions to influence short-term earnings.

In time-series tests that focus only on misstating firms, we find that the reversal of accruals is particularly important for detecting the misstatement. We find that, in the years prior to the manipulation, all accrual measures are unusually high and in fact are not significantly different from those of manipulation years. There are two explanations for this finding. First, managers are likely to utilize the flexibility within generally accepted accounting principles (GAAP) to report higher accruals and earnings *before* resorting to the aggressive manipulation identified by the SEC. Therefore, growing accruals in earlier years is consistent with “within GAAP” earnings management. Second, the positive accruals in earlier years could reflect an overinvestment problem. Managers in misstating firms could be relaxing credit policies, building up inventory and fixed asset capacity in anticipation of future growth. When that growth is not realized, managers then resort to the manipulation identified by the SEC. The two explanations are not mutually exclusive, because a manager who is optimistic and overinvesting is also likely to be optimistic in terms of assumptions and forecasts that relate to asset values and earnings.

We examine various models of *discretionary accruals* developed in prior accounting research including the cross-sectional modified Jones model (Dechow et al. 1995; DeFond and Jiambalvo 1994), the performance-matched discretionary accruals model (Kothari, Leone, and Wasley 2005), and a signed version of the earnings quality metric developed by Dechow and Dichev (2002). Our results indicate that the residuals from the modified Jones model and the performance-matched Jones model have less power to

identify manipulation than unadjusted accrual measures (i.e., working capital accruals and the broader measure of accruals) or the signed Dechow and Dichev model. This suggests that conventional approaches of controlling for industry and performance induce considerable estimation error into the estimation of discretionary accruals.

We examine whether the manipulations occur to hide diminishing firm *performance*. We find that returns on assets are generally declining; however, contrary to our initial expectations, we find that cash sales are increasing during misstatement periods. We failed to anticipate the cash sales result because we expected firms to boost sales by overstating credit sales. There are two explanations for the unexpected cash sale 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, 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.

We find that one *nonfinancial measure*, abnormal reductions in the number of employees, is useful in detecting misstatements. This measure is new to the literature and is measured as year-over-year percentage change in employee headcount less year-over-year percentage change in total assets. This result can be interpreted in two ways. First, reductions in the number of employees are likely to occur when there is declining demand for a firm's product. In addition, cutting employees directly improves short-run earnings performance by lowering wage expenses. Second, if physical assets and employees are complements, then a decrease in employees relative to total assets could signal overstated asset balances.

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. We find that the use of operating leases is unusually high during misstatement firm-years. In addition, more firms begin leasing in manipulation years (relative to earlier years). We also find that misstating firms have higher expected returns on their pension plan assets than other firms. The effect of higher expected return assumptions is to reduce reported pension expense. The results for leases and pensions are consistent with misstating firms exhausting "legal" earnings management options before resorting to more aggressive financial misstatements.

Our final set of variables relates to *stock and debt market incentives*. Dechow et al. (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 are unusually high at the time of equity issuances. However, the evidence in Beneish

1999b suggests that leverage and stock issuances do not motivate misstatements. Therefore, revisiting this question using our more comprehensive data is warranted. We find that the comparison group is critical for evaluating whether raising financing is a motivation for the misstatement. Inconsistent with Beneish, we find that misstating firms are actively raising financing in misstating years relative to the broad population of firms. However, consistent with Beneish, we find no significant difference in the extent of financing when we compare earlier years to manipulation years for the same AAER firm. These results can be reconciled by the fact that we find misstating firms are actively raising financing *before* and during the manipulation period. Thus, one interpretation of these findings is that managers of misstating firms are concerned with obtaining financing and this motivates earnings management in earlier years, as well as the more aggressive techniques identified by the SEC in misstating years. Also consistent with Beneish, we do not find evidence that misstating firms tend to have higher financial leverage than nonmisstating firms.

We examine the *growth expectations* embedded in misstating firms' stock market valuations. We find that the price-earnings and market-to-book ratios are unusually high for misstatement firms compared to other firms, suggesting that investors are optimistic about the future growth opportunities of these firms. We also find that the misstating firms have unusually strong stock return performance in the years prior to misstatement. This is consistent with managers engaging in aggressive techniques in misstating years in the hopes of avoiding disappointing investors and losing their high valuations (Skinner and Sloan 2002).

Our final tests aim at developing a prediction model that can synthesize the financial statement variables that we examine and provide insights into which variables are relatively more useful for detecting misstatements. The model is built in stages based on the ease of obtaining the information 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 nonfinancial measures. Model 3 adds market-related variables. 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 1.4, over 50 percent of misstating firms have *F*-scores of 1.4 or higher. We also investigate the time-series pattern of *F*-scores for misstating firms. We show that average *F*-scores for misstating firms increase for up to three years prior to the misstatement, but decline rapidly to more normal levels in the years following the misstatement. This is consistent with the *F*-score identifying within-GAAP earnings management as well as the more aggressive techniques identified by the SEC. We discuss interpretation issues concerning Type I and Type II errors related to the *F*-score and provide marginal analysis and sensitivity analysis showing that variation in the

F-score is not driven by one specific variable. We also conduct several robustness tests that confirm the stability of the variables selected for our models, our coefficient estimates, and the predictive ability of the *F*-score over time.

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

Understanding the types of firms that will misstate financial statements is an extensive area of research. We briefly discuss some of the key findings but do not attempt to document all literature examining characteristics of AAER firms. Dechow, Ge, and Schrand (2010) provide a comprehensive review of this literature.

Early work by Feroz, Park, and Pastena 1991 examines 224 AAERs issued between April 1982 and April 1989 covering 188 firms, of which 58 have stock price information. Feroz et al. document that receivables and inventory are commonly misstated. Two pioneering papers analyzing misstating firms are Beneish 1997 and Beneish 1999a. Beneish (1997) analyzes 363 AAERs covering 49 firms and a further 15 firms whose accounting was questioned by the news media between 1987 and 1993. The 64 firms are classified as manipulators. He creates a separate sample of firms using the modified Jones model to select firms with high accruals that he terms “aggressive accruals”. His objective is to distinguish the manipulators from the aggressive accruals. Beneish (1997) finds that accruals, day’s sales in receivables, and prior performance are important for explaining the differences between the two groups. Beneish (1999a) matches the sample of manipulators to 2,332 COMPUSTAT nonmanipulators 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, with higher index values indicating a higher likelihood of an earnings overstatement. Beneish shows that the day’s sales in receivables index, gross margin index, asset quality index, sales growth index, and accruals (measured as the change in noncash working capital plus depreciation) are important. He provides a probit model and analyzes the probability cutoffs that minimize the expected costs of misstatements.

Our research builds on and is complementary to Beneish (1997, 1999a). We take a different perspective from Beneish that leads us to make a number of different choices. However, such differences should not be viewed as a critique of his approach; rather, they stem from our objectives. One of our objectives is to develop a measure that can be directly calculated from the financial statements. Therefore, we do not use indexes for any of our variables. A second objective is to enable researchers and practitioners to calculate an *F*-score for a random firm and to easily assess the probability

of misstatement. Therefore, we do not match AAER firms to a control group by industry or size. Matching by industry and size provides information on whether a variable is significantly different relative to a control firm. However, it is more difficult when matching to determine Type I and Type II error rates that users will face in an unconditional setting. Models could be developed for individual industries and size categories. We choose not to do this because it would add greatly to the complexity of our analysis and the presentation of our results. A third objective is to evaluate the usefulness of financial statement information beyond that contained in the primary financial statements; therefore we include other information disclosed in the 10-K either in item 1 (discussion of the business), item 5 (stock price information), or the footnotes.

Concurrent research provides additional insights into variables that are useful for detecting misstatements. Ettredge, Sun, Lee, and Anandaraman (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 over-the-counter firm. Brazel, Jones, and Zimbelman (2009) examine whether several nonfinancial measures (e.g., number of patents, employees, and products) can be used to predict misstatement in 50 AAER firms. They find that growth rates between financial and nonfinancial variables are significantly different for AAER firms. Bayley and Taylor (2007) study 129 AAER firms and a matched 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. We agree with Bayley and Taylor and view our work as moving in the direction that they recommend.

There has also been work using AAER firms to examine the role of corporate governance and incentive compensation in encouraging earnings manipulation (see, e.g., Dechow, Sloan, and Sweeney 1996; Beasley 1996; Farber 2005; Skousen and Wright 2006; for a summary, Dechow et al. 2010). We chose not to investigate the role of governance variables and compensation because these variables are available for only limited samples or must be hand collected. Therefore, adding these variables would have limited our analysis to a smaller sample with various biases in terms of data availability. However, a useful avenue for future research is to analyze the role of governance, compensation, insider trading, short selling, incentives to meet and beat analyst forecasts, and so on and to determine the relative importance of these variables over financial statement information in detecting overstatements of earnings.

3. Data and sample formation

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. Thus we focus our data collection on the SEC's series of published AAERs.⁴

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 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, because 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 Government Accountability Office (GAO) Financial Statement Restatement Database.* This database consists of approximately 2,309 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 because (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

4. The AAER series began on May 17, 1982, with the SEC's issuance of AAER No. 1. The SEC states in the first AAER that the series would include "future . . . enforcement actions involving accountants" and "enable interested persons to easily distinguish enforcement releases involving accountants from other Commission releases" (AAER No 1). Although the AAERs often directly involve accountants, the AAER series also includes enforcement actions against nonaccountant employees that result from accounting misstatements and manipulations.

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 2010 suggest that many restatements are a consequence of misinterpreting accounting rules rather than intentional misstatements. Another shortcoming of the GAO database is that it specifies only the year in which the restatement was identified in the press and not the reporting periods that were required to be restated.⁵

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 price decline, even when there is no clear evidence supporting the allegation. In contrast, the SEC issues an enforcement action only when it has established intent or gross negligence on the part of management in making the misstatement.

Using the SEC's AAERs as a sample of misstatement firms has several advantages relative to other potential samples. First, the use of AAERs as a proxy for manipulation is a straightforward and consistent methodology. This methodology avoids potential biases induced in samples based on researchers' individual classification schemes and can be easily replicated by other researchers. Second, AAERs are also likely to capture a group of economically significant manipulations as the SEC has limited resources and likely pursues the most important cases. Relative to other methods of identifying a sample of firms with managed earnings, such as the modified Jones abnormal accruals model, using misstatements identified in AAERs as an indicator is expected to generate a much lower Type I error.

Despite the advantages of using AAERs to identify accounting misstatements, there are caveats. We can investigate only those firms identified by the SEC as having misstated earnings. The inclusion of the misstatements that are not identified by the SEC in our control sample is likely to reduce the predictive ability of our model. Therefore, our analyses can be interpreted as joint tests of engaging in an accounting misstatement and receiving an enforcement action from the SEC. If it is assumed that the SEC selection criteria are highly correlated with our prediction variables, then another criticism is that identified variables could reflect SEC selection. However, as noted above, the SEC identifies firms from a variety of sources

5. 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.

and not just from its own internal reviews, and many cases are brought to its attention because the firm itself either restates or takes a large write-off. Thus, selection choices are unlikely to be a complete explanation for our findings. In addition, from a firm's perspective, being subject to an SEC enforcement action brings significantly negative capital market consequences (Dechow et al. 1996; Karpoff, Lee, and Martin 2008). Therefore, avoiding these characteristics could be useful and thus affect firm and market behavior.

Data sets

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. There is only one observation per firm in the Detail file. The Annual and Quarterly files are compiled from the Detail file and are formatted by reporting period so that each quarter or year affected by the violation is a separate observation. The Appendix lists the variable names and description for each file in the database.

Data collection

The original AAERs are the starting point for collecting data. Copies of the AAERs are obtained from the SEC website and the LexisNexis 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 we are unable to locate 30 of the 2,261 AAERs, because they were either 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.

Panel B of Table 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., chief executive officer (CEO) or chief

TABLE 1
Sample description

Panel A: Sample selection of Accounting and Auditing Enforcement Releases (AAERs)

Number of AAERs	Number
AAER No. 1–No. 2261 from May 1982 to June 2005	2,261
Less: missing AAERs	(30)
Less: AAERs that do not involve specific company names	(41)
Total	2,190

Note:

Among 30 missing AAERs, 11 AAERs are intentionally omitted and 19 AAERs are missing.

Panel B: Percent of the 2,190 AAERs that are against various parties

Party	Number	Percentage
Officer of the company	1,077	49.18
Auditor	348	15.89
Officer and company	331	15.11
Company	308	14.06
Other	58	2.65
Other combination of parties	68	3.11
Total	2,190	100.00

Panel C: Frequency of AAERs by year

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

(The table is continued on the next page.)

TABLE 1 (Continued)

Panel D: Frequency of AAERs by firm			
Number of AAERs for each firm	Number of firms	Percent of firms	Total AAERs
1	370	41.3	370
2	235	26.2	470
3	108	12.1	324
4	70	7.8	280
5	40	4.5	200
6	33	3.7	198
7	13	1.5	91
8	10	1.1	80
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	896	100.0	2,218

Note:

There are 28 (2,218 less 2,190) AAERs involving multiple companies.

