DO MODELS OF DISCRETIONARY ACCRUALS DETECT ACTUAL CASES OF FRAUDULENT AND RESTATED EARNINGS? AN EMPIRICAL EVALUATION

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ABSTRACT

We examine the association between the existence and the magnitude of a fraudulent event, non-fraudulent restatements of financial statements, and nine competing models of discretionary accruals, accrual estimation errors (Dechow and Dichev 2002 and McNichols 2002), and the Beneish (1999) M-score. We use the size of the downward earnings restatement following the discovery of the fraud to proxy for the degree of discretion exercised to perpetrate the fraud. We find that while total accruals are associated with the existence of fraud, discretionary accruals derived from the Jones model, the modified Jones model, and performance-matched models are not associated with fraud. Accrual estimation errors and M-score have explanatory power for fraud beyond total accruals. We also find that commonly used measures of discretionary accruals, accrual estimation errors, and the M-score are associated with the magnitude of the fraud. Only the accrual estimation errors are associated with non-fraud restatements.

Keywords: *Discretionary accruals; Earnings management; Fraud; Restatements; M-score.*

Data Availability: Data used in this study are gathered from publicly available sources.

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I. INTRODUCTION

Earnings management continues to be a popular topic in accounting research and researchers often employ discretionary accruals (also known as abnormal accruals) models to test the presence of earnings management. Thus, empirical evidence on the ability of the discretionary accruals models to detect earnings management, particularly fraudulent financial reporting is of fundamental interest to regulators, auditors, researchers, analysts, and others who are interested in studying earnings management. The objective of this study is to evaluate the ability of the popular discretionary accruals models to detect extreme cases of earnings management – fraudulent earnings and non-fraudulent restatements of financial statements. Our intent is not to develop a new model, but to provide empirical evidence to those who employ the extant discretionary accruals models to study earnings management as well as those who interpret studies that employ those models about the ability of the commonly used models to detect extreme cases of earnings management.

The models we examine are: the Jones model (Jones 1991), the modified Jones model (DeFond and Subramanyam 1998), the modified Jones model with book-to-market ratio and cash flows as additional independent variables (Larcker and Richardson 2004), the modified Jones model with either current year or prior year return on assets (*ROA*) included as an additional independent variable, performance-matched discretionary accruals estimated from the modified Jones model (Kothari et al. 2005), two measures of accrual quality following Dechow and Dichev (2002) and McNichols (2002), and the Beneish (1999) unweighted and weighted probabilities of earnings manipulation. In all, we examine ten measures of earnings management that are used in prior research. Due to sample size restrictions, our measures of discretionary accruals are estimated from cross-sectional models. Similarly, our measures of accrual quality are residuals from cross-sectional models of working capital changes on past, current and future cash flows.

Our fraud sample consists of 118 firms that were charged by the SEC with having committed fraud between the years 1988 through 2001. We include multiple fraud-years and the total number of fraud-years observations equals 188. We are able to collect restated earnings data for 142 fraud-year observations. Restated earnings data is unavailable for the remaining observations for various reasons (e.g. filed for bankruptcy, merged with another company, restated only retained earnings several years later). Our sample firms include some of the recent high profile accounting scandals, such as Enron, HealthSouth, Qwest, Rite Aid, Tyco, Waste Management, and Xerox. The total amount of restated earnings for the fraud-year observations is $13.34 billion. The mean and median restated earnings over beginning assets are, respectively, 14% and 4.4%. Our control sample consists of the entire population of *Compustat* firms for which data are available to estimate the discretionary accrual models.

Our restatement sample is compiled from a study by the General Accounting (now Accountability) Office (GAO 2002) of firms that announced their intention to restate their financial statements due to accounting irregularities between January 1, 1997 and June 30, 2002. We focus only on those restatements that are likely to be motivated by managerial discretion. We examine the following types of restatements: revenue recognition, restructuring, assets, or inventory, and cost or expense. We exclude the following types of restatements: quarterly restatements, restatements due to adoption of new accounting standards or changes in accounting principles, and restatements that had no effect on income. We also exclude restatements associated with a fraudulent event. Our restatement sample consists of 25 firm-year observations for which we have the necessary data to estimate the empirical models. The mean and median voluntarily restated earnings over beginning assets are, respectively, 1.40% and 0.09%. As with the fraud firms, our control sample consists of the entire population of *Compustat* firms.

We examine three questions concerning fraud. First, are the various measures of discretionary accruals associated with the existence of a fraudulent event in the first place? Second, are the measures associated with the magnitude of the fraud? The second question could potentially, shed light on the usefulness of the various measures in detecting small *vs.* large frauds. To answer the first question, we estimate a logit model to examine the relationship between fraudulent earnings and discretionary accruals, accrual estimation errors, and the Beneish (1999) probabilities of earnings manipulation.[1] Similarly, we estimate a logit model to test the association between the voluntary restatements of financial statements and the various measures of discretionary accruals. In both models we include total assets, cash flow, return on assets, leverage, and auditor type as controls. To address the second question, we use the amount of earnings restated following the discovery of the fraud as a proxy for the degree of discretion exercised to perpetrate the fraud. Our final question is whether the various measures of discretionary accruals have power incremental to total accruals (a low-cost alternative) in detecting fraud and voluntary restatement.

In univariate tests, we find that the percentage of discretionary accruals that are positive (i.e., income-increasing) is significantly higher for the fraud sample relative to the control group for all discretionary accruals models. However, the percentage of observations with negative discretionary accruals ranges from about 27% for the Jones model to 39% for the performance-matched discretionary accruals estimated from the modified Jones model. This is despite the fact that all fraud firms in our sample overstated income. Thus, it appears that the popular discretionary accrual measures do not capture many instances of extreme earnings management, which raises concerns about the measures' ability to detect subtle cases of earnings management that do not violate GAAP.

Results from the logit models indicate that while total accruals are associated (significant at the 0.01 level) with a fraudulent event, discretionary accruals derived from the Jones model, the modified Jones model, and performance-matched models are not associated with fraud. Accrual estimation errors estimated from cross-sectional models of working capital changes on past, present, and future cash flows (Dechow and Dichev 2002), McNichols (2002) modification of Dechow and Dichev (2002), and the Beneish (1997) probability of earnings manipulation have explanatory power for fraud beyond total accruals. Accrual estimation errors estimated from a cross-sectional model based on Dechow and Dichev have the highest impact on *FRAUD*. While a one unit increase in total accruals scaled by total assets increases the probability of fraud by 1.39%, a one unit increase in the accrual estimation errors increases fraud by 34%.

For a sub-sample of firms reporting the amount of earnings restated following the discovery of the fraud, commonly used measures of discretionary accruals as well as the measures of accrual estimation errors and the Beneish measure are associated with the magnitude of the fraud. In other words, only the accrual estimation errors and the Beneish probability of earnings manipulation are associated with both the very existence of a fraudulent event as well as the magnitude of the fraud. Results from a sample of firms that voluntarily restated their financial statements indicate that only the accrual estimation errors are associated with restatements.

We contribute to the literature on earnings management and measurement of discretionary accruals in several ways. First, we evaluate a more comprehensive set of discretionary models than prior research (Dechow et al. 1995; Bartov et al. 2001; and Kothari et al. 2005). Performance-matched discretionary accruals and accrual estimation errors have become the standard measures of earnings management, yet there is very limited empirical evidence on how they compare with each other, or whether they are superior to total accruals in detecting earnings management. Prior research also did not examine the performance of a model developed by Beneish (1997) (also known as the M-score) that uses both total accruals as well as specific accruals to detect earnings management for firms with large discretionary accruals relative to other models. This is important because researchers face a trade-off between a simple model that maximizes the sample size and a richer model with greater data requirements. Thus, evidence on the performance of the Beneish model relative to other models is potentially useful to those who study earnings management. Our findings suggest that only the Beneish measure and the accrual estimation errors have predictive power for fraud. When we include the Beneish measure and the accrual estimation errors in the same model, only the accrual estimation error is significantly associated with fraud.

Second, while prior research has examined a sample of firms subject to enforcement action by the SEC for fraudulent reporting (Dechow et al. 1995; and Beneish 1997), the relation between the magnitude of the fraud and the discretionary accruals has not been fully examined. We examine the association between the various measures of discretionary accruals and the size of the downward earnings restatement after the discovery of the fraud. We believe that the size of the earnings restatement is a good measure of the extent of the actual managerial discretion and therefore, correlating the various measures of discretionary accruals with the magnitude of the restatement can shed light on the ability of the discretionary accruals models to detect overstated earnings.

We partition the sample into two groups at the median value of the size of the restatement and estimate the logit model separately for each group. For the small magnitude fraud observations, total accruals have incremental explanatory power for fraud over several measures, including the performance-matched discretionary accruals and the Beneish measures. Only the accrual estimation errors have incremental explanatory power over total accruals. These results suggest that total accruals could be a low-cost alternative to many commonly used measures of discretionary accruals in detecting smaller fraud. For larger frauds, our results suggest that only the accrual estimation errors and the Beneish measure have incremental explanatory power over total accruals. A one unit increase in Dechow and Dichev's accrual estimation errors increases the probability of a larger fraud by 44.82%. Performance-matched discretionary accruals do not have power for detecting larger frauds. We recommend that researchers consider using the accrual estimation errors as well as the Beneish's unweighted measure to study earnings management.

Third, we also develop a composite measure of earnings management using principal components analysis to extract a common factor from performance-matched discretionary accruals, accrual estimation errors, and the Beneish measures. We find that the composite measure is significantly associated with the existence of fraud as well as the magnitude of the fraud. Further, we find that the composite measure is useful for detecting larger frauds, but not smaller frauds.

Finally, while a number of firms have restated their earnings in the recent years, there is very little empirical evidence on whether the popular measures of discretionary accruals are associated with voluntary restatements. While prior research has focused on fraud firms, voluntary restatement of earnings is more common than a (forced) restatement following a fraud and thus, evidence on the ability of discretionary accruals to detect a potential restatement is important to the participants of the capital markets. Our results suggest that the accrual estimation errors are positively and significantly associated with restatements.

The rest of this paper is organized as follows. The next section describes the various measures of discretionary accruals. Section three explains our research methodology. Section four describes how we identified the fraud sample. Results are in section five. Sample selection process and results of the restatement sample appears at the end of section five. Conclusions are in section six.

II. MEASURES OF DISCRETIONARY ACCRUALS

Based on a review of the extant earnings management literature, we identify nine competing models that are commonly used to capture earnings management (see Dechow et al. 1995; McNichols 2000; and Kothari et al. 2005 for a review of model features). The models examined in this study are described below.

Jones Model

Following Jones (1991), the residual from model (1) is our first measure of discretionary accruals.[2] We refer to this measure as *JONES*.

$$TA_{it} = \beta_0 + \beta_1(1/AT_{it-1}) + \beta_2\Delta REV_{it} + \beta_3 PPE_{it} + \varepsilon_{it} \tag{1}$$

where TA_{it} is total accruals firm *i* calculated as the difference between income before extraordinary items (*Compustat* data item #123) and operating cash flows (#308) for year *t*; AT_{it-1} is assets at the beginning of the year (#6); ΔREV is the change in sales from year *t-1* to *t* (#12); and *PPE* is gross property, plant, and equipment (#8). In model (1) *TA*, ΔREV, and *PPE* are scaled by AT_{it-1}.

Due to sample restrictions, we estimate model (1) and other models discussed below cross-sectionally. Further, Bartov et al. (2001) find that the cross-sectional Jones model and the cross-sectional modified Jones model outperform their time-series counterparts in detecting earnings management. We estimate model coefficients from cross-sectional industry regressions by two-digit SIC codes for each year using all observations available on *Compustat* except financials and utilities. We require a minimum of 10 observations for each two-digit SIC code and year combinations.

Modified Jones Model

Following Dechow et al. (1995), we estimate the modified Jones model as follows:

$$TA_{it} = \beta_0 + \beta_1(1/AT_{it-1}) + \beta_2(\Delta REV_{it} - \Delta AR_{it}) + \beta_3 PPE_{it} + \varepsilon_{it} \tag{2}$$

where ΔAR is the change in accounts receivable from year *t-1* to *t* (#2) and other variables are the same as defined before. Dechow et al. point out that the Jones (1991) model implicitly assumes that discretion is not exercised over revenue in either in the estimation period or the event period. The modified Jones model assumes that all changes in credit sales in the event period are due to earnings management. Dechow et al. do find that the modified Jones model outperforms the

Jones model in detecting earnings management. The residual from model (2) is referred to as *MJONES*.

Modified Jones Model with Book-to-Market Ratio and Cash Flows

Larcker and Richardson (2004) add the book-to-market ratio (*BM*) and operating cash flows (*CFO*) to model (2) to mitigate measurement error associated with the discretionary accruals. *BM* controls for expected growth in operations and if left uncontrolled, growth will be picked up as discretionary accruals. *CFO* controls for current operating performance. Controlling for performance is important because Dechow et al. (1995) find that discretionary accruals are likely to be misspecified for firms with extreme levels of performance. Larcker and Richardson (2004) note that their model is superior to the modified Jones model in several ways: it has far greater explanatory power, identifies unexpected accruals that are less persistent than other components of earnings, the estimated discretionary accruals detect earnings management identified in SEC enforcement actions, and identifies discretionary accruals that are associated with lower future earnings and lower future stock returns. *MJONES2*, our next measure of discretionary accruals, is based on model (3).

$$TA_{it} = \beta_0 + \beta_1(1/AT_{it-1}) + \beta_2(\Delta REV_{it} - \Delta AR_{it}) + \beta_3 PPE_{it} + \beta_4 BM_{it} + \beta_5 CFO_{it} + \varepsilon_{it} \tag{3}$$

where *BM* equals the book value of common equity (#60) over the market value of common equity (#25 X #199) and *CFO* is operating cash flows (#308) over AT_{t-1}. Other variables are the same as defined before.

Modified Jones Model with ROA

Kothari et al. (2005) argue that accruals of firms that have experienced unusual performance are expected to be systematically non-zero, and therefore, firm performance is correlated with accruals. Kothari et al. (2005) examine two ways to control for performance in estimating discretionary accruals. A performance variable such as, *ROA* could be included as an additional independent variable in the discretionary accrual regression. Alternatively, performance-matched discretionary accruals can be calculated by first matching the firm-year observation of the treatment firm with the firm-year observation for the control firm from the same two-digit SIC code and year with the closest *ROA* in the current year or the prior year and then subtracting the control firm's discretionary accruals from the treatment firm's discretionary accruals. Kothari et al. (2005) find that matching based on the current year *ROA* performs better than matching on the prior year *ROA* and this performance-matched approach is superior to including a performance variable in the discretionary accruals regression.