Panel E: Number of distinct firms

Number of distinct firms mentioned in the AAERs	Number
AAER No. 1–No. 2261 from May 1982 to June 2005	896
Less: Enforcements that are unrelated to earnings misstatement (e.g., bribes, disclosure, etc.) or firms with misstatements that cannot be linked to specific reporting periods	220
Earnings misstatement firms	676
Less: firms without CUSIP	132
Firms with at least one quarter of misstated numbers	544
Firms with total assets on COMPUSTAT	457
Firms with stock price data on COMPUSTAT	435
Less: firms with quarterly misstatements corrected by the end of the fiscal year	92
Firms with at least one annual misstated number	451
Firms with total assets on COMPUSTAT	387
Firms with stock price data on COMPUSTAT	362

(The table is continued on the next page.)

TABLE 1 (Continued)

Panel F: Type of misstatements identified by the SEC in the AAERs

Type of misstatement	Percent of 676 misstatement firms (1)	Percent of 435 firms with at least one quarterly misstatement and stock price data (2)	Percent of 451 firms with at least one annual misstatement (3)	Percent of 387 firms with at least one annual misstatement and total assets data (4)
Misstated revenue	54.0	59.5	58.3	60.2
Misstatement of other expense/ shareholder equity account	25.1	25.1	24.6	24.8
Capitalized costs as assets	27.2	20.5	21.7	20.9
Misstated accounts receivable	19.1	20.0	21.1	20.7
Misstated inventory	13.2	14.5	16.2	16.3
Misstated cost of goods sold	11.4	13.1	13.7	14.2
Misstated liabilities	7.4	7.1	8.4	8.0
Misstated reserve account	5.9	4.4	5.1	4.4
Misstated allowance for bad debt	4.3	4.1	4.7	4.4
Misstated marketable securities	3.6	3.4	3.8	3.4
Misstated payables	1.6	2.3	2.2	2.6

Note:

There are a total of 1,272 misstatements mentioned in column 1, 770 misstatements in column 2, 826 misstatements in column 3, and 709 misstatements in column 4, so percentages sum to more than 100 percent.

financial officer (CFO), 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 a combination of various parties (e.g., auditor and officer), and in 2.65 percent (58) of cases the party was classified as “other”, which includes consultants and investment bankers.

Table 1, panel C 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 10 2005, so our sample does not include the full year. Table 1, panel D 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 (370 firms) to a high of 24 per firm (Enron). From our reading of the AAERs we obtain a list of 896 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 E of Table 1 indicates that of the 896 original firms identified, 220 firms involved either wrongdoing 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 676 firms with alleged financial misstatements. We lose a further 132 firms because we are unable to obtain a valid CUSIP (Committee on Uniform Security Identification Procedures) identifier.⁶ 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 E of Table 1 indicates that, for 544 firms, the misstatement involved one or more quarters. We provide the number of firms with assets and share price data because firms can have a CUSIP but no data. In 92 firms the misstatement involved only quarterly financial statements and was corrected by the end of the year. Therefore the Annual file contains misstatements of annual data for 451 firms. Among these 451 firms, 387 firms have total assets listed on COMPUSTAT during the misstatement period.

For each annual/quarterly period that was misstated, an additional field was added to the Annual/Quarterly file. If an understatement of earnings

6. Further investigation revealed that, among these 132 firms, 33 were traded on non-major exchanges or over the counter but had no CUSIP, 12 were initial public offering firms that never went public, 12 were sanctioned when registering securities under 12(g), and 13 were subsidiaries of parent firms already included in the sample or private companies that helped a public company commit the misstatement. The rest of the firms are brokerage firms, have unregistered securities traded, or simply do not have sufficient detail to identify a CUSIP.

or revenues occurred during the quarter or year of the violation, we code the *understatement* variable 1. Because most AAERs involve the overstatement of earnings or revenues, this flag is helpful in conducting earnings management and other discretionary accruals tests. In our empirical analyses in Tables 4–9, we delete firm-year observations that understated earnings. We also exclude banks and insurance companies because many accruals-related variables are not available for these firms. The Annual file contains 837 firm-year observations with CUSIPs, and the Quarterly file contains 3,612 firm-quarter observations with CUSIPs.

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. Table 1, panel F reports the frequency of misstatement accounts for various samples based on available data. The patterns are quite similar across the four samples. For example, column 2 indicates that 770 accounts were affected across the 435 misstating firms that have stock price data. Most misstatements relate to revenue recognition, which occurs in 59.5 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), and 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 cost of goods sold and inventory (13.1 percent and 14.5 percent, respectively). Other types of misstatements include capitalizing expenses or creating fictitious assets (e.g., WorldCom). This occurs in about 20 percent 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.

4. Empirical results

In this section, we first discuss the characteristics of misstatement firms. We then develop our logistic model and associated *F*-score.

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

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	5.1
2	36	8.3
3	37	8.5
4	44	10.1
5	38	8.7
6	53	12.2
7	48	11.0
8	55	12.6
9	38	8.7
10	64	14.7
Total	435	100.0

Panel B: Frequency of the misstating firms by industry

Industry	Misstating firms (percent)	COMPUSTAT population (percent)
Agriculture	0.2	0.4
Mining & Construction	2.7	3.0
Food & Tobacco	2.5	2.1
Textile and Apparel	2.5	1.7
Lumber, Furniture, & Printing	2.2	3.1
Chemicals	2.2	2.0
Refining & Extractive	1.0	4.7
Durable Manufacturers	19.4	18.9
Computers	20.4	11.1
Transportation	4.7	5.8
Utilities	1.6	3.2
Retail	12.9	9.9
Services	12.7	10.4
Banks & Insurance	12.0	20.8
Pharmaceuticals	3.1	3.2
Total	100.0	100.0

(The table is continued on the next page.)

TABLE 2 (Continued)

Notes:

There are 435 misstating firms in the annual and quarterly files that have data to calculate market value and 490 misstating firms that have SIC codes. Industries are based on the following SIC codes: Agriculture: 0100–0999; Mining & Construction: 1000–1299, 1400–1999; Food & Tobacco: 2000–2141; Textiles and Apparel: 2200–2399; Lumber, Furniture, & Printing: 2400–2796; Chemicals: 2800–2824, 2840–2899; Refining & Extractive: 1300–1399, 2900–2999; Durable Manufacturers: 3000–3569, 3580–3669, 3680–3999; Computers: 3570–3579, 3670–3679, 7370–7379; Transportation: 4000–4899; Utilities: 4900–4999; Retail: 5000–5999; Services: 7000–7369, 7380–9999; Banks & Insurance: 6000–6999; Pharmaceuticals: 2830–2836, 3829–3851.

Panel C: Distribution of misstated firm-years

Year	Firm-years	Percentage	Year	Firm-years	Percentage
1971	1	0.12	1987	24	2.87
1972	1	0.12	1988	27	3.23
1973	1	0.12	1989	42	5.02
1974	2	0.24	1990	33	3.94
1975	2	0.24	1991	44	5.26
1976	1	0.12	1992	47	5.62
1977	1	0.12	1993	41	4.90
1978	4	0.48	1994	35	4.18
1979	9	1.08	1995	37	4.42
1980	17	2.03	1996	40	4.78
1981	23	2.75	1997	43	5.14
1982	31	3.70	1998	53	6.33
1983	25	2.99	1999	66	7.89
1984	25	2.99	2000	60	7.17
1985	17	2.03	2001	38	4.54
1986	29	3.46	2002	15	1.79
			2003	3	0.36
			Total	837	100.00

Note:

This table is calculated based on the sample of 451 misstating firms (as shown in Table 1, panel E) with at least one misstated annual financial statement.

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, so misstatements are more likely to be identified. Note also that only 5.1 percent of misstating firms are in decile 1. Recall that 132 firms are excluded from our analysis because we could not obtain their firm identifiers. These are likely to be smaller firms.

Panel B of Table 2 reports the industry distribution of both misstatement firm-years and all available firm-years on COMPUSTAT. The SIC-based industry classification scheme is based on Frankel, Johnson, and Nelson's 2002. The bolded results highlight industries that are significantly overrepresented for misstating firms. Over 20 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. 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 percent versus 9.9 percent). Examples of retail firms in our sample include Crazy Eddie, Kmart, and Rite Aid. Services are also overrepresented (12.7 percent versus 10.4 percent). Examples of service firms include Tyco International, ZZZZ Best, Healthsouth Corporation, Future Healthcare Inc., and Rent-Way, Inc. These firms typically capitalized expenses as assets and misstated sales. Note also that 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. AAERs are not timely and are often released several years after the manipulation takes place. 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 (7.89 percent and 7.17 percent, 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 performance.

Variables analyzed

In this section we discuss the motivation and the selection of the financial statement variables that we hypothesize to be associated with misstatements. Each variable is briefly discussed, with more detailed definitions provided in Table 3. The variables we analyze focus on accrual quality, financial performance, nonfinancial 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

TABLE 3
Variable definitions

Variable	Abbreviation	Pred sign	Calculation
<i>Misstatement flag</i>	<i>misstate</i>	N/A	Indicator variable equal to 1 for misstatement firm-years and 0 otherwise
Accruals quality related variables			
<i>WC accruals</i>	<i>WC_acc</i>	+	$[(\Delta \text{Current Assets (DATA 4)} - \Delta \text{Cash and Short-term Investments (DATA 1)}) - (\Delta \text{Current Liabilities (DATA 5)} - \Delta \text{Debt in Current Liabilities (DATA 34)} - \Delta \text{Taxes Payable (DATA 71)})] / \text{Average total assets}$
<i>RSST accruals</i>	<i>rsst_acc</i>	+	$(\Delta \text{WC} + \Delta \text{NCO} + \Delta \text{FIN}) / \text{Average total assets}$, where $\text{WC} = [\text{Current Assets (DATA 4)} - \text{Cash and Short-term Investments (DATA 1)}] - [\text{Current Liabilities (DATA 5)} - \text{Debt in Current Liabilities (DATA 34)}]$; $\text{NCO} = [\text{Total Assets (DATA 6)} - \text{Current Assets (DATA 4)} - \text{Investments and Advances (DATA 32)}] - [\text{Total Liabilities (DATA 181)} - \text{Current Liabilities (DATA 5)} - \text{Long-term Debt (DATA 9)}]$; $\text{FIN} = [\text{Short-term Investments (DATA 193)} + \text{Long-term Investments (DATA 32)}] - [\text{Long-term Debt (DATA 9)} + \text{Debt in Current Liabilities (DATA 34)} + \text{Preferred Stock (DATA 130)}]$; following Richardson et al. 2005.
<i>Change in receivables</i>	<i>ch_rec</i>	+	$\Delta \text{Accounts Receivable (DATA 2)} / \text{Average total assets}$
<i>Change in inventory</i>	<i>ch_inv</i>	+	$\Delta \text{Inventory (DATA 3)} / \text{Average total assets}$
<i>% Soft assets</i>	<i>soft_assets</i>	-	$(\text{Total Assets (DATA 6)} - \text{PP\&E (DATA 8)} - \text{Cash and Cash Equivalent (DATA 1)}) / \text{Total Assets (DATA 6)}$

(The table is continued on the next page.)

TABLE 3 (Continued)

Variable	Abbreviation	Pred sign	Calculation
<i>Modified Jones model discretionary accruals</i>	<i>da</i>	+	The modified Jones model discretionary accrual is estimated cross-sectionally each year using all firm-year observations in the same two-digit SIC code: $WC\ Accruals = \alpha + \beta(1/Beginning\ assets) + \gamma(\Delta Sales - \Delta Rec)/Beginning\ assets + \rho \Delta PPE / Beginning\ assets + \varepsilon.$ The residuals are used as the modified Jones model discretionary accruals.
<i>Performance-matched discretionary accruals</i>	<i>dadif</i>	+	The difference between the modified Jones discretionary accruals for firm <i>i</i> in year <i>t</i> and the modified Jones discretionary accruals for the matched firm in year <i>t</i> , 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.
<i>Mean-adjusted absolute value of DD residuals</i>	<i>resid</i>	+	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.
<i>Studentized DD residuals</i>	<i>sresid</i>	+	The scaled residuals are calculated as $\frac{\hat{\varepsilon}_i}{\hat{\sigma}\sqrt{1-h_{ii}}}$ where h_{ii} is the <i>ii</i> element of the hat matrix, $X(X^T X)^{-1} X^T$ and $\hat{\sigma} = \sqrt{\frac{1}{n-m} \sum_{j=1}^m \varepsilon_j^2}$ where <i>m</i> is the number of parameters in the model and <i>n</i> 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.

(The table is continued on the next page.)