Following Kothari et al. (2005), we develop three measures of discretionary accruals to control for performance. Models (4) and (5) include, respectively, current year and prior year *ROA*. We refer to the residuals from models (4) and (5) as respectively, *PMATCHC* and *PMATCHP*.

$$TA_{it} = \beta_0 + \beta_1(1/AT_{it-1}) + \beta_2(\Delta REV_{it} - \Delta AR_{it}) + \beta_3 PPE_{it} + \beta_4 ROA_{it} + \varepsilon_{it} \tag{4}$$

$$TA_{it} = \beta_0 + \beta_1(1/AT_{it-1}) + \beta_2(\Delta REV_{it} - \Delta AR_{it}) + \beta_3 PPE_{it} + \beta_4 ROA_{it-1} + \varepsilon_{it} \tag{5}$$

where ROA_t is income before extraordinary items for year *t* (#123) over AT_{t-1}. Next, we match the fraud firm with the control firm by year, two-digit SIC code, and ROA_t and calculate the net discretionary accrual, *PMATCH* by subtracting the control firm's discretionary accruals estimated from model (2) from the fraud firms discretionary accruals also estimated from model (2).

Measures of Accrual Quality

Our next measure is Dechow and Dichev's (2002) model of accrual estimation errors. Dechow and Dichev estimate the following firm-level time-series regression to derive a measure of working capital accrual quality:

$$\Delta WC_{it} = \beta_0 + \beta_1 CFO_{it-1} + \beta_2 CFO_{it} + \beta_3 CFO_{it+1} + \varepsilon_{it} \tag{6}$$

where ΔWC is the change in working capital from year *t-1* to year *t* is computed as follows. ΔWC = - (#302 + #303 + #304 + #305 + #307). All variables in model (6) are deflated by beginning total assets. Dechow and Dichev (2002) use the standard deviation of the residuals from model (6) as a firm-specific measure of accrual quality. Dechow and Dichev (2002) require at least eight years of data to estimate model (6). We do not have eight years of data for all the fraud firms and therefore, we estimate model (6) cross-sectionally and use the residual from model (6) as a measure of accrual quality called *DD*. We also identify 47 firms with eight years of data to estimate Dechow and Dichev's firm-specific measure of accrual quality. Results from this sub-sample are discussed in a later section.

McNichols (2002) presents evidence that model (6) can be enhanced by including Δ*REV* and *PPE*. She finds that when these two variables are added to model (6), the adjusted R^2 increases from 0.201 to 0.301. Following McNichols (2002), we estimate the following model cross-sectionally:

$$\Delta WC_{it} = \beta_0 + \beta_1 CFO_{it-1} + \beta_2 CFO_{it} + \beta_3 CFO_{it+1} + \beta_4 \Delta REV_{it} + \beta_5 PPE_{it} + \varepsilon_{it} \tag{7}$$

As in McNichols (2002), we scale variables in model (7) by beginning total assets and refer to the residual from model (7) as *MDD*.

Beneish Model

Using a sample of firms that were either subject to the SEC's enforcement actions or were identified as manipulators by the news media, Beneish (1999) estimates a probit model of earnings manipulation using a variety of financial statement variables (see below). His model is not a discretionary accrual model, but has been used to detect earnings management. His results provide evidence of a systematic relationship between the likelihood of manipulation and selected financial statement data. He reports that the median probability of earnings manipulation for non-manipulators in the estimation sample is 0.011 compared to 0.099 for the manipulators and concludes that his model is a cost-effective classification tool. He further reports that for the estimation sample, the percentage of manipulators correctly classified ranges from 58% to 76% for the unweighted probit model. We use the following unweighted probit model as our final model:

$$\begin{aligned} MI_{it} = &-4.840 + 0.920DSRI_{it} + 0.528GMI_{it} + 0.404AQI_{it} + 0.892SGI_{it} + 0.115DEPI_{it} + \\ &-0.172SGAI_{it} + 4.679TATA_{it} - 0.327LVGI_{it} \end{aligned} \tag{8}$$

where MI is the manipulation index which is converted to a probability of earnings manipulation using a standard normal distribution table; $DSRI$ is days' sales receivable index ([AR/REV] / [AR_{t-1}/REV_{t-1}]); GMI is gross margin index ([REV_{t-1} – Cost of goods sold$_{t-1}$ (#41) / REV_{t-1}] / [REV_t – cost of goods sold$_t$ / REV_t]); AQI is asset quality index ([1 – Current assets$_t$ (#4)] + PPE_t / AT_t]) / ([1 – Current assets$_{t-1}$] + PPE_{t-1} / AT_{t-1}); SGI is sales growth index (REV_t / REV_{t-1}); $DEPI$ is depreciation index ((Depreciation$_{t-1}$ (#14 - #65) / (Depreciation$_{t-1}$ + PPE_{t-1})) / ((Depreciation$_t$ / Depreciation$_t$ + PPE_t)); $SGAI$ is sales, general, and administrative expenses index ((Sales, general, and administrative expense$_t$ (#189) / REV_t)) / ((Sales, general, and administrative expense$_{t-1}$ / REV_{t-1})); $TATA$ is total accruals to total assets ((ΔCurrent assets$_t$ - ΔCash$_t$ (#1) -

ΔCurrent liabilities$_t$ (#5) - ΔCurrent maturities of long-term debt$_t$ (#44) - ΔIncome tax payable$_t$ (#71) – Depreciation and amortization$_t$ (#14)) / AT_t; and *LVGI* is leverage index ((Long-term debt$_t$ (#9) + Current liabilities$_t$) / AT_t)) / ((Long-term debt$_{t-1}$ + Current liabilities$_{t-1}$) / AT_{t-1})). We also use his weighted exogenous sample maximum likelihood probit model. We refer to the probability of earnings manipulation calculated from the unweighted and the weighted probit models as, respectively, *BPROB* and *BPROBW*.

III. RESEARCH METHOD

We evaluate the abilities of the ten measures of discretionary accruals and probabilities of earnings manipulation derived from the nine models to detect fraudulent earnings in two ways. First, by pooling the fraud firms and the control firms we estimate model (9) to test whether the various measures are associated with fraudulent earnings. We include total assets, cash flow, return on assets, leverage, and auditor type as control variables. We begin with total accruals and examine whether the model's power is enhanced when total accruals are replaced by each of the discretionary accruals or the Beneish measures. In an alternate specification, we include the discretionary accrual measure and total accruals in the same model to examine whether the discretionary accrual measure has power incremental to total accruals in detecting fraud. Since discretionary accruals are a component of total accruals, when both are included in the same model, due to multicollinearity, discretionary accruals could become insignificant. This outcome is more likely when the model used to estimate the discretionary accruals has low R^2. On the other hand, if the underlying model is well-specified, discretionary accruals may have power for fraud incremental to total accruals. Since the adjusted R^2 are higher for models from which accrual estimation errors are derived (Dechow and Dichev 2002 and McNichols 2002) relative to the Jones model (1991), our expectation is that *DD* and *MDD* are likely to have incremental power for fraud beyond total accruals. However, this is an empirical issue. We estimate the following logit model:

$$FRAUD_{it} = \alpha_0 + \alpha_1 AT_{it} + \alpha_2 CFO_{it} + \alpha_3 ROA_{it} + \alpha_4 LEVERAGE_{it} + \alpha_5 BIG4_{it} + \alpha_6 DACC_{it} \quad (9)$$

where *FRAUD* is an indicator variable that equals 1 for fraud firms and 0 for control firms (*i* and *t* are, respectively, firm and year subscripts); *AT* is total assets (data #6); *CFO* is cash flow from operations scaled by total assets at *t-1* (#308); *ROA* is income before extraordinary items (#123) over total assets at *t-1*; *LEVERAGE* is long-term debt (#9) plus debt in current liabilities (#34) over total assets; *BIG4* equals 1 for clients of Big4 (or Big 8) auditors and 0 otherwise; and *DACC* equals either total accruals *(TA*) or one of the discretionary accrual measures or accrual estimation errors (*JONES* through *MDD*) or the Beneish measures (*BPROB* or *BROPBW*). A positive and statistically significant α_6 is consistent with the notion that the measure of discretionary accruals is capable of detecting fraudulent earnings. We also estimate a variation of model (9) by using data from the year prior to the first year of the fraud and those results are presented in a later section.

Next, for the fraud firms that restated their earnings following the discovery of the fraud, we estimate the following regression model. The size of the earnings restatement reflects the extent of the actual managerial discretion exercised to perpetrate the fraud. Therefore, correlating the various measures of discretionary accruals with the magnitude of the restatement can shed light on the ability of the discretionary accruals models to detect the extent of the fraud.

$$AMTRESTAT_{it} = \chi_0 + \chi_1 AT_{it} + \chi_2 CFO_{it} + \chi_3 ROA_{it} + \chi_4 LEVERAGE_{it} + \chi_5 BIG4_{it} + \chi_6 DACC_{it} \quad (10)$$

where *AMTRESTAT* is the difference between actual reported earnings and the restated earnings scaled by AT_{t-1}. Other variables are the same as defined before. As in model (9), we include the measures of discretionary accruals one at a time. If the discretionary accrual models are well-specified, α_6 should be 1. Again, a positive and significant χ_6 is consistent with the ability of the discretionary accruals measure to detect the extent of fraudulent earnings.

There is an important difference between models (9) and (10). While model (9) examines whether the various measures of discretionary accruals are associated with the existence of a fraudulent event in the first place, model (10) examines whether the measures are associated with the magnitude of the fraud. While both questions are of interest to regulators, auditors, and users of financial statements, we believe the former is fundamentally more important than the latter. If fraud is not expected in the first place, there is no need to examine the second question. Taken together, both models could potentially offer insight on the ability of the discretionary accrual measures to detect fraud.

IV. SAMPLE SELECTION

Our fraud sample only includes firms that fraudulently report annual data (i.e. the firm misstated at least one 10-K filing). We describe the restatement sample in a later section. We did not include frauds that misstated quarterly data because the earnings management models in our study are designed to detect earnings management of annual data. We also limited our sample to firms for which we had access to the original 10-K filing and subsequent filings of restated data (i.e. 10-K/A's, 8-K's, etc.). We did this for two reasons. First, it was necessary to access the subsequent filing to identify the size of the restatement. Second, our primary data source was *Compustat*. We found that *Compustat* does not consistently report restatement data.

It appears that if the restated data is available when *Compustat* enters the data in their database, the restated data is entered and the fraudulent numbers are discarded. It does not appear that *Compustat* changes data upon restatements several years after the original data is entered in their database. Therefore, we compared *Compustat* data with the original 10-K filing to verify that the data in *Compustat* is the fraudulently reported numbers and not the restated data. We found that *Compustat* reports restated data for 19 of the 118 fraud firm years in our fraud sample. We hand-collect the original fraudulent data for those 19 firm years. SEC filings are available on EDGAR beginning in 1994. SEC filings for selected companies are available on *Lexis/Nexis* for years prior to 1994. However, we were able to locate data for a few firms prior to 1994.

We identified our fraud sample from three sources. First, COSO published a report "Fraudulent Financial Reporting: 1987-1997 - An Analysis of U.S. Public Companies" (Beasley et al. 1999). The COSO study investigated frauds that were identified in SEC Accounting and Auditing Enforcement Releases (AAERs) issued during the period of 1987-1997.[3] COSO identifies 204 fraud firms. Second, we performed our own search of AAERs issued during 1998 to 2004. We used "fraud" as a search term and identified an additional 240 fraud firms. Third, we identified another six firms by searching the popular press and the AAA (American Accounting Association) Monograph on litigation involving Big4 auditors and their predecessor firms. We excluded firms from our sample for one or more of the following reasons: that didn't misreport at least one 10-K (e.g. fraudulent reported quarterly data), non-financial frauds (e.g. insider trading, omitted disclosures), did not manage earnings (e.g. reported sales on a gross rather than a net basis which increased sales and cost of sales by the same amount), unable to locate company data (e.g. small firms, foreign companies, frauds prior to 1992) or the firm did not have enough data available to compute discretionary accruals (e.g. firm committed fraud in an IPO and did not report a sufficient amount of data in prior years or the company was a financial services firm). Our final fraud sample consists of 118 firms. Table 1 summarizes our sample selection procedure. Several of the firms misreported in more than one year. Thus, our sample includes a total of 188 firm-years that were fraudulently reported. Since the data requirements vary across the discretionary accrual measures, the total number of fraud observations available to estimate model (9) ranges from 188 to 146 depending on the discretionary measure examined. Similarly, the number of observations for which the magnitude of the fraud is available to estimate model (10) ranges from 118 to 142.

[Insert Table 1 About Here]

We gathered size of the restatement in one of two ways. For frauds that restated their earnings and we are able to gather that restatement data from subsequent 10-K's, 10-K/A's, 8-K's or annual reports reported on the SEC website or Lexis/Nexis, we compared earnings before extraordinary items (Data #18 on *Compustat*) before and after the restatement. For firms for which we couldn't find restated data (e.g. they filed for bankruptcy prior to restating or the restated numbers were not available on the SEC website or Lexis/Nexis), we searched the AAER's about the firm. The AAER occasionally reports the SEC's estimate of income overstatement. We use the size of the earnings restatement to estimate the extent of earnings management.