TABLE 3 (Continued)

Variable	Abbreviation	Pred sign	Calculation
Performance variables			
<i>Change in cash sales</i>	<i>ch_cs</i>	-	Percentage change in cash sales [Sales (DATA 12) - ΔAccounts Receivable (DATA 2)]
<i>Change in cash margin</i>	<i>ch_cm</i>	-	Percentage change in cash margin, where cash margin is measured as $1 - [(Cost\ of\ Good\ Sold\ (DATA\ 41) - \Delta Inventory\ (DATA\ 3) + \Delta Accounts\ Payable\ (DATA70)) / (Sales(DATA\ 12) - \Delta Accounts\ Receivable\ (DATA\ 2))]$
<i>Change in return on assets</i>	<i>ch_roa</i>	+	$[Earnings_t\ (DATA\ 18) / Average\ total\ assets_t] - [Earnings_{t-1} / Average\ total\ assets_{t-1}]$
<i>Change in free cash flows</i>	<i>ch_fcf</i>	-	$\Delta[Earnings\ (DATA\ 18) - RSST\ Accruals] / Average\ total\ assets$
<i>Deferred tax expense</i>	<i>tax</i>	+	Deferred tax expense for year <i>t</i> (DATA 50) / total assets for year <i>t</i> - 1 (DATA 6)
Nonfinancial variables			
<i>Abnormal change in employees</i>	<i>ch_emp</i>	-	Percentage change in the number of employees (DATA 29) - percentage change in assets (DATA 6)
<i>Abnormal change in order backlog</i>	<i>ch_backlog</i>	-	Percentage change in order backlog (DATA 98) - percentage change in sales (DATA 12)
Off-balance-sheet variables			
<i>Existence of operating leases</i>	<i>leasedum</i>	+	An indicator variable coded 1 if future operating lease obligations are greater than zero
<i>Change in operating lease activity</i>	<i>oplease</i>	+	The change in the present value of future noncancelable operating lease obligations (DATA 96, 164, 165, 166 and 167) deflated by average total assets following Ge 2007
<i>Expected return on pension plan assets</i>	<i>pension</i>	+	Expected return on pension plan assets (DATA 336)

(The table is continued on the next page.)

TABLE 3 (Continued)

Variable	Abbreviation	Pred sign	Calculation
<i>Change in expected return on pension plan assets</i>	<i>ch_pension</i>	+	Δ Expected return on pension plan assets [DATA 336 at t] – (DATA 336 at $t - 1$)
Market-related incentives			
<i>Ex ante financing need</i>	<i>exfin</i>	+	An indicator variable coded 1 if [(CFO – past three year average capital expenditures)/Current Assets] < –0.5
<i>Actual issuance</i>	<i>issue</i>	+	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 DATA 111 > 0)
<i>CFF</i>	<i>cff</i>	+	Level of finance raised (DATA 313/Average total assets)
<i>Leverage</i>	<i>leverage</i>	+	Long-term Debt (DATA 9)/ Total Assets (DATA 6)
<i>Market-adjusted stock return</i>	<i>ret_t</i>	+	Annual buy-and-hold return inclusive of delisting returns minus the annual buy-and-hold value-weighted market return
<i>Lagged market-adjusted stock return</i>	<i>ret_{t-1}</i>	+	Previous year's annual buy-and-hold return inclusive of delisting returns minus the annual buy-and-hold value-weighted market return
<i>Book-to-market</i>	<i>bm</i>	–	Equity (DATA 60)/ Market Value (DATA 25 × DATA 199)
<i>Earnings-to-price</i>	<i>ep</i>	–	Earnings (DATA 18)/ Market Value (DATA 25 × DATA 199)

Note:

Predicted sign shows the expected direction of the relations between various firm-year characteristics and misstatements.

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 Allen, Larson, and Sloan 2009. Prior research typically includes depreciation expense as part of working capital accruals. We exclude depreciation because, as discussed by Barton and Simko 2002, managing earnings through depreciation is more transparent because firms are required to disclose the effects of changes in depreciation policies (Beneish 1998). Our next measure, which we term *RSST accruals*, is

from Richardson, Sloan, Soliman, and Tuna 2005. 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 noncash net operating assets. We also examine 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 examine *% soft assets*. This is defined as the percentage of assets on the balance sheet that are neither cash nor PP&E. Barton and Simko (2002) provide evidence consistent with firms with greater net operating assets having more accounting flexibility to report positive earnings surprises. In their Table 5 they decompose net operating assets into working capital assets, long-term assets, and other assets. Their results suggest that the level of working capital has a much stronger effect (the coefficient is 9 to 28 times larger) on the odds of reporting a predetermined earnings surprise than on the level of PP&E. We therefore assume that, when firms have more soft assets on their balance sheet, there is more discretion for management to change assumptions to meet short-term earnings goals.⁷

We examine several “discretionary accrual” models commonly used in the accounting literature. 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 of discretionary accruals (see Dechow et al. 1995 for the 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 et al. 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.

7. PP&E is subject to discretion in the sense that managers can overcapitalize costs and delay write-offs. Changes in the level of PP&E that reflect such adjustments and choices will be reflected in the RSST accrual measure.

Performance

Our next set of variables gauges the firm's financial performance on various dimensions and examines whether managers misstate their financial statements to mask deteriorating performance (Dechow et al. 1996; Beneish 1997, 1999b). The first variable 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 return on assets* is also analyzed because managers appear to prefer to show positive growth in earnings (Graham, Harvey, and Rajgopal 2005). 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 because 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 Ohlft-Rego 2003).

Nonfinancial measures

Economics teaches us that a firm trades 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 expenditures 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. Brazel et al. (2009) make a similar argument for the use of nonfinancial measures for detecting misstatements. In their discussion of Del Global Technologies they state, "it is improbable that the company would double in profitability while laying off employees, and it is even less probable that employee layoffs would correspond with a significant increase in revenue". 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 and earnings (Rajgopal, Shevlin, and Venkatachalam 2003). 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 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 noncancelable operating lease obligations following Ge 2007.

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 so reduce future 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 incentive for misstating earnings is to maintain a high stock price. We investigate whether managers who misstate their financial statements are particularly concerned with 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. We use four 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 identify 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 et al. 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. Fourth, 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 (*leverage*).

A second motivation for why managers may be particularly dependent on a high stock price is that 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 because 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*.

Time-series analysis of misstating firms

In this subsection we analyze misstating firms and compare years that are identified as misstated by the SEC to all nonmisstatement years. We calculate means at the firm level for misstatement years versus all nonmisstatement years and conduct tests of pairwise differences in means. Therefore, each firm is directly compared to itself during manipulation years versus other years. This approach reduces the number of observations used to calculate *t*-statistics and could lower the power of our tests, but its advantage is that it accurately weights the observations used to calculate means. In the next subsection we follow the same approach and compare misstatement years to years prior to the misstatement. This analysis provides insights into the predictive nature of the variables analyzed, because hindsight does not affect the calculations. One issue of concern for the power of our tests is the proportion of firms that end up restating their financial statements and filing an amended 10-K (versus taking a write-down and/or reporting the restated numbers for prior years in future 10-Ks). According to discussions with Standard & Poor's, COMPUSTAT will backfill misstated numbers when a company files an amended 10-K. In order to determine whether filing amended 10-Ks is common among manipulation firms, we randomly select nine companies that provide detailed information on misstated numbers in 2000 and 2001. We find that only one of the nine firms' financial data on COMPUSTAT has been backfilled with restated numbers. In addition, many of the misstatements are discovered and revealed more than a year after they occur, and so firms are less likely to file amended financial statements. Thus backfilling, although a concern for the power of our tests, does not appear to be highly prevalent in the sample.

Comparisons using all available years

Table 4 provides results for our comparisons of misstating years versus other nonmisstating years. In Tables 4–6, we shade cells that are significant and have the correct sign. We predict and find that accruals are larger in misstatement years. The results indicate that *WC accruals* has a slightly larger *t*-statistic than the *RRST accruals* measure. The reason is likely to be the greater weighting of receivables in *WC accruals*. In Table 1 we document that almost half of the misstating firms are alleged to have misstated sales, and *change in receivables* has the highest *t*-statistic of all accrual variables (6.12). *% soft assets* is also significantly different, suggesting more reporting flexibility in misstating years.

The next set of accrual variables relates to various models of accruals. The objective of these models is to provide more powerful measures of earnings management by controlling for “nondiscretionary” or “normal” accruals that are required under GAAP. However, interestingly, the *t*-statistic on the *modified Jones discretionary accruals* is lower than that on either the *WC accruals* or *RSST accruals*, and *performance-matched discretionary accruals* is lower still. This suggests that estimating the modified Jones model at an industry level appears to add greater error to estimates of discretionary accruals. Performance adjusting appears to add further error. The next measure is a variant of the Dechow and Dichev 2002 measure of quality. This measure uses the absolute value of residuals and is therefore unsigned. However, our sample consists only of income-increasing earnings manipulations, which are likely to be reversed in future years. Therefore, the use of the absolute value reduces the power of the test because the reversal is also likely to have a high absolute value (the *t*-statistic is 1.44). Our next measure, signed *studentized DD residuals*, does not suffer from this problem. The residuals are almost 10 times larger in manipulation years than in nonmanipulation years. This measure has a *t*-statistic of 5.92 and is second only to receivables in terms of statistical significance.

We next examine measures of financial performance. We predict that misstatements are 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 can increase with this type of misstatement, providing an explanation for the finding. Management of cash sales could also play a role in the low power of the modified Jones model. If cash-sale manipulation is positively correlated with other types of accrual manipulation, then the modified Jones model could incorrectly classify part of this discretion as nondiscretionary. The other performance measures, *change in cash margin*, *return on assets*, and *free cash*

TABLE 4
Descriptive statistics of misstatement years versus all nonmisstatement years for AAER firms

Variable	Misstatement years			Nonmisstatement years			Misstate – Nonmisstate			
	N	Mean	Median	N	Mean	Median	Pred sign	Pairwise diff. in mean	One-tailed p-value	Pairwise t-statistics
Accruals quality variables										
<i>WC accruals</i>	296	0.072	0.050	296	0.018	0.019	+	0.053	<i>0.001</i>	4.43
<i>RSST accruals</i>	294	0.135	0.090	294	0.044	0.043	+	0.091	<i>0.001</i>	3.85
<i>Change in receivables</i>	298	0.071	0.042	298	0.028	0.017	+	0.043	<i>0.001</i>	6.12
<i>Change in inventory</i>	294	0.046	0.020	294	0.023	0.011	+	0.022	<i>0.001</i>	4.22
<i>% Soft assets</i>	327	0.647	0.696	327	0.611	0.616	+	0.036	<i>0.001</i>	3.87
<i>Modified Jones model discretionary accruals</i>	294	0.055	0.028	294	-0.009	-0.001	+	0.063	<i>0.001</i>	3.10
<i>Performance-matched discretionary accruals</i>	294	0.061	0.044	294	0.008	0.003	+	0.053	<i>0.006</i>	2.55
<i>Mean-adjusted absolute value of DD residuals</i>	184	0.022	-0.009	184	0.013	-0.010	+	0.010	<i>0.076</i>	1.44
<i>Studentized DD residuals</i>	184	0.529	0.355	184	0.058	0.021	+	0.471	<i>0.001</i>	5.92
Performance variables										
<i>Change in cash sales</i>	263	0.466	0.233	263	0.257	0.165	-	0.209	<i>0.001</i>	3.88
<i>Change in cash margin</i>	256	0.016	0.006	256	0.011	0.001	-	0.005	<i>0.441</i>	0.15
<i>Change in return on assets</i>	263	-0.032	-0.014	263	-0.025	-0.002	+	-0.006	<i>0.354</i>	-0.38
<i>Change in free cash flows</i>	259	0.024	0.007	259	0.015	0.006	-	0.009	<i>0.359</i>	0.36
<i>Deferred tax expense</i>	318	0.002	0.000	318	0.001	0.000	+	0.001	<i>0.202</i>	0.83

(The table is continued on the next page.)

TABLE 4 (Continued)

Variable	Misstatement years			Nonmisstatement years			Misstate – Nonmisstate			
	N	Mean	Median	N	Mean	Median	Pred sign	Pairwise diff. in mean	One-tailed p-value	Pairwise t-statistics
Nonfinancial variables										
<i>Abnormal change in employees</i>	263	-0.221	-0.108	263	-0.163	-0.073	-	-0.058	0.150	-1.04
<i>Abnormal change in order backlog</i>	77	0.091	-0.049	77	0.056	0.040	-	0.036	0.355	0.37
Off-balance-sheet variables										
<i>Change in operating lease activity</i>	298	0.020	0.006	298	0.013	0.005	+	0.007	0.007	2.37
<i>Existence of operating leases</i>	327	0.841	1.000	327	0.752	0.900	+	0.089	0.001	5.36
<i>Expected return on pension plan assets</i>	40	0.084	0.090	40	0.081	0.089	+	0.004	0.017	2.21
<i>Change in expected return on plan assets</i>	33	-0.032	0.000	33	-0.113	-0.100	+	0.081	0.007	2.58
Market-related variables										
<i>Ex ante financing need</i>	224	0.179	0.000	224	0.177	0.000	+	0.002	0.473	0.07
<i>Actual issuance</i>	325	0.938	1.000	325	0.869	1.000	+	0.068	0.001	4.75
<i>CFF</i>	233	0.247	0.134	233	0.151	0.072	+	0.096	0.001	3.94
<i>Leverage</i>	327	0.187	0.161	327	0.192	0.163	+	-0.006	0.276	-0.60
<i>Market-adjusted stock return</i>	237	0.234	0.028	237	-0.004	0.022	+	0.238	0.021	2.06
<i>Book-to-market</i>	291	0.520	0.351	291	0.354	0.395	-	0.166	0.001	3.04
<i>Earnings-to-price</i>	185	0.056	0.039	185	0.072	0.057	-	-0.016	0.001	-3.97

Notes:

In this table, we calculate means at the firm level for misstatement years versus all nonmisstatement years and conduct tests of pairwise differences in means. Each firm is directly compared to itself during manipulation years versus other years. 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 years versus firm-years prior to misstatement years for AAER firms

Variable	Misstatement years				Early years				Misstate – Early years		
	N	Mean	Median	N	Mean	Median	Pred sign	Pair-wise diff. in mean	One-tailed p-value	Pair-wise t-statistics	
Accruals quality variables											
<i>WC accruals</i>	263	0.069	0.047	263	0.068	0.056	+	0.001	0.452	0.12	
<i>RSST accruals</i>	261	0.120	0.076	261	0.173	0.100	+	-0.053	0.025	-1.97	
<i>Change in receivables</i>	265	0.069	0.040	265	0.073	0.047	+	-0.004	0.328	-0.46	
<i>Change in inventory</i>	262	0.043	0.019	262	0.049	0.027	+	-0.006	0.168	-0.96	
<i>% Soft assets</i>	299	0.649	0.692	299	0.595	0.605	+	0.054	0.001	5.07	
Performance variables											
<i>Change in cash sales</i>	209	0.410	0.206	209	0.473	0.287	-	-0.063	0.126	-1.15	
<i>Change in cash margin</i>	201	0.034	0.007	201	-0.001	0.002	-	0.035	0.210	0.81	
<i>Change in return on assets</i>	210	-0.026	-0.014	210	0.009	-0.001	+	-0.034	0.014	-2.23	
<i>Change in free cash flows</i>	205	0.020	0.006	205	0.017	0.003	-	0.003	0.445	0.14	
<i>Deferred tax expense</i>	268	0.002	0.000	268	0.004	0.000	+	-0.002	0.085	-1.37	
Nonfinancial variables											
<i>Abnormal change in employees</i>	223	-0.128	-0.102	223	-0.330	-0.120	-	0.202	0.001	3.32	
<i>Abnormal change in order backlog</i>	68	0.031	-0.063	68	-0.001	-0.013	-	0.032	0.375	0.33	
Off-balance-sheet variables											
<i>Change in operating lease activity</i>	266	0.020	0.006	266	0.024	0.009	+	-0.004	0.120	-1.18	
<i>Existence of operating leases</i>	299	0.857	1.000	299	0.685	0.833	+	0.172	0.001	9.41	

(The table is continued on the next page.)

TABLE 5 (Continued)

Variable	Misstatement years			Early years			Misstate – Early years			
	N	Mean	Median	N	Mean	Median	Pred sign	Pair-wise diff. in mean	One-tailed p-value	Pair-wise t-statistics
<i>Expected return on pension plan assets</i>	32	0.084	0.090	32	0.081	0.091	+	0.002	<i>0.190</i>	0.89
<i>Change in expected return on plan assets</i>	25	-0.041	0.000	25	-0.076	0.000	+	0.035	<i>0.167</i>	1.01
Market-related variables										
<i>Ex ante financing need</i>	191	0.143	0.000	191	0.186	0.000	+	-0.043	<i>0.053</i>	-1.63
<i>Actual issuance</i>	296	0.941	1.000	296	0.905	1.000	+	0.035	<i>0.008</i>	2.44
<i>CFF</i>	199	0.210	0.121	199	0.266	0.129	+	-0.056	<i>0.025</i>	-1.98
<i>Leverage</i>	299	0.189	0.164	299	0.181	0.149	+	0.008	<i>0.232</i>	0.73
<i>Market-adjusted stock return</i>	188	0.226	0.008	188	0.208	0.107	-	0.018	<i>0.451</i>	0.12
<i>Book-to-market</i>	245	0.555	0.363	245	0.510	0.412	+	0.045	<i>0.141</i>	1.08
<i>Earnings-to-price</i>	168	0.053	0.039	168	0.063	0.051	-	-0.010	<i>0.008</i>	-2.45

Notes:

In this table, we calculate means at the firm level for misstatement years versus years prior to misstatement years and conduct tests of pairwise differences in means. Each firm is directly compared to itself during manipulation years versus other years. 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 6
Descriptive statistics on misstatement firm-years versus COMPUSTAT firm-years for the sample from 1979 to 2002

Variable	Misstatement firm-years				COMPUSTAT firm-years				Misstate – COMPUSTAT	
	N	Mean	Median	N	Mean	Median	Pred sign	Diff. in mean	One-tailed p-value	t-statistics
Accruals quality variables										
<i>WC accruals</i>	559	0.062	0.036	152170	0.007	0.006	+	0.055	<i>0.001</i>	7.55
<i>RSST accruals</i>	557	0.126	0.074	151862	0.032	0.026	+	0.094	<i>0.001</i>	6.30
<i>Change in receivables</i>	561	0.061	0.036	151928	0.017	0.008	+	0.044	<i>0.001</i>	8.97
<i>Change in inventory</i>	557	0.039	0.008	152741	0.011	0.000	+	0.028	<i>0.001</i>	7.30
<i>% Soft assets</i>	604	0.642	0.682	167982	0.509	0.535	+	0.133	<i>0.001</i>	14.65
<i>Modified Jones model discretionary accruals</i>	524	0.057	0.027	145472	0.000	0.001	+	0.058	<i>0.001</i>	4.39
<i>Mean-adjusted absolute value of DD residuals</i>	338	0.017	-0.011	81369	0.000	-0.019	+	0.017	<i>0.001</i>	3.16
<i>Studentized DD residuals</i>	338	0.428	0.284	81369	0.001	0.015	+	0.427	<i>0.001</i>	6.82
Performance variables										
<i>Change in cash sales</i>	501	0.492	0.217	135333	0.208	0.079	-	0.283	<i>0.001</i>	6.38
<i>Change in cash margin</i>	490	0.010	0.006	132352	0.013	0.001	-	-0.003	<i>0.462</i>	-0.10
<i>Change in return on assets</i>	506	-0.024	-0.012	140380	-0.010	-0.002	+	-0.013	<i>0.082</i>	-1.39
<i>Change in free cash flows</i>	501	0.041	0.007	137686	0.021	0.005	-	0.020	<i>0.147</i>	1.05
<i>Deferred tax expense</i>	579	0.001	0.000	166164	0.001	0.000	+	0.000	<i>0.405</i>	-0.24
Nonfinancial variables										
<i>Abnormal change in employees</i>	489	-0.223	-0.103	134837	-0.093	-0.049	-	-0.130	<i>0.001</i>	-3.30
<i>Abnormal change in order backlog</i>	139	0.006	-0.062	35766	0.088	-0.040	-	-0.082	<i>0.130</i>	-1.12

(The table is continued on the next page.)

TABLE 6 (Continued)

Variable	Misstatement firm-years				COMPUSTAT firm-years				Misstate – COMPUSTAT	
	N	Mean	Median	N	Mean	Median	Pred sign	Diff. in mean	One-tailed p-value	t-statistics
Off-balance-sheet variables										
<i>Change in operating lease activity</i>	561	0.018	0.004	154469	0.009	0.000	+	0.009	<i>0.001</i>	4.32
<i>Existence of operating leases</i>	604	0.821	1.000	168481	0.710	1.000	+	0.111	<i>0.001</i>	7.11
<i>Expected return on pension plan assets</i>	73	0.082	0.090	22617	0.073	0.085	+	0.009	<i>0.002</i>	3.00
<i>Change in expected return on plan assets</i>	61	-0.001	0.000	18604	-0.041	0.000	+	0.040	<i>0.143</i>	1.08
Market-related variables										
<i>Ex ante finance need</i>	422	0.185	0.000	100436	0.170	0.000	+	0.015	<i>0.210</i>	0.81
<i>Actual issuance</i>	599	0.932	1.000	166712	0.826	1.000	+	0.105	<i>0.001</i>	10.18
<i>CFF</i>	434	0.210	0.101	103471	0.140	0.007	+	0.069	<i>0.001</i>	4.17
<i>Leverage</i>	604	0.201	0.171	168161	0.199	0.140	+	0.002	<i>0.408</i>	0.23
<i>Mkt-adj return</i>	463	0.194	-0.113	110303	0.008	-0.114	+	0.185	<i>0.006</i>	2.55
<i>Lagged mkt-adj return</i>	393	0.332	0.031	99197	0.030	-0.099	+	0.301	<i>0.001</i>	3.86
<i>Book-to-market</i>	548	0.529	0.348	135946	0.605	0.527	-	-0.076	<i>0.006</i>	-2.53
<i>Earnings-to-price</i>	343	0.064	0.043	84911	0.084	0.066	-	-0.020	<i>0.001</i>	-5.18

Note:

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.

flows, are all statistically insignificant in our time-series tests. *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 generalize, then this could explain why deferred taxes are not unusually high during misstatement years.

We next examine nonfinancial variables, *abnormal change in employees* and *abnormal change in order backlog*. Both variables show insignificant changes 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 exploit the financial reporting flexibility afforded by operating leases. For defined benefit pension plans we have only a small sample size. We find that both the *expected return on pension plan assets* and *change in expected return on pension plan assets* are significantly greater in misstatement years.

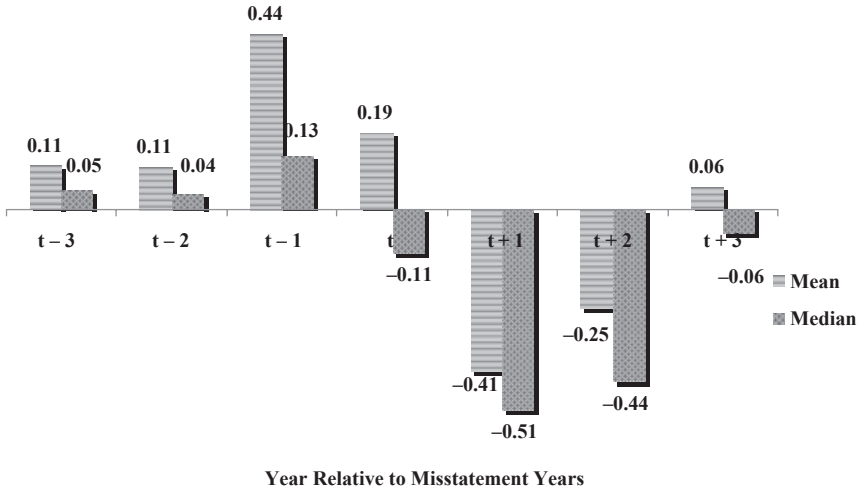
The final set of variables relates to market incentives. As predicted, we find that during misstating years more firms are issuing either debt or equity (93.8 percent versus 86.9 percent) and cash from financing is significantly higher (24.7 percent versus 15.1 percent). We argue that incentives to misstate are higher during issuing periods. However, the SEC is probably more likely to perform a review when a firm is raising capital and hence detect the misstatement. Therefore, it is possible that SEC bias could also explain this result. Both *leverage* and *ex ante financing need* are insignificantly different for misstatement years. *Market-adjusted stock return* is higher during misstatement years (23.4 percent versus -0.4 percent). We analyze this finding in more detail in Figure 1, discussed in the next section. *Book-to-market* ratios are in the opposite direction from what we predicted 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.

In summary, the results are generally consistent with our expectations. Misstating firms have high accruals, show declining performance, are raising financing, and have high growth expectations embedded in their stock prices.

Comparisons using only years before the misstatement

Using all firm-years, as in Table 4, provides more powerful tests because we capture information in accrual reversals and declines in performance, as well as changes in market expectations in the years after the misstatements. In many settings such information is readily available (e.g., for a researcher or regulator). However, it is important also to determine the predictive nature of the variables. Table 5 replicates the analysis in Table 4 but uses only the years prior to the misstatement as nonmisstatement years. In Table 5 we do not report the results for accrual models. The modified Jones model pools across

Figure 1 Annual market-adjusted stock returns surrounding misstatement years.



Notes:

For all firm-years with available returns data on the Center for Research in Security Prices. Returns include delisting returns. For year $t - 3$ $n = 137$, for year $t - 2$ $n = 166$, for year $t - 1$ $n = 188$, for year t $n = 474$, for year $t + 1$ $n = 250$, for year $t + 2$ $n = 202$, and for year $t + 3$ $n = 153$. Year t is the average return for all misstatement firm-years. Market-adjusted returns are calculated as the difference between annual raw returns and value-weighted market returns.

firms in each industry and over time and so is not typically used by researchers in a predictive setting. The Dechow and Dichev 2002 model uses future cash flows in the regression and so is not applicable to a predictive setting.⁸

The first thing to note in Table 5 is that, in contrast to Table 4, the accrual variables are not significant; in fact, *RSST accruals* is the wrong sign and significant. This suggests that, in years prior to the manipulation, accruals are the same as or higher than in the manipulation years identified by the SEC. Only *% soft asset* is significantly higher in misstating years relative to prior years, suggesting a buildup of assets whose values are more subject to manipulation in the misstating years.

There are several potential explanations for the lack of accrual results. First, managers could use “within GAAP” accounting flexibility to overstate earnings before resorting to the accounting techniques viewed as “outside” of GAAP by the SEC. Thus the high prior accruals are indicative of

8. Both models could be adjusted in various ways to make them predictive. We chose not to do this because it would detract from the main focus of our paper (i.e., the use of variables easily identified in the financial statements).

more estimation error and reliability concerns (e.g., Richardson et al. 2005). Second, the high prior accruals could reflect manipulation that was too difficult for the SEC to identify or prove and so was not reported in the AAER. Third, the high prior accruals could indicate overinvestment by managers. Many of the AAER firms are raising financing, and both managers and investors could believe that greater investment will lead to more growth. Managers could therefore be optimistic about the value of inventory, credit sales, PP&E, and other assets. However, when growth slows, managers may not wish to reveal the decline in sales or their overinvestment and so resort to the aggressive accounting techniques identified by the SEC.