A few firms did not restate because they went out of business (or were acquired). For example, HBO & Co allegedly committed fraud from 1997 through 1999. The company was acquired by McKesson in 1999. McKesson eventually restated consolidated numbers (for several reasons) but not HBO & Co's pre-merged data. Another firm, AremisSoft, allegedly committed fraud in 2000. The company filed for bankruptcy and later reincorporated as a new company called Softbrands. A few other firms chose not to restate because the fraud was uncovered several years after the first year of the fraud and the company simply stated the non-restated years were not to be relied on. For example, Adelphia Communications allegedly committed fraud in 1998 and 1999. The fraud was reported in an AAER in July of 2002. Adelphia did not issue a 10-K for 2002. The company's 2003 10-K does not restate any income statement numbers prior to December 2000, it simply attempts to construct an accurate balance sheet as of December 2000. For three of the firms that elected not restate, we were able to estimate what the restatement would have been based on information in the AAER's and from changes in retained earnings. We use the entire population of *Compustat* firms with available data as our control sample. The total number of firm-year observations for the control sample ranges from 89,571 to 61,257 depending on the discretionary measure used.[4]

[Insert Table 2 About Here]

[Insert Table 3 About Here]

Table 2 summarizes the type of alleged accounting fraud associated with the fraud sample. Total number of fraud events exceeds the 188 fraud-years from Table 1 because several firms are accused of engaging in multiple types of fraudulent behavior. The top three accounts that were used to overstate earnings were, respectively, revenues, accounts receivable, and expenses. These results are consistent with prior research (Dechow et al. 1996 and Nelson et al. 2003). Frequency of sample firms by industry and year are, respectively, in panels A and B of Table 3. More than 21% of the fraud observations occurred in business services. A majority of the frauds (about 52%) occurred between 1996 and 2000.

V. RESULTS

Fraud Sample

Results of univariate analysis and correlations for the fraud sample are discussed first. Descriptive statistics and tests of mean and median differences between the fraud and the control samples for firm size, cash flows, total accruals, performance, leverage, auditor type and the various measures of discretionary accruals are in Table 4. *AMTRESTAT* for the fraud sample also appears in Table 4. To mitigate the effect of outliers, we estimate models (9) and (10) after winsorizing *ROA, TA,* and *CFO* at the top and bottom 1%.

[Insert Table 4 About Here]

The number of observations for accrual estimation errors, *BPROB* and *BPROBW* are lower because more data are needed to compute those measures. Both mean and median differences between the two groups of firms are statistically significant at the 0.05 level or better for *AT*, *CFO, TA, ROA, LEVERAGE*, and *BIG4*. On average, relative to the control firms, fraud firms are larger, have less cash flow, report a higher *ROA* and are less levered. Further, total accruals are more positive (income-increasing) for the fraud sample relative to the control sample (49.4% *vs.* 23.7%) and the mean and median differences in total accruals are significant at the 0.001 level. The mean and median differences for total accruals scaled by beginning assets are, respectively, 9.9% and 5.6%. Both the mean and median values for *all* the discretionary accruals measures and the Beneish measures are greater for the fraud sample relative to the control sample and the differences in mean are significant at the 0.05 level or better while the median differences are significant at the 0.001 level. The amount of earnings restated scaled by beginning assets appear to be economically significant with a mean of 14% and a median of 4.4%.

Finally, note that the percentage of discretionary accruals that are positive (i.e., income-increasing) is significantly higher for the fraud sample relative to the control firms for *JONES, MJONES, MJONES2, PMATCHC, PMATCHP,* and *PMATCH*. However, the percentage of observations with negative discretionary accruals ranges from about 27% for *JONES* to 39% for *PMATCH*.[5] This is despite the fact that all of our fraud firms overstated income. McNichols (2003) notes that Enron had negative total accruals for the year 2000. Similarly, we find negative discretionary accruals for Enron and Healthsouth. Thus, it appears that discretionary accrual measures fail to capture a substantial amount of earnings management. Despite this limitation, the results in Table 4 indicate that accruals, particularly the level of discretionary accruals distinguish fraud firms from the control firms. Thus, measures of discretionary accruals and the probabilities of earnings manipulation appear to have some power in detecting fraudulent earnings.

[Insert Table 5 About Here]

Correlations between *FRAUD* and the various measures of discretionary accruals are in panel A of Table 5 while correlations between *AMTRESTAT* and the discretionary accruals are in panel B of Table 5. Recall that *AMTRESTAT* is unavailable for the control sample. In panel A, most correlations are statistically significant at the 0.001 level. Accrual estimation errors *(DD* and *MDD*) exhibit the highest correlations with *FRAUD*. In panel B, while the correlations between *AMTRESTAT* and *TA* are not significant at the 0.10 level, the correlations between *AMTRESTAT* and several measures of discretionary accruals are statistically significant at the

0.05 level or better. In particular, both the Pearson and Spearman correlations between *AMTRESTAT* and *PMATCH, DD, MDD, BPROB,* and *BPROBW* are positive and significant at the 0.05 level. Both *BPROB* and *BPROBW* exhibit the highest correlations with *AMTRESTAT*. Overall, the results in Table 5 indicate that the various measures of discretionary accruals are positively and significantly associated with fraud and the magnitude of the fraud.

[Insert Table 6 About Here]

Association Between Fraud and Discretionary Accrual Measures

Next, we discuss the results of logit model (9). Panels A through K of Table 6 present the results for the various measures of discretionary accruals. In all specifications we include *AT, CFO, ROA, LEVERAGE,* and *BIG4* as controls. Recall that mean and median differences between the control firms and the fraud firms were statistically significant for these variables. We also include earnings volatility and prior-period stock returns as additional controls and those results are discussed under sensitivity checks. The chi-square statistic in all panels is significant at the 0.01 level. All the control variables with the exception of *LEVERAGE* are significant in most panels. The coefficient on *AT* is zero in all panels. *CFO* is consistently negative, indicating that fraud firms have lower cash flow. *ROA* is consistently positive. This is consistent with the notion that fraud enhances the reported earnings. The coefficient on *BIG4* is negative, indicating that audit quality mitigates fraud. The variables of interest are positive in all panels but only *DD, MDD,* and *BPROB* are statistically significant at the 0.01 level or better. Interestingly, *TA* (total accruals) is positive and significant at the 0.01 level. Based on pseudo R^2, *DD* exhibits the highest association with the *FRAUD* variable. Note that the odds ratios are highest for *DD* and *MDD*, indicating that increases in *DD* or *MDD* will increase the likelihood of reporting fraudulent earnings. Converting the coefficients into probabilities of fraud indicate that *DD* has the highest impact on *FRAUD*, a probability of 34% followed by *MDD* (3.33%) and *TA* (1.39%).[6]

[Insert Table 7 About Here]

We re-estimate all the models in Table 6 including *TA* to assess the incremental contribution of each discretionary accrual measure beyond total accruals, and those results are in Table 7. Note that *TA* is positive and statistically significant at the 0.01 level or better in all panels except panels H and I. After controlling for total accruals, most discretionary accrual measures do not have incremental ability in detecting fraudulent earnings. *MJONES2* is negative and marginally significant at the 0.10 level. Consistent with results in Table 6, *DD, MDD,* and *BPROB* continue to be significant at the 0.01 level. Overall, results in Table 7 indicate that accrual estimation errors (*DD* and *MDD*) and the Beneish probability of earnings manipulation have predictive value for fraud incremental to total accruals. When we include *BPROB* or *BPROBW* with *DD* or *MDD*, the accrual estimation errors are significant at the 0.0001 level, but *BPROB* and *BPROBW* are not significant.

[Insert Table 8 About Here]

We also estimate the logit model using data from the year *prior* to the year of earnings manipulation and those results are in Table 8. The number of observations available to estimate the various measures ranges from 65 for the discretionary accrual measures to 54 for the Beneish measures. *DD* and *MDD* are significant at the 0.01 level and *BPROB* is significant at the 0.10 level. *DD* has the highest pseudo R^2 value. In terms of probabilities, the coefficients on *DD* and

MDD translate into a probability of 10.44% and 5.08%, respectively. The results presented in Tables 6 through 8 collectively present evidence on the linkage between the measures of discretionary accruals and fraudulent events. Overall, the results suggest that only the accrual estimation errors and the Beneish's unweighted probability of earnings manipulation are consistently associated with fraudulent events. This finding holds even after controlling for total accruals, indicating that accrual estimation errors and the Beneish measure contain information that is not reflected in total accruals.

[Insert Table 9 About Here]

[Insert Table 10 About Here]

Association Between the Magnitude of the Fraud and Discretionary Accrual Measures

Our next set of analysis examines the association between the *AMTRESTAT,* the amount of earnings restated following the discovery of the fraud and the various discretionary accrual measures. We estimate model (10) without and with *TA* as a control and those results are, respectively, in Tables 9 and 10. In Table 9, most discretionary accrual measures are positively and significantly associated with *AMTRESTAT* except *MJONES2* and *PMATCHC*. *DD* and *MDD* exhibit the highest adjusted R^2 values. The *F*-statistic in all panels in Tables 9 and 10 are significant at the 0.05 level. However, the coefficients on discretionary accrual measures are significantly less than 1 in all cases, suggesting that the discretionary accrual models are not well-specified. When total accruals are included and a common set of 101 observations are used, all measures are significantly associated with *AMTRESTAT* except *DD* (significance level = 0.1061 for a two-tailed test). When we estimate panel H in Table 10 using 118 observations as in Table 9, *DD* is 0.352 and significant at the 0.05 level. Thus, the results for *DD* are weaker when the sample is reduced.[7] Compared to the results in Table 6 results in Tables 9 and 10 indicate that commonly used measures of discretionary accruals, such as *JONES, MJONES*, and *PMATCH* are not able to discriminate between fraudulent and non-fraudulent events, but once the fraud is financially quantified, the above measures have power in assessing the extent of the fraud.

Next, we discuss how our findings relate to prior research. Based on a sample of 173 firms that received a qualified report, Bartov et al. (2001) conclude that cross-sectional versions of the Jones model and the modified Jones model are better able to detect audit qualifications than their time-series counterparts. The authors do not examine fraud and therefore, it is not clear what their findings mean for fraud detection. A qualified audit opinion does not necessarily imply the presence of earnings management by the client. Alternatively, the lack of a qualified opinion does not imply the absence of earnings management. For example, firms that were involved in high-profile accounting scandals, such as Enron and WorldCom did not receive a qualified report from their auditor. Kothari et al. (2005) conduct a simulation to assess the power of the Jones model and the modified Jones model and find that performance-matched discretionary accrual measures enhance the reliability of inferences from earnings management. The authors note that their results may not generalize to other research settings, for example fraud. Further, Kothari et al. do not examine the accrual estimation errors or the Beneish measures.

Dechow et al. (1995) and Beneish (1997) also used a sample of firms targeted by the SEC to evaluate discretionary accrual models. Dechow et al. find that *MJONES* exhibits the most power in detecting earnings management. However, Dechow et al. do not estimate a logit model to examine the association between fraud and the discretionary accrual measures and further, their sample covers pre-1992 period and the number of AAER firms is small, 32 firms representing 56 firm-years. In our logit models, neither *JONES* nor *MJONES* is significant. Results from Tables 9 and 10 indicate that *MJONES* is significantly associated with the magnitude of the fraud. Further, *MJONES* is associated with larger frauds (to be discussed below). Beneish (1997) sample of 64 AAER firms come from 1987-1993. The magnitude of earnings restated following the fraud in his sample is comparable to ours (a mean of 11.4% and the median is 5.5%). Beneish finds that his model is cost effective relative to the modified Jones model. We find that Beneish's unweighted probability of earnings manipulation is significantly associated with the existence of a fraudulent event as well as the magnitude of the fraud. Thus, our findings are consistent with Beneish.

In summary, results from Tables 6 through 10 indicate that only accrual estimation errors and the Beneish probability of earnings manipulation are associated with both the very existence of a fraudulent event as well the magnitude of the fraud. While empirical evidence on both aspects of a fraud is relevant to the users of financial statements, we believe the ability of the discretionary accrual models to detect the very existence of a fraud is more important as it is the first step in uncovering the fraud.

Detecting Small vs. Large Frauds

To provide some evidence on how the various measures perform in detecting smaller *vs.* larger frauds, we partition the observations for which *AMTRESTAT* is available into two equal groups where group 1 consists of smaller magnitude fraud observations (median value of *AMTRESTAT* is 1.43%) and group 2 consists of larger magnitude fraud (11.97%) observations.[8] We estimate model (9) separately for each group using the ten measures of discretionary accruals. In all specifications we include *TA* as a competing measure. We first discuss the results for group 1. When *TA* is the only accrual measure, *TA* is positive and significant at the 0.10 level. In the presence of *TA*, all measures are negative with the exception of *DD* and *MDD*. *TA* continues to be positive and significant at the 0.01 level or better when included with *JONES, MJONES, MJONES2, PMATCHC, PMATCHP* and *PMATCH*. The coefficients on *DD* and *MDD* are, respectively, 3.765 (significant at the 0.004 level) and 1.593 (significant at the 0.01 level). *TA* is not significant in either of these specifications. Only *TA* is positive and significant at the 0.05 level when included with the Beneish measures. In short, *DD* exhibits the highest probability for fraud. A one unit increase in *DD* increases the probability of fraud by 1.33%.

For group 2, when *TA* is the only accrual measure, *TA* is positive and significant at the 0.01 level. *JONES, PMATCHC,* and *PMATCHP* are not significant. *MJONES* is significant at the 0.10 level. *MJONES2* is not significant but *TA* is at the 0.05 level. *PMATCH* is not significant, but *TA* is significant at the 0.10 level. The coefficients on *DD* and *MDD* are, respectively, 7.328 (significant at 0.0001) and 2.379 (significant at the 0.05 level). *TA* is not significant when included with *DD* or *MDD*. Both *BPROB* and *TA* are significant at the 0.05 level but only *TA* is significant at the 0.05 when included with *BPROBW*. As with smaller frauds, *DD* exhibits the highest probability for fraud (44.82%).

In summary, for the small magnitude fraud observations, total accruals have incremental explanatory power for fraud over several measures, including the performance-matched discretionary accruals and the Beneish measures. Only *DD* and *MDD* have incremental explanatory power over total accruals. This finding is important because a vast majority of the *Compustat* population is likely to be associated with smaller or no frauds. The results suggest that total accruals could be a low-cost alternative to many commonly used measures of discretionary accruals in detecting smaller fraud. For larger frauds, our results suggest that only *MJONES* (marginally significant), *DD, MDD,* and *BPROB* have incremental explanatory power over total accruals. In short, only the accrual estimation errors (*DD* and *MDD*) have incremental explanatory power over total accruals for <u>both</u> smaller and larger fraudulent events.