Turning to the performance variables, we see that most variables are not significantly different at conventional levels. The two exceptions are *return on assets*, which, as in Table 4, is the wrong sign (i.e., manipulating firms' return on assets is lower in misstating years) and *deferred tax expense* (also the wrong sign). Turning to the nonfinancial measures, we see that *abnormal change in employees* is higher in manipulation years. We predicted that employee growth would be slower than asset growth (due to the inflation of assets) in manipulation years. Thus the results are inconsistent with our expectations. Recall that net operating assets are increasing at a faster rate in earlier years (*RSST accruals* is the wrong sign), so the inconsistent results could be due to the change in assets rather than change in employees. For off-balance-sheet variables, the proportion of firms with operating leases is higher in manipulation years than in earlier years (0.857 versus 0.685), consistent with firms switching to off-balance-sheet assets. Operating leases tend to have lower expenses than capitalizing the lease, early in the asset's life, so switching to leasing will improve earnings in growing firms. For market-related variables, we find that the need for financing (*ex ante financing need*) is higher in earlier years, while *actual issuance* is higher in manipulation years. This suggests that the firm needed to raise capital in earlier years and did so (*CFF* is also higher in earlier years) but that more firms actually issued debt or equity financing in manipulation years. This is consistent with managers manipulating the financial statements to obtain the financing. Market-to-book ratios and stock price performance are similar in earlier years and manipulation years. However, the earnings-to-price ratio is lower in manipulation years, consistent with managers being able to maintain investor expectations during manipulation years even though earnings declined.

Figure 1 provides a graphical timeline of 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. The graph reveals 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 et al. 1991; Karpoff et al. 2008).

Note that the strong positive stock price performance during and prior to manipulation years, combined with the negative stock price performance that followed, could be one factor that triggered the SEC investigation.

Taken together, misstating firms appear to be engaging in more off-balance-sheet financing through leases, with relatively more of their asset bases being composed of soft assets whose values are more subject to manipulation. Moreover, misstating firms could be concerned about investor expectations. Their stock price performance is very high (around 20 percent) prior to and in the year of misstatement, and they are issuing equity and raising financing. They also appear to be either overinvesting in their assets or engaging in accrual manipulation prior to and at the time of the misstatement. Misstating firms have high accruals followed by significant declines in return on assets during misstatement years.

Cross-sectional analysis of misstating firm-years

Our next test reported in Table 6 compares misstating firm-years to all firms listed on the COMPUSTAT Annual File between 1979 and 2002. We limit the sample to these years because the first AAER release occurred in 1982, and very few firms are identified as misstating prior to 1979. The objective of this test is to identify unusual characteristics of misstating firms relative to the population. As mentioned earlier, we do this broad comparison (rather than an industry size match comparison) because when we develop our *F*-score model we want a measure that can be easily applied to all firms. Industry adjustments would add complexity to this objective, although we acknowledge that industry adjustment could improve the model's predictive ability. We provide some insights into this issue later in our robustness tests, reported in Table 9.

The first set of variables reported in Table 6 relates to accrual quality. We exclude performance-matched discretionary accruals, because this adjustment is redundant when using the entire population. The results indicate that all accrual variables are unusual and in the predicted direction in misstating years, relative to the population. For example, in misstating years the *RSST accrual* measure is 12.6 percent of assets, whereas for the population, this measure is 3.2 percent of assets. Similarly, *change in receivables* is 6.1 percent for misstating firms and only 1.7 percent for the population. *% soft assets* is also higher for misstating firms. The *studentized DD* measure indicates that misstating firms' residuals are on average 0.428 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 (0.492 versus 0.208). However, *change in return on assets* is significantly lower for misstating firms (−0.024 versus −0.010). The results for nonfinancial variables and off-balance-sheet variables are significant in most cases and all in the predicted direction. Notably, for firms with pension plans we find that misstating firms assume significantly higher expected returns on their plan assets (8.20 percent versus

7.30 percent). However, the change in expected return on plan assets is insignificant.

Finally, for the market-related variables, the results are all in the predicted direction and significant in all but two variables (*ex ante finance need* and *leverage* are insignificant). 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. In contrast to Table 4, *book-to-market* now loads in the correct direction. Thus both *book-to-market* and *earnings-to-price* are significantly lower for misstating firms (i.e., they have high valuations relative to fundamentals).

Prediction analysis and development of the F-score

In this section we provide multivariate analysis of variables discussed in Table 6. 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 auditors (in terms of lawsuits), to investors (in terms of negative stock returns), to regulators like the 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 can be used as a first-pass screen to identify firms that warrant further investigation.

Table 7 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 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 nonfinancial-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.⁹ We then use the computational algorithm of Lawless and

9. 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 6, and order backlog and pension variables because these are available for a limited set of firms.

TABLE 7
Logistic regressions and development of the *F*-score

Panel A: Logistic regressions examining the determinants of misstatements

Variable	Model 1 Financial statement variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)	Model 2 Add off-balance- sheet and nonfinancial variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)	Model 3 Add stock market-based variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)
<i>Intercept</i>	-7.893 1180.0 0.001	-8.252 973.1 0.001	-7.966 708.5 0.001
<i>RSST accruals</i>	0.790 24.1 0.001	0.665 12.5 0.001	0.909 11.1 0.001
<i>Change in receivables</i>	2.518 28.5 0.001	2.457 23.7 0.001	1.731 7.4 0.003
<i>Change in inventory</i>	1.191 4.4 0.019	1.393 5.4 0.010	1.447 4.0 0.023
<i>% Soft assets</i>	1.979 86.3 0.001	2.011 74.3 0.001	2.265 68.4 0.001

(The table is continued on the next page.)

TABLE 7 (Continued)

Variable	Model 1	Model 2	Model 3
	Financial statement variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)	Add off-balance-sheet and nonfinancial variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)	Add stock market-based variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)
<i>Change in cash sales</i>	0.171 17.0 0.001	0.159 11.6 0.001	0.160 5.9 0.008
<i>Change in return on assets</i>	-0.932 19.9 0.001	-1.029 20.6 0.001	-1.455 20.1 0.001
<i>Actual issuance</i>	1.029 28.5 0.001	0.983 22.4 0.001	0.651 8.2 0.002
<i>Abnormal change in employees</i>		-0.150 4.2 0.020	-0.121 1.5 0.113
<i>Existence of operating leases</i>		0.419 8.4 0.002	0.345 4.4 0.019
<i>Market-adjusted stock return</i>			0.082 8.4 0.002

(The table is continued on the next page.)

TABLE 7 (Continued)

Variable	Model 1 Financial statement variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)	Model 2 Add off-balance- sheet and nonfinancial variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)	Model 3 Add stock market-based variables Coefficient estimate (Wald Chi-square) (<i>p</i> -value)
<i>Lagged market-adjusted stock return</i>			0.098
			8.9
Misstating firm-years	494	449	0.001
Nonmisstating firm-years	132,967	122,366	354
			88,032

Notes:

Dependent variable is equal to one if the firm-year misstated earnings, zero otherwise. 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. The reported *p*-values are based on one-tailed tests.

(The table is continued on the next page.)

TABLE 7 (Continued)

	Model 1			Model 2			Model 3		
	<i>N</i>	Min. <i>F</i> -score	% of total	<i>N</i>	Min. <i>F</i> -score	% of total	<i>N</i>	Min. <i>F</i> -score	% of total
Quintile 1									
Misstate firms	16	0.053	3.24	13	0.042	2.90	10	0.052	2.82
No-misstate firms	26,676	0.009	20.06	24,550	0.008	20.06	17,667	0.008	20.07
Quintile 2									
Misstate firms	43	0.390	8.70	37	0.393	8.24	36	0.386	10.17
No-misstate firms	26,649	0.385	20.04	24,526	0.351	20.04	17,641	0.382	20.04
Quintile 3									
Misstate firms	84	0.615	17.00	76	0.600	16.93	61	0.631	17.23
No-misstate firms	26,609	0.614	20.01	24,487	0.598	20.01	17,617	0.630	20.01
Quintile 4									
Misstate firms	99	0.936	20.04	94	0.926	20.94	77	0.940	21.75
No-misstate firms	26,593	0.933	20.00	24,469	0.925	20.00	17,600	0.935	19.99
Quintile 5									
Misstate firms	252	1.397	51.01	229	1.418	51.00	170	1.415	48.02
No-misstate firms	26,440	0.933	19.88	24,334	0.925	19.89	17,507	0.935	19.89

Notes:

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.

(The table is continued on the next page.)

TABLE 7 (Continued)

Observed	Model 1 predicted		Model 2 predicted		Model 3 predicted	
	Misstate	No-misstate	Misstate	No-misstate	Misstate	No-misstate
Misstate	339	155	494	144	238	116
No-misstate	48,282	84,685	132,967	78,370	31,934	56,098
	48,621	84,840	133,461	78,514	32,172	56,214
Misstate	68.6%	31.4%	0.4%	32.1%	67.2%	32.8%
No-Misstate	36.3%	63.7%	99.6%	64.0%	36.3%	63.7%
Correct classification		63.71% (1)		64.06%		63.74%
Sensitivity		68.62% (2)		67.93%		67.23%
Type I errors		36.31% (3)		35.95%		36.28%
Type II errors		31.38% (4)		32.07%		32.77%
			449	122,366	449	122,366
			122,815	0.4%	122,815	0.4%
			99.6%	99.6%	99.6%	99.6%

Notes:

- (1) Correct classification is calculated as [(339 + 84,685)/133,461].
- (2) Sensitivity is calculated as (339/494).
- (3) Type I errors are calculated as (48,282/132,967).
- (4) Type II errors are calculated as (155/494).

Singhal 1978 to compute a first-order approximation of the remaining slope estimates for subsequent variable eliminations. Variables are removed based on these approximations. We set the significance level for elimination at the 15 percent level.¹⁰

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*, *% soft assets*, *change in cash sales*, *change in return on assets*, and *actual issuance*. For Model 2, we retain the variables from Model 1 and add the nonfinancial 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*). The two return measures, *lagged market-adjusted stock return* and *market-adjusted stock return* in the current year, are retained in the model after backward elimination. Table 7, panel A provides the resulting coefficient estimates for the models.

Next, we examine the quality of our models. As we suggested above, it is important to remember that, because we cannot identify firms that misstate and are not subsequently caught and investigated by the SEC, our analysis of errors is based on the joint fact that a firm misstated and received an enforcement action from the SEC. To examine the quality of our models, we analyze the predicted probabilities that the model assigns to each observation. It is not possible to test how well our model performs at predicting firms that misstate but are not subsequently caught by the SEC. 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:

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

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 in 2000.

10. 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

$$\begin{aligned} \text{Predicted Value} = & -7.893 + 0.790 \times (rsst_acc) + 2.518 \times (ch_rec) \\ & + 1.191 \times (ch_inv) + 1.979 \times (soft_assets) \\ & + 0.171 \times (ch_cs) + (-0.932) \times (ch_roa) + 1.029 \times (issue) \end{aligned}$$

$$\begin{aligned} \text{Predicted Value} = & -7.893 + 0.790 \times (0.01659) + 2.518 \times (0.17641) \\ & + 1.191 \times (.00718) + 1.979 \times (0.79975) \\ & + 0.171 \times (1.33335) + (-0.932) \times (-0.01285) + 1.029 \times (1) \end{aligned}$$

$$\begin{aligned} \text{Predicted Value} & = -4.575 \\ \text{Probability} & = e^{(-4.575)} / (1 + e^{(-4.575)}) \\ e & = 2.71828183 \end{aligned}$$

$$\text{Probability} = 0.01020$$

$$\text{Unconditional probability} = 494 / (132,967 + 494) = 0.0037$$

$$F\text{-score} = 0.01020 / 0.0037$$

$$F\text{-score for Enron} = 2.76$$

An *F*-score of 1.00 indicates that the firm has the same probability of misstatement as the unconditional expectation. *F*-scores greater than one indicate higher probabilities of misstatement than the unconditional expectation. Enron has an *F*-score of 2.76. This suggests that Enron has more than twice the probability of having misstated compared to a randomly selected firm from the population.

Table 7, panel B ranks firm-years into five portfolios based on the magnitude of their *F*-scores. We report the frequency with which misstating and nonmisstating firms fall into each quintile and the minimum *F*-score required to be included in each quintile. If our models do a good job of identifying misstatement firms, then we expect misstatement firms to be clustered in the fifth portfolio. The results for Model 1 indicate that 51.01 percent of misstatement firms are in quintile 5, compared to the expected level of 20 percent. The cutoff to be included in quintile 5 (i.e., the minimum value) is 1.397, so Enron's score for 2000 of 2.76 easily places it in quintile 5. Model 2 adds nonfinancial and off-balance-sheet variables to the variables in Model 1, and 51 percent of misstating firms are in quintile 5. For Model 3, which includes market-related variables, 48.02 percent of misstating firms are in quintile 5.

In panel C of Table 7, we evaluate the sensitivity of our models and determine Type I and Type II error rates for an *F*-score cutoff of 1.00. The results for Model 1 indicate that we correctly classify 339 of the 494 firms (sensitivity equal to 68.62 percent). A Type II error occurs when our model *incorrectly classifies a misstating firm* as a nonmisstating firm. The Type II error rate is 31.38 percent (155 divided by 494). A Type I error occurs when our model *incorrectly classifies a nonmisstating firm* as a misstating firm.