Composite Measure

We also develop a composite measure using principal components analysis to extract a common factor from *PMATCH, DD, MDD, BPROB,* and *BPROBW*. Results in Table 6 indicate that *DD, MDD,* and *BPROB* are significantly associated with *FRAUD*. We include *PMATCH* because it is a commonly used measure of discretionary accruals. We refer to this composite measure as *FACOMBO*. The Pearson and Spearman correlations between *FACOMBO* and *FRAUD* are, respectively, 0.038 and 0.031 (both are significant at the 0.0001 level). The corresponding correlations between *FACOMBO* and *AMTRESTAT* are, respectively, 0.390 and 0.300 (both are significant at the 0.002 level). When we estimate models (9) and (10) using *FACOMBO* in the logit model, the coefficient on *FACOMBO* is 0.444 and significant at 0.0001 level. In model (10), the coefficient on *FACOMBO* is 0.048 and significant at the 0.0003 level. We also examine the ability of *FACOMBO* in detecting small *vs.* large frauds. Once again, we include *TA* as a control and find that for small magnitude fraud observations, *FACOMBO* is not associated with fraud (significance = 0.12). For the large magnitude fraud observations, *FACOMBO* is significant at the 0.0001 level. Thus, it appears that our composite measure is useful for detecting larger frauds, but not smaller frauds.

Sensitivity Checks

We perform several sensitivity checks to assess the robustness of our results. First, we add two additional control variables, earnings volatility, measured over five years and prior year 12-

month cumulative stock returns to models (9) and (10).[9] The rationale for including earnings volatility is that fraud could be high in environments that are very volatile. We include pre-event stock returns because stock returns, particularly high stock returns could have triggered the fraud, i.e., the pressure to keep the stock price growing or the stock returns may have been anticipating the fraud. We do not include these variables for main results because including them would drastically reduce our sample for model (9) and even more for model (10). Including these variables has no effect on model (9). The two variables are never significant and do not change our inferences. In model (10), the discretionary accrual measures are not significant. However, this result is not because of the inclusion of these two variables, but due to limiting the sample to 64 observations for which we have the necessary data to estimate model (10).

Second, we re-estimate the models using the restated earnings data for the fraud firms to compute their discretionary accruals.[10] The objective is to provide some evidence on whether the discretionary accrual models are well-specified. If the accrual models are indeed well-specified, then when estimated using the restated data, the coefficients on the discretionary accrual measures are not likely to be significant. Untabulated results indicate that the coefficients on *JONES, MJONES, MJONES2, PMATCHC, PMATCHP* are negative and significant at the 0.10 level or better. *TA* is negative, but not significant. *PMATCH* is negative and insignificant. While *DD* is positive, *MDD* is negative and both are insignificant. Both *BPROB* and *BPROBW* are negative and only *BPROB* is significant at the 0.10 level. These results suggest that models that estimate *PMATCH, DD, MDD,* and *BPROBW* are well-specified.

Next, as in Dechow and Dichev (2002), we calculate the standard deviation of residuals from models (6) and (7) for 47 unique fraud firms for which eight years of data are available.

The untabulated results indicate that in logit models the coefficient on *DD* and *MDD* are, respectively, 8.617 and 11.057 (both are significant at the 0.0004 level). The corresponding coefficients for model (10) are, 0.423 and 0.574 (neither is significant at the 0.10 level for a two-tailed test). Recall that when models (6) and (7) are estimated cross-sectionally using a larger sample, in model (10) both *DD* and *MDD* are significant at the 0.01 level (see Table 9). However, we do not conclude from this finding that the accrual estimation errors estimated from a cross-sectional model is superior to the standard deviation of residuals from the time-series model. Dechow and Dichev (2002) require a minimum of eight years of data per firm and this data requirement significantly reduces our sample size.

Following Ball and Shivakumar (2006) we include two additional variables in all discretionary accrual models: a dummy variable that equals 1 when the current period operating cash flow is negative and 0 for positive cash flow and interact this dummy variable with the operating cash flow scaled by total assets at the beginning of the year. Ball and Shivakumar (2006) argue that the relation between accruals and cash flows is not linear because while unrealized losses are immediately recognized via accruals unrealized gains are delayed. We replicate models in Table 7 using the above specification and the untabulated results indicate that the coefficients on *JONES, MJONES, MJONES2,* and *PMATCHP* are negative and significant at the 0.05 level. The coefficients on *DD*, *MDD*, and *BPROB* are, respectively, 5.456 (significant at 0.0001), 2.008 (0.002), and 0.791 (0.008). *BPROBW* is positive but not significant. For model (10), results are similar to results in Table 10. The coefficient on *DD* is 0.184 (significance level = 0.122 for a two-tailed test). Further, incorporating Ball and Shivakumar's specification has very little effect on the adjusted R^2.

Restatement Sample

Next, we describe the steps involved in identifying our second set of sample firms, firms that were not in involved in a financial statement fraud, but voluntarily restated their financial statements. First, our sample search begins with General Accountability Office (GAO) listing of 919 firms that announced their intention to restate their financial statements due to accounting irregularities (GAO 2002). The announcement dates spanned the period of January 1, 1997 through June 30, 2002. The purpose of the GAO study was to measure the impact of stock returns on announcement of restatements. After excluding firms that were privately held or gone bankrupt, the final sample comes to 575 firms. Second, we are interested in only those restatements that are related earnings management. Firms restate for a myriad of reasons (e.g. acquisitions and mergers, reclassifications, restructuring, inadequate disclosure) and most do not have anything to do with earnings management. Thus, we exclude restatements that didn't appear to have any connection to earnings management. Third, we are not concerned with the restatement announcement, but with the restatement itself. We read the restatement announcement to determine when the restatement occurred and then find the actual restatement. A restatement announcement does not necessarily mean there was a restatement of an SEC filing. Some firms announced they were restating previous earnings announcements and not a previous SEC filing. We cannot use those restatements because we do not have access to the non-restated numbers. Four, we are only concerned with annual restatements. We exclude all announcements related to restatements of only quarterly data. Also, we require a very comprehensive list of data items in order to estimate the discretionary accrual models and the M-Score. We hand-collect much of the data because of *Compustat's* inconsistent reporting of restated data. Finally, many of the restatements that were earnings management related are already included in our fraud sample. These restatements were also excluded from our restatement sample. Thus, our restatement sample is small. However, we attempt to increase the size of the restatement sample by including all years of restatements when a firm restates multiple years. Our final restatement sample consisting of non-fraud restatements is 25 firm-years. We are able to collect data on the magnitude of the amount voluntarily restated for 17 observations. As with the fraud sample, we use the entire population of *Compustat* firms with available data as our control sample.

[Insert Table 11 About Here]

Descriptive statistics for the restatement sample are presented in Table 11. On average, relative to the control firms, restating firms are smaller, have higher cash flow, report a higher *ROA* and less levered. *TA* is more positive for restating firms. However, the mean difference between restating and controls firms is significant at the 0.10 level only for *ROA, LEVERAGE,* and *TA*. In contrast to fraud firms, restating firms appear to be smaller, have better cash flow, lower leverage, and more negative total accruals. Further, the amount of earnings voluntarily restated (*AMTRESTAT2*) as a percent of beginning total assets is quite low, mean of 1.4% (median 0.9%) compared to a mean of 14% for fraud firms.

Untabulated Pearson and Spearman correlations between *RESTATE*, an indicator variable that equals 1 for restating firms and 0 for control firms and *DD* are, respectively, 0.01 (significant at the 0.05 level) and 0.008 (significant at the 0.10 level). Corresponding correlations for *MDD* are, 0.005 (not significant) and 0.008 (significant at the 0.05 level). Correlations for other discretionary accrual measures are not significant at the 0.10 level.