For an F -score cutoff of 1.00, we incorrectly classify 48,282 nonmisstating years out of 132,967 total misstating years (our Type I error is 36.31 percent). Similar results are found for Model 2 and Model 3.¹¹

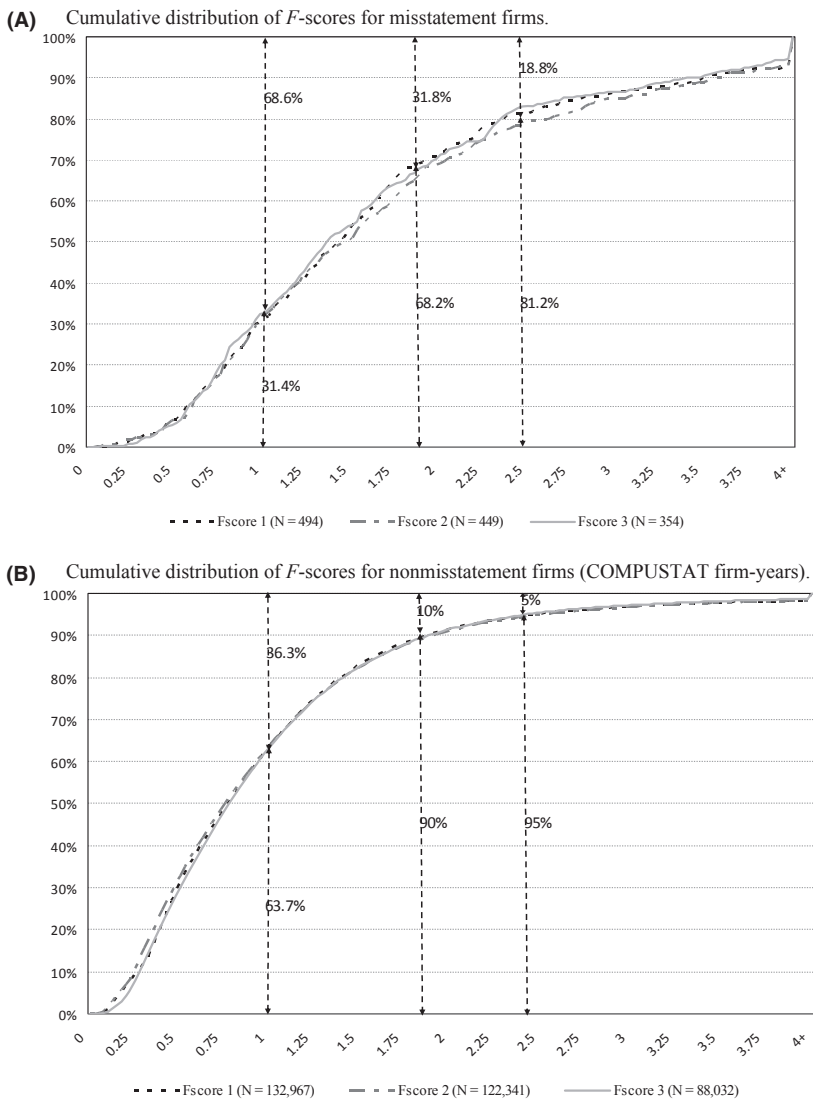
We provide further insights into sensitivity and Type I and Type II error rates in Figure 2. Figure 2A provides the cumulative distribution of F -scores for misstating firm-years. Figure 2B reports the cumulative distribution for all nonmisstating firms. These figures can be used to assess sensitivity and Type I error rates for any F -score cutoff. For example, for an F -score of 2.45, Figure 2A reveals that the sensitivity is 18.8 percent (93 of 494 misstating firms have F -scores above this cutoff) and the Type II error rate is 81.2 percent (401 of 494 misstating firms are classified as “clean”), while the Type I error rate is 5 percent (6,665 of 132,967 nonmisstating firms have F -scores above this cutoff), while 95 percent of nonmisstating firms are correctly classified. As a simple rule of thumb, we classify an F -score greater than 1 as “above normal risk” and an F -score greater than 2.45 as “high risk”.

Figure 2 can also provide insights into the likelihoods of Type I and Type II errors. The cost of these errors is not the same. From an auditor’s perspective the cost of Type I and Type II errors is likely to differ, with Type II errors being more costly. When a misstatement goes undetected (and is later revealed), the auditor is likely to be sued by investors, to be sanctioned by regulatory bodies such as the SEC and the PCAOB and to suffer a loss of reputation. A Type I error (a nonmisstating firm is suspected of misstatement) is not costless and may result in lost fees, as the auditor may choose to drop a client. Because Type II errors are more costly to the auditor, an auditor is likely to prefer an F -score cutoff that makes more Type I errors than Type II errors.

Figure 2C provides insights into how a user might make the trade-off between Type I and Type II errors and provides a *relative cost of errors ratio*. For each F -score, Figure 2C provides the total number of firms

11. 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 reestimated Models 1 and 2 using only observations available for Model 3 and find that variable selection does not change, with the exception of abnormal change in employees dropping from the model (not tabulated). When using the variables in Table 6 and setting an F -score cutoff of 1.00, we find that with a consistent set of observations, Model 3 correctly classifies 66.95 percent (237/354) of misstatement firms and 63.86 percent (55,225/88,032) of nonmisstatement firms. For Model 1 the correct classification of misstatement firms increases slightly to 67.23 percent (238/354), while the correct classification of nonmisstatement firms decreases slightly to 63.55 percent (55,947/88,032). Model 2 correctly classifies 65.53 percent (232/354) of misstatement firms and 63.51 percent (55,908/88,032) of nonmisstatement firms. This suggests that, when considering only firms with stock price information, Model 3 offers a slight improvement in classifying nonmisstatement firms over Model 1 and Model 2 and a slight deterioration in classifying misstatement firms relative to Model 1.

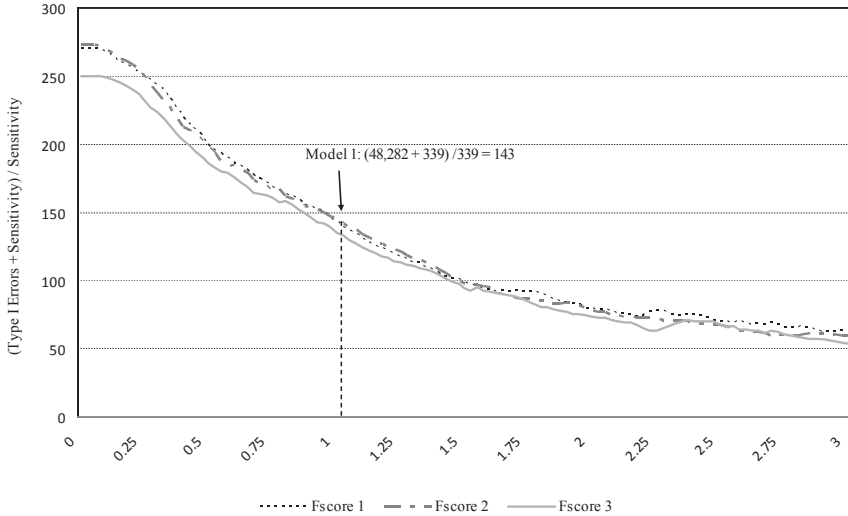
Figure 2 Evaluating the likelihood of a given *F*-score.



Notes:

Interpreting F-score 1 (Similar interpretation for F-score 2 and F-score 3)			
F-score 1 greater than 2.45	5% of non-misstatement firms	18.8% of misstating firms	“High” risk
F-score 1 greater than 1.85	10% of non-misstatement firms	32.6% of misstating firms	“Substantial” risk
F-score 1 greater than 1	36.3% of non-misstatement firms	68.6% of misstating firms	“Above normal” risk
F-score 1 less than 1	63.7% of non-misstatement firms	31.4% of misstating firms	“Normal or low” risk

(C) Relative cost ratio: An analysis of error rates across *F*-scores.



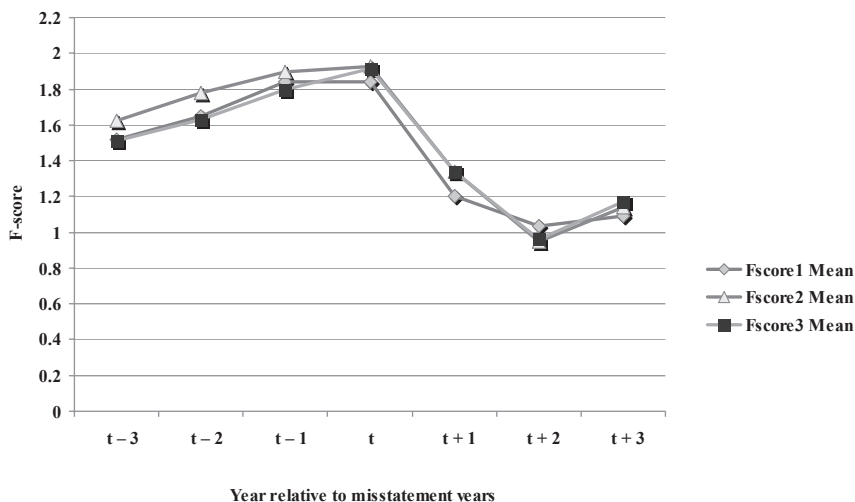
Notes:

Type I errors = misclassified nonmisstating firm; Type II errors = misclassified misstating firms; Sensitivity = correctly classified misstating firms. At an *F*-score cutoff of 1.00, the total number of nonmisstating firms is 132,967, of which 48,282 have *F*-scores greater than 1.00 (Type I error) and 339 of the 494 misstating firms have *F*-scores greater than 1.00. At this *F*-score cutoff the relative cost ratio is 143 [(48,282 + 339)/339]. If the cost of investigating a firm is \$1 and investigations accurately identify misstating firms, then it is worth investigating all firms with *F*-scores greater than or equal to one, if the cost of a misstating firm is greater than \$143.

with an *F*-score equal to or greater than that *F*-score divided by the total number of misstating firms with an *F*-score equal to or greater than that *F*-score. This is calculated as the number of Type I errors (incorrectly classified nonmisstatement firms) plus the sensitivity (the number of correctly classified misstating firms) divided by the sensitivity. Assume that the cost of investigating a firm is \$1 and an investigation always detects misstatements if they exist. At an *F*-score cutoff of 1.00, the relative cost ratio is 143 [(48,282 + 339)/339]. A cost of \$48,621 is incurred to avoid the 339 misstating firms. Therefore, if the cost of missing a fraud firm is \$143 or more, then an *F*-score cutoff of 1.00 should be used by the auditor. If the cost is over \$250, then all firms should be investigated (because the *F*-score cutoff is equal to zero). If the cost is less than \$50, it is cheaper not to do the investigation and just pay the extra cost of the misstatement firms as they are identified.

Next, we examine the time-series properties of the *F*-score for misstating firms. Figure 3 plots the mean *F*-score for misstating firms for the three years prior to misstatement years, during misstatement years, and for the

Figure 3 Mean F -scores surrounding misstatement firm-years.



Note:

This figure plots the mean F -score for misstatement firms for the three years prior to misstatement years, during misstatement years, and the three years following misstatement years.

three years following misstatement years. Figure 3 indicates that the average F -score for misstating firms is 1.5 prior to the misstatement, peaks at around 1.9 during misstatement years, and declines to approximately 1.0 following misstatement years. It is interesting to note the high average F -scores prior to the misstatement years in light of our Table 5 results indicating that accruals and many other variables do not differ significantly in misstatement years relative to years before the misstatement. If we assume that firms first use the flexibility to manage earnings within GAAP before resorting to more aggressive earnings management identified by the SEC, then the elevated F -scores in years $t - 3$ to $t - 1$ indicate that the F -score reflects earnings management within GAAP. Further, the significant number of Type I errors reported in Table 7 could include a disproportionate number of nonmisstating firms that actually are managing earnings. To the extent that this is true, the number of actual Type I errors in our model is overstated.

Marginal analysis and robustness tests of F -score models

In this section we evaluate the influence of each of the variables in the models for determining the magnitude of F -scores (marginal effect analysis). We then provide a number of tests to examine how sensitive the variables classification is to time periods and industry clustering.

Table 8 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 interquartile 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); and (v) repeat steps (ii) through (iv) for the next independent variable.

Table 8, 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 Models 1 through 3. The first thing to note is that the average F -score for Model 1 is 0.728.¹² When *RSST accruals* are at their lower quartile value and all other variables are at their mean values, the F -score changes from 0.728 to 0.694. Moving *RSST accruals* to their upper quartile value changes the F -score to 0.771, giving an interquartile range of 0.077. The results for Model 1 indicate that the three variables with the greatest impact are *change in receivables* (0.099), *% soft assets* (0.595), and *actual issuance* (0.559). Because 82.5 percent of the sample firms issue securities in a given year, a firm that does not issue has a far lower risk of being a misstating firm. In Table 9, panel C (discussed next) we investigate whether industry factors could be influencing the importance of *% soft assets*. The joint marginal effect (when moving all independent variables in the predicted direction between the first and third quartiles or between zero and one for indicator variables) increases the F -score from 0.169 to 1.547. For Model 2, *existence of operating leases (leasedum)* has a relatively large marginal impact on the F -score (0.264); note that 73.4 percent of firms have leases. For Model 3, the return variables appear to have little marginal impact on the F -score. Finally, in panel C we provide the Spearman and Pearson correlations of the variables with the F -score. The correlations are all significant and are generally consistent with the marginal effect analysis in the sense that variables with a higher correlation have higher marginal effects.