Pearson and Spearman correlations between *AMTRESTAT*2 and *DD* are, respectively, 0.375 (not significant) and 0.482 (significant at the 0.10 level). Corresponding correlations for *MDD* are, 0.470 and 0.450 (both are significant at the 0.10 level). Pearson and the Spearman correlations between *AMTRESTAT2* and *JONES* and *MJONES* are also significant at the 0.10 level. Correlations for other discretionary measures are not significant.

[Insert Table 12 About Here]

[Insert Table 13 About Here]

[Insert Table 14 About Here]

We first estimate model (9) by replacing *FRAUD* with *RESTATE* and those results are in Table 12. *PMATCH* is negative and significant at the 0.10 level. *DD* and *MDD* are positive and significant at the 0.05 level. None of the other measures are significant. These results are interesting because despite the small size of restating firms, both *DD* and *MDD* have some power in detecting earnings restatements. The odds ratios are also the highest for *DD* and *MDD*, indicating that increases in *DD* or *MDD* will increase the likelihood of earnings restatements. Results in Table 12 are also consistent with the results in Table 6 in that *DD* and *MDD* are strongly associated with the existence of a fraudulent event. Results in Table 13 indicate that when *TA* is included as a control, *DD* and *MDD* continue to be positive and significant at the 0.05 level. When we estimate model (9) using data from the prior year for 16 restatement observations, all the discretionary accrual measures are negative. While *JONES, MJONES,* and *PMATCH* are significant at the 0.05 level, *MJONES2* and *PMATCHP* are significant at the 0.10 level (results not tabulated). When model (10) is estimated on a common sample of 14 restatement observations none of the discretionary accrual measures are significant (see Table 14). Overall, despite the small sample, results from a sample of firms that voluntarily restated their financial statements are consistent with the results based on a sample fraud firms in that only accrual estimation errors, *DD* and *MDD* appear to have predictive power for both fraud and restatements.

As a sensitivity check, we pool our fraud sample with the non-fraud restatement sample and replicate specifications in Tables 6 and 9 (respectively, models (9) and (10)). The results for the logit model are consistent with the results in Table 6. The coefficient on *DD* is 5.304 (significant at the 0.001 level). *DD* also exhibits the highest pseudo R^2. *MDD* is also significant at the 0.001 level. Both *TA* and *BPROB* are significant at the 0.01 level (results not tabulated). Results for model (10) are consistent with the results in Table 9. The coefficients on *DD* and *MDD* are, respectively, 0.361 (significant at the 0.01 level) and 0.540 (significant at the 0.001 level). The adjusted R^2 are the highest for *MDD* (0.361) and *DD* (0.341). Overall, the findings for *DD* and *MDD* are robust and suggest that the accrual estimation errors are able to discriminate between treatment firms comprising of fraudulent and non-fraudulent restatements and control firms.

VI. CONCLUSIONS

Analyzing total accruals into normal and discretionary components has become a standard feature of research on earnings management. The discretionary or abnormal accruals are often used as a proxy for earnings management. We evaluate the ability of ten measures derived from the extant discretionary accruals models to detect the very existence of fraudulent events, the extent of fraudulent earnings, and voluntarily earnings restatements. We also include total accruals, a low-cost alternative to discretionary accruals. We find that while total accruals are associated with a fraudulent event, many commonly used measures, such as discretionary accruals derived from the Jones model, the modified Jones model, and performance-matched models are not associated with fraud. The following three measures have explanatory power for detecting fraud beyond total accruals: accrual estimation errors estimated from cross-sectional models of working capital changes on past, present, and future cash flows (Dechow and Dichev 2002), McNichols (2002) modification of Dechow and Dichev, and the Beneish (1999) probability of earnings manipulation. For a sub-sample of firms reporting the amount of restated earnings following the discovery of the fraud, commonly used measures of discretionary accruals as well as the measures of accrual estimation errors and the Beneish measure are associated with the magnitude of the fraud. Overall, only the accrual estimation errors have predictive power for both fraud and non-fraudulent restatements of earnings.

Our findings have important implications for several constituents who use financial statements and researchers who employ models of discretionary accruals to discern earnings management as well as for those who interpret empirical evidence on accrual-based earnings management. Our results suggest that the extant models of discretionary accruals do not capture fraudulent events or voluntary restatements of earnings. Auditors and regulators could devise analytical procedures based on accrual estimation errors to uncover fraud. We recommend that researchers consider using multiple measures to detect earnings management. There is certainly room for improvement. For example, future research could develop better measures by including corporate governance and other characteristics.

NOTES

1. We refer to measures of accrual estimation errors as measures of discretionary accruals.
2. Some studies estimate the Jones model without an intercept. However, Kothari et al. (2005) argue that using an intercept is an additional control for heteroskedasticity, and that discretionary accruals are more symmetric when using an intercept. Therefore, we include the intercept.
3. Prior studies (Pincus et al. 1988; Feroz et al. 1991; Dechow et al. 1996) provide more detail on AAERS and the SEC's process in investigating firms. The COSO reports frauds that were identified in AAER's issued during the period 1987-1997 rather than the firms that committed fraud during that period.
4. Note our control samples include the entire population of *Compustat* data for which data are available to estimate the necessary models, including the treatment firms. This biases against finding significant results.
5. Note that these percentages are significantly different from 100% and 50% (based on a random model) for fraud firms. The percentage of observations with negative discretionary accruals is significantly different from 100% and 50% for non-fraud firms for all measures, except *PMATCH* is not significantly different from 50%.
6. Probability of fraud for *DD* is calculated as follows. The log odds = -6.108+5.443 = -0.665. The odds = $e^{-0.665}$ = 0.5143. The probability of fraud = (0.5143) / (1+0.5143) = 0.3396.
7. The adjusted R^2 is also higher when *DD* is estimated on 118 observations (0.355 compared to 0.193 in panel H). When *MDD* is estimated on 119 observations with total accruals included, the coefficient on *MDD* is 0.512 (significant at the 0.01 level) and the adjusted R^2 0.371.

8. We thank an anonymous reviewer for this suggestion.

9. We thank an anonymous reviewer for suggesting these controls.

10. We thank an anonymous reviewer for this suggestion.

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TABLE 1
Sample Selection

Frauds from COSO's Report on Fraudulent Financial Reporting from 1987-1997	204
Total number of firms identified from Accounting and Auditing Enforcement Releases (AAERs) attributable to alleged or actual accounting fraud (non-duplicates) issued since COSO's 1987-1997 Report on Fraudulent Financial reporting to December 2004	240
Additional Frauds identified through other sources (e.g. popular press search and AAA Monograph on litigation involving Big Four auditors and their predecessor firms)	6
Firms with either no data or missing data on Compustat, Edgar, or Lexis/Nexis (e.g. small or foreign firms)	(150)
Frauds related to quarterly (10-Q's) but not annual data (10-K's)	(72)
Frauds dropped for other reasons (e.g. financial services or insurance firms, fraud had no affect earnings, or very little information available about fraud)	(54)
Frauds with insufficient data to calculate discretionary accruals	(56)
Total fraud sample	118
Total number of fraud-year observations (average fraud lasted 1.6 years)	188
Total number of fraud