Overall, the results in Table 8 suggest that while accrual variables are important contributors to the F -score they are not unduly influencing the F -score; other variables in the model also play an important role. This suggests that the F -score is likely to provide incremental information beyond accruals for researchers investigating earnings management.

Table 9 provides a variety of robustness tests related to our models. Here we focus on Model 3 because this provides all the variables we analyze. Similar results are obtained for Models 1 and 2.

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

TABLE 8
Marginal effect analysis on *F*-scores for each model

Panel A: Descriptive statistics

	<i>rsst_acc</i>	<i>ch_rec</i>	<i>ch_inv</i>	<i>soft_assets</i>	<i>ch_cs</i>	<i>ch_roa</i>	<i>issue</i>	<i>ch_emp</i>	<i>leasedum</i>	<i>ret_t</i>	<i>ret_{t-1}</i>
Mean	0.019	0.014	0.009	0.518	0.210	-0.010	0.825	-0.071	0.734	0.017	0.036
Std dev	0.267	0.085	0.068	0.250	0.766	0.205	0.380	0.466	0.442	1.039	0.868
Lower quartile	-0.043	-0.013	-0.006	0.315	-0.048	-0.043	1.000	-0.158	0.000	-0.396	-0.370
Median	0.024	0.007	0.000	0.545	0.080	-0.002	1.000	-0.047	1.000	-0.105	-0.091
Upper quartile	0.091	0.041	0.024	0.719	0.245	0.026	1.000	0.063	1.000	0.208	0.219
1%	-0.975	-0.293	-0.253	0.030	-0.987	-0.876	0.000	-2.087	0.000	-1.000	-0.961
99%	0.974	0.328	0.268	0.961	5.459	0.837	1.000	1.442	1.000	2.989	3.016

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	<i>rsst_acc</i>	<i>ch_rec</i>	<i>ch_inv</i>	<i>soft_assets</i>	<i>ch_cs</i>	<i>ch_roa</i>	<i>issue</i>
Coefficient estimate	0.790	2.518	1.191	1.979	0.171	-0.932	1.029
<i>F</i> -score at upper quartile ^b	0.771	0.779	0.742	1.083	0.733	0.751	0.871
<i>F</i> -score at lower quartile ^a	0.694	0.680	0.716	0.488	0.697	0.704	0.312
Interquartile marginal change in <i>F</i> -score ^c	0.077	0.099	0.026	0.595	0.036	0.047	0.559

Notes:

F-score when all variables are at their mean values (0.728); lower quartile (0.169); upper quartile (1.547). Change in *F*-score for joint interquartile marginal effect (moving all variables from the lower to the upper quartile) (1.378).

(The table is continued on the next page.)

TABLE 8 (Continued)

Model 2	<i>rsst_acc</i>	<i>ch_rec</i>	<i>ch_inv</i>	<i>soft_assets</i>	<i>ch_cs</i>	<i>ch_roa</i>	<i>issue</i>	<i>ch_emp</i>	<i>leasedum</i>
Coefficient estimate	0.665	2.457	1.393	2.011	0.159	-1.029	0.983	-0.150	0.419
<i>F</i> -score at upper quartile	0.725	0.738	0.706	1.034	0.695	0.715	0.820	0.700	0.772
<i>F</i> -score at lower quartile	0.663	0.646	0.677	0.460	0.663	0.666	0.307	0.677	0.508
Interquartile marginal change in <i>F</i> -score	0.062	0.091	0.029	0.574	0.032	0.049	0.513	0.023	0.264

Notes:

F-score when all variables are at their mean values (0.6911); lower quartile (0.120); upper quartile (1.651). Change in *F*-score for joint interquartile marginal effect (1.531).

Model 3

	<i>rsst_acc</i>	<i>ch_rec</i>	<i>ch_inv</i>	<i>soft_assets</i>	<i>ch_cs</i>	<i>ch_roa</i>	<i>issue</i>	<i>ch_emp</i>	<i>leasedum</i>	<i>ret_{t-1}</i>
Coefficient estimate	0.909	1.731	1.447	2.265	0.160	-1.455	0.651	-0.121	0.345	0.082
<i>F</i> -score at upper quartile	0.737	0.723	0.706	1.088	0.695	0.725	0.774	0.698	0.757	0.702
<i>F</i> -score at lower quartile	0.653	0.659	0.676	0.437	0.663	0.656	0.404	0.680	0.537	0.668
Interquartile marginal change and <i>F</i> -score	0.085	0.064	0.030	0.651	0.032	0.069	0.370	0.018	0.220	0.034

Notes:

F-score when all variables are at their mean values (0.6908); lower quartile (0.146); upper quartile (1.679). Change in *F*-score for joint interquartile marginal effect (1.533).

Notes:

- ^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_roa*, *ch_emp*), *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 Interquartile 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.

(The table is continued on the next page.)

TABLE 8 (Continued)

Panel C: Correlation between *F*-score and its components

	<i>rsst_acc</i>	<i>ch_rec</i>	<i>ch_inv</i>	<i>soft_assets</i>	<i>ch_cs</i>	<i>ch_roa</i>	<i>issue</i>	<i>ch_emp</i>	<i>leasedum</i>	<i>ret_t</i>	<i>ret_t - 1</i>
Spearman correlation											
<i>F</i> -score (Model 1)	0.340	0.455	0.353	0.685	0.302	-0.043	0.534				
<i>F</i> -score (Model 2)	0.302	0.430	0.344	0.693	0.282	-0.055	0.498	-0.130	0.433		
<i>F</i> -score (Model 3)	0.312	0.395	0.354	0.776	0.262	-0.059	0.349	-0.110	0.382	0.194	0.106
Pearson correlation											
<i>F</i> -score (Model 1)	0.326	0.512	0.385	0.490	0.359	-0.066	0.296				
<i>F</i> -score (Model 2)	0.300	0.486	0.381	0.484	0.328	-0.074	0.272	-0.238	0.259		
<i>F</i> -score (Model 3)	0.306	0.397	0.361	0.486	0.259	-0.100	0.194	-0.193	0.218	0.303	0.190

Notes:

All the correlation coefficient estimates are significant at a less than 1% level. All variables are defined in Table 3. Each of the continuous variables is winsorized at 1% and 99% to mitigate outliers.

TABLE 9
Robustness tests

Panel A: Logistic regressions examining the determinants of misstatements estimated for Model 3

Variable	(1) Variables selected for Model 3 for 1979–1998 period Coefficient estimate (Wald Chi-square)	(2) Variables selected for Model 3 excluding boom years (1998–2000) Coefficient estimate (Wald Chi-square)	(3) Adding industry variables to Model 3 in Table 7 Coefficient estimate (Wald Chi-square)
<i>Intercept</i>	-7.560*** 550.9	-7.597*** 612.0	-8.005*** 705.5
<i>RSST accruals</i>	1.049*** 10.9	0.885*** 8.8	0.849*** 9.8
<i>Change in receivables</i>	1.227** 2.8	1.639*** 5.5	1.543*** 6.0
<i>Change in inventory</i>	1.813** 4.9	1.797*** 5.3	1.680** 5.2
<i>% Soft assets</i>	1.768*** 33.2	1.963*** 45.2	2.214*** 64.7
<i>Change in cash sales</i>	0.195*** 8.2	0.188*** 8.2	0.153** 5.2
<i>Change in return on assets</i>	-1.280*** 10.5	-1.317*** 13.5	-1.328*** 17.3
<i>Actual issuance</i>	0.521** 4.7	0.501** 4.8	0.639*** 7.9
<i>Abnormal change in employees</i>			-0.122 1.5

(The table is continued on the next page.)

TABLE 9 (Continued)

Variable	(1) Variables selected for Model 3 for 1979–1998 period Coefficient estimate (Wald Chi-square)	(2) Variables selected for Model 3 excluding boom years (1998–2000) Coefficient estimate (Wald Chi-square)	(3) Adding industry variables to Model 3 in Table 7 Coefficient estimate (Wald Chi-square)
<i>Existence of operating leases</i>	0.406** 5.1	0.329** 3.7	0.274* 2.5
<i>Book-to-market</i>	-0.157** 4.1	-0.159*** 5.4	
<i>Market-adjusted stock return</i>			0.095*** 8.1
<i>Lagged market-adjusted stock return</i>	0.092*** 9.5	0.090*** 9.9	0.079*** 7.4
<i>Computer</i>			0.515*** 13.2
<i>Retail</i>			0.443 0.5
<i>Services</i>			0.305** 3.1
<i>Retail X Existence of operating leases</i>			-0.259 0.2

(The table is continued on the next page.)

TABLE 9 (Continued)

Variable	(1) Variables selected for Model 3 for 1979–1998 period Coefficient estimate (Wald Chi-square)	(2) Variables selected for Model 3 excluding boom years (1998–2000) Coefficient estimate (Wald Chi-square)	(3) Adding industry variables to Model 3 in Table 7 Coefficient estimate (Wald Chi-square)
Misstating firm-years	269	299	354
Nonmisstating firm-years	74,510	83,090	88,032

Notes:

Dependent variable is equal to one if the firm-year misstated earnings, zero otherwise. All variables are define in Table 3. Each of the continuous variables (except stock return variables) is winsorized at 1% and 99% to mitigate outliers. We do not report *p*-values because of space limitation. ***, **, * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively, under one-tailed tests.

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

Quintile 1	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 7		
	<i>N</i>	Min. <i>F</i> -score	% of total	<i>N</i>	Min. <i>F</i> -score	% of total	<i>N</i>	Min. <i>F</i> -score	% of total
Misstake firms	3	0.358	2.8	12	0.060	4.01	12	0.084	3.39
No-misstake firms	3,553	0.012	20.1	16,665	0.014	20.06	17,665	0.009	20.07

(The table is continued on the next page.)

TABLE 9 (Continued)

	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 7		
	<i>N</i>	Min. <i>F</i> -score	% of total	<i>N</i>	Min. <i>F</i> -score	% of total	<i>N</i>	Min. <i>F</i> -score	% of total
Quintile 2									
Misstate firms	8	0.481	7.48	29	0.427	9.70	29	0.382	8.19
No-misstate firms	3,549	0.456	20.08	16,649	0.415	20.04	17,648	0.370	20.05
Quintile 3									
Misstate firms	17	0.722	15.89	53	0.657	17.73	59	0.613	16.67
No-misstate firms	3,540	0.697	20.03	16,625	0.652	20.01	17,619	0.609	20.01
Quintile 4									
Misstate firms	24	1.019	22.43	59	0.950	19.73	78	0.930	22.03
No-misstate firms	3,533	0.977	19.99	16,619	0.938	20.00	17,599	0.905	19.99
Quintile 5									
Misstate firms	55	1.414	51.40	146	1.388	48.83	176	1.395	49.72
No-misstate firms	3,501	0.977	19.81	16,532	0.938	19.90	17,501	0.905	19.88

Notes:

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.

TABLE 9 (Continued)

Observed	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	
	Misstate	No-misstate	Misstate	No-misstate	Misstate	No-misstate
Misstate	79	28	107	104	237	117
No-misstate	6,778	10,898	17,676	52,971	30,560	57,472
Misstate	6,857	10,926	17,783	53,075	30,797	57,589
No-misstate	73.8%	26.2%	0.6%	34.8%	66.9%	33.1%
Correct classification	38.3%	61.7%	99.4%	63.8%	34.7%	65.3%
Sensitivity		61.73% (1)		63.76%		65.29%
Type I errors		73.83% (2)		65.22%		66.95%
Type II errors		38.35% (3)		36.25%		34.71%
		26.17% (4)		34.78%		33.05%

Notes:

- (1) Correct classification is calculated as [(79 + 10,898)/17,783].
- (2) Sensitivity is calculated as (79/107).
- (3) Type I errors are calculated as (6,778/17,676).
- (4) Type II errors are calculated as (28/107).

We first investigate the sensitivity of our models to the time period examined. In Table 7 we develop our prediction model and evaluate its effectiveness using the same sample. Therefore, the models suffer from a hindsight bias and could overrepresent 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. However, for Model 2, we find that *abnormal change in employees* no longer loads, and for Model 3, *book-to-market* loads, but *market-adjusted return* does not. We report the results for 1979–1998 Model 3 in Table 9, panel A, column 1. We use the new estimates from this model to predict the *F*-scores for a holdout sample of firm-years from 1999 to 2002. We rank the holdout sample firms into quintiles and report the frequency and mean probabilities for misstating and nonmisstating firms by quintiles. The results are reported in Table 9, panel B. Compared to the results in Table 7, panel B for Model 3, the model shows a slight improvement in the percentage of misstating firms classified in quintile 5 (51.4 percent versus 48.02 percent in Table 7). However, generally the model does not appear to be too time specific.¹³

Another concern is that the Internet boom years (1998 to 2000) represent a large proportion of misstatements and so could unduly affect variable selection. We therefore rerun our backward elimination technique for our models excluding these years. The results are reported in column 2 of Table 9. We find that *abnormal change in employees* no longer loads, while *book-to-market* loads. In panels B and C we find similar results to those

13. We also conduct a rolling-window out-of-sample test. For Model 1 (financial statement variables), starting in 1990, we conducted backward elimination using all available data up until that point beginning with the significant variables from Table 6. Then we used the model to select variables and estimate coefficients. Using the results, we applied the model to the following year's data. We then did this for every year (the last year is estimated using the data through 2001 and applying this to 2002). The variables selected are quite consistent over time. For the 12 years, the variables differ from the model in Table 7 as follows: 1990 – *RSST accruals* and *change in inventory* are excluded while *WC accruals* is included; 1991 – *RSST accruals* and *change in return on assets* are excluded; 1992 – identical variables; 1993 – identical variables; and 1994 – *change in inventory* is excluded while *WC accruals* is included; 1995 – *change in inventory* is excluded; 1996 – *change in inventory* is excluded while *WC accruals* is included; 1997–2001 – identical variables. Out of 12 years, the model is identical for seven years. The changes in other years primarily involve substituting working capital accruals for total accruals or the elimination of inventory. This should not be surprising as the three variables are highly correlated. An analysis of the predicted out of sample *F*-scores for misstatement and nonmisstatement firms shows results similar to the out of sample results presented in Table 9.

reported in Table 7. Therefore, the models do not appear to be overly sensitive to Internet firms and their specific accounting problems.

A final concern is related to the undue impact of certain industries. Table 2, panel B documents that the computer, retail, and service industries appear to be overrepresented in the population of misstating firms. In addition, because leasing is used extensively in retail, another concern is that our leasing results could be due to the overrepresentation of retail firms in our sample. Further, we find that *% soft assets* is an important influencing variable, and this is likely to vary with industry composition and be higher in computer and service industries.¹⁴ Therefore, our next test investigates whether our models are unduly influenced by these industries and the existence of operating leases. We create industry dummies and an interactive dummy (*retail* × *existence of operating leases*) and add these variables to the estimation of Model 3 in Table 7. The results in Table 9, panel A, column 3 indicate that the coefficient on *% soft assets* declines slightly from 2.265 in Table 7 to 2.214 in Table 9 but remains highly statistically significant. In addition, the coefficients on the service industry and the computer industry are significant. Table 9, panel B indicates that the number of firms classified in quintile 5 is 176, which is only six more firms than the number (170) in Table 7, panel B. In addition, using a cutoff *F*-score of 1.00, we find that the number of correctly classified misstatement firms is similar in Table 9 (237 firm-years) and Table 7 (238 firm-years). Overall, the model does not appear to be unduly driven by characteristics of the computer, retail, or service industries.

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 AAERs available between 1982 and 2005 and identify firms with misstated quarterly or annual earnings. We document the most common types of misstatements and find that the overstatement of revenues, misstatement of expenses, and capitalizing costs 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, nonfinancial

14. *% soft assets* is likely to vary by industry because the need for “soft” versus “hard” assets such as PP&E varies with output technologies. The average *% soft assets* is the following for each industry: Textile and Apparel 0.687; Retail 0.594; Durable Manufacturers 0.589; Computers 0.56; Lumber, Furniture, & Printing 0.551; Chemicals 0.543; Food & Tobacco 0.537; Services 0.503; Agriculture 0.466; Pharmaceuticals 0.46; Mining & Construction 0.453; Transportation 0.385; Utilities 0.277; Refining & Extractive 0.243. Note that in Table 5, each firm acts as its own control and we find significantly higher *% soft assets* in manipulation years relative to earlier years. This suggests that industry effects are not the only determinant of the higher soft asset ratio for AAER firms.

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 nonfinancial 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 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.

Many accounting researchers use measures of "discretionary accruals" as their proxy for earnings management. Our paper contributes to this line of research by showing that financial statement information beyond accruals is useful for identifying earnings manipulation. Our composite measure of the likelihood of manipulation (*F*-score) offers researchers a complementary and supplementary measure to discretionary accruals for identifying low-quality-earnings firms. In addition, our paper shows that the modified Jones model tends to have less power than unadjusted measures of accruals (such as working capital accrual or RSST accruals) to identify misstatement years. We also 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.

We emphasize that one unavoidable issue in developing models to detect misstatement is that the revelation of a misstatement by the SEC 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 identify only 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 the characteristics of high-*F*-score firms that are not identified by the SEC. For example, do high-*F*-score firms engage in earnings management within the realm 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?

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.

Appendix

Variable definitions of the enforcement releases data sets

Panel A: Detail file (detail.sas7bdat)

Variable name	Description
<i>coname</i>	Name from AAER
<i>CIK</i>	Central Index Key
<i>cnum</i>	6-digit CUSIP
<i>ticker</i>	COMPUSTAT ticker
<i>gvkey</i>	COMPUSTAT Gvkey
<i>permno</i>	CRSP Permno
<i>iticker</i>	IBES ticker
<i>eticker</i>	Exchange ticker
<i>explanation</i>	Two-sentence explanation of the violation
Indicator variables (file inclusion):	
<i>annual</i>	Equals 1 if the firm is in the Annual file, 0 otherwise
<i>quarter</i>	Equals 1 if the firm is in the Quarterly file, 0 otherwise
<i>reason</i>	Reason firm is not included in Annual or Quarterly files
Indicator variables (exclusion from Annual or Quarterly files):	
<i>audit</i>	Equals 1 if the AAER was brought against the auditor and there was no misstatement, 0 otherwise
<i>bribes</i>	Equals 1 if the AAER was for bribe charges, 0 otherwise
<i>disclosure</i>	Equals 1 if related to disclosure issue only and not earnings misstatement, 0 otherwise
<i>nodates</i>	Equals 1 if the time period of the financial misstatements cannot be determined from the AAER, 0 otherwise
<i>other</i>	Equals 1 if related to other issues not listed above, 0 otherwise
Indicator variables (accounts affected):	
<i>rev</i>	Equals 1 if misstatement affected revenues, 0 otherwise
<i>rec</i>	Equals 1 if misstatement affected accounts receivable, 0 otherwise
<i>cogs</i>	Equals 1 if misstatement affected cost of goods sold, 0 otherwise
<i>inv</i>	Equals 1 if misstatement affected inventory, 0 otherwise
<i>res</i>	Equals 1 if misstatement affected reserves accounts, 0 otherwise
<i>debt</i>	Equals 1 if misstatement affected bad debts, 0 otherwise
<i>mkt_sec</i>	Equals 1 if misstatement affected marketable securities, 0 otherwise

(The table is continued on the next page.)

Appendix (Continued)

Variable name	Description
<i>pay</i>	Equals 1 if misstatement affected accounts payable, 0 otherwise
<i>asset</i>	Equals 1 if misstatement affected an asset account but could not be classified in an asset account above, 0 otherwise
<i>liab</i>	Equals 1 if misstatement affected liabilities, 0 otherwise
<i>inc_exp_se</i>	Equals 1 if misstatement could not be classified in an income, expense or equity account above, 0 otherwise
<i>figure</i>	Equals 1 if the actual amount of the misstatement can potentially be obtained from the AAER, 0 otherwise
<i>AAER columns</i>	There are 24 columns that identify all AAERs related to the firm
<i>Total AAERs</i>	Total number of AAERs for the firm
<i>Reason for no Cnum</i>	0 if firm has a CUSIP or a number that identifies why the firm has no CUSIP

Panel B: Annual file (ann.sas7bdat)

Variable name	Description
<i>coname</i>	Name from AAER
<i>CIK</i>	Central Index Key
<i>permno</i>	CRSP Permno
<i>yeara</i>	COMPUSTAT convention year
<i>fyr</i>	Fiscal month end
<i>date</i>	Actual misstatement date collected from AAER (DD/MM/YYYY)
<i>p_aaer</i>	Primary AAER used to collect data
<i>understatement</i>	Equals 1 if earnings/revenues were understated in the year, 0 otherwise

Panel C: Quarterly file (qtr.sas7bdat)

Variable name	Description
<i>coname</i>	Name from AAER
<i>CIK</i>	Central Index Key
<i>permno</i>	CRSP Permno
<i>yeara</i>	COMPUSTAT convention year

(The table is continued on the next page.)

Appendix (Continued)

Variable name	Description
<i>fyr</i>	Fiscal month end
<i>qtr</i>	Quarter (1, 2, 3 or 4)
<i>date</i>	Actual date collected from AAER (DD/MM/YYYY)
<i>p_aaer</i>	Primary AAER used to collect data
<i>understatement</i>	Equals 1 if earnings/revenues were understated in the quarter, 0 otherwise

References

- Allen, E., C. Larson, and R. Sloan. 2009. Accrual reversals, earnings and stock returns. Working paper, Washington University in St. Louis.
- Barton, J., and P. Simko. 2002. The balance sheet as an earnings management constraint. *The Accounting Review* 77 (Supplement): 1–27.
- Bayley, L., and S. Taylor. 2007. Identifying earnings overstatements: A practical test. Working paper, ABN Amro Sydney and University of New South Wales.
- Beasley, M. 1996. An empirical analysis of the relation between the board of director composition and financial statement fraud. *The Accounting Review* 71 (4): 443–65.
- Beneish, M. D. 1997. Detecting GAAP violations: Implications for assessing earnings management among firms with extreme financial performance. *Journal of Accounting and Public Policy* 16 (3): 271–309.
- Beneish, M. D. 1998. Discussion of “Are accruals during initial public offerings opportunistic?” *Review of Accounting Studies* 3 (1–2): 209–21.
- Beneish, M. D. 1999a. The detection of earnings manipulation. *Financial Analysts Journal* 55 (5): 24–36.
- Beneish, M. D. 1999b. Incentives and penalties related to earnings overstatements that violate GAAP. *The Accounting Review* 74 (4): 425–57.
- Brazel, J. F., K. L. Jones, and M. F. Zimbelman. 2009. Using nonfinancial measures to assess fraud risk. *Journal of Accounting Research* 47 (5): 1135–66.
- Comprix, J., and K. A. Mueller, III. 2006. Asymmetric treatment of reported pension expense and income amounts in CEO cash compensation calculations. *Journal of Accounting and Economics* 42 (3): 385–416.
- Dechow, P. M., and I. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35–59.
- Dechow, P. M., W. Ge, and C. Schrand. 2010. Understanding earnings quality. *Journal of Accounting and Economics*. Forthcoming.
- Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70 (2): 193–226.
- Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1996. Causes and consequences of earnings misstatement: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research* 13 (1): 1–36.

- DeFond, M. L., and J. Jiambalvo. 1994. Debt covenant violation and misstatement of accruals. *Journal of Accounting and Economics* 17 (1): 145–76.
- Erickson, M., M. Hanlon, and E. L. Maydew. 2004. How much will firms pay for earnings that do not exist? Evidence of taxes paid on allegedly fraudulent earnings. *The Accounting Review* 79 (2): 387–408.
- Ettredge, M., L. Sun, P. Lee, and A. Anandarajan. 2006. Do deferred tax data signal earnings fraud? Working paper, University of Kansas School of Business.
- Farber, D. 2005. Restoring trust after fraud: Does corporate governance matter? *The Accounting Review* 80 (2): 539–61.
- Feroz, E., K. Park, and V. Pastena. 1991. The financial and market effects of the SEC's accounting and auditing enforcement releases. *Journal of Accounting Research* 29 (Supplement): 107–42.
- Frankel, R. M., M. F. Johnson, and K. K. Nelson. 2002. The relation between auditors' fees for no audit services and earnings management. *The Accounting Review* 77 (Supplement): 71–103.
- Ge, W. 2007. Off-balance-sheet activities, earnings persistence and stock prices: Evidence from operating leases. Working paper, University of Washington.
- Graham, J., C. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics* 40 (1–3): 3–73.
- Healy, P. 1985. The effect of bonus schemes on accounting decisions. *Journal of Accounting and Economics* 7 (1): 85–107.
- Karpoff, J., S. Lee, and G. Martin. 2008. The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis* 43 (3): 581–611.
- Kothari, S. P., A. Leone, and C. Wasley. 2005. Performance-matched discretionary accrual measures. *Journal of Accounting and Economics* 39 (1): 163–97.
- Lawless, J. F., and K. Singhal. 1978. Efficient screening of nonnormal regression models. *Biometrics* 34 (2): 318–27.
- Miller, G. S. 2006. The press as a watchdog for accounting fraud. *Journal of Accounting Research* 44 (5): 1001–33.
- Phillips, J., M. Pincus, and S. Ohlft-Rego. 2003. Earnings management: New evidence based on deferred tax expense. *The Accounting Review* 78 (2): 491–521.
- Plumlee, M., and T. L. Yohn. 2010. An analysis of the underlying causes attributed to restatements. *The Accounting Review* 24 (1): 41–64.
- Rajgopal, S., T. Shevlin, and M. Venkatachalam. 2003. Does the stock market fully appreciate the implications of leading indicators for future earnings? Evidence from order backlog. *Review of Accounting Studies* 8 (4): 461–92.
- Rangan, S. 1998. Earnings management and the performance of seasoned equity offerings. *Journal of Financial Economics* 50 (1): 101–22.
- Richardson, S., R. Sloan, M. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence, and stock prices. *Journal of Accounting and Economics* 39 (3): 437–85.

- Skinner, D. J., and R. G. Sloan. 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7 (2-3): 289-312.
- Skousen, C. J., and C. J. Wright. 2006. Contemporaneous risk factors and the prediction of financial statement fraud. Working paper, University of Texas at Arlington.
- Teoh, S. H., I. Welch, and T. J. Wong. 1998. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics* 50 (1): 63-99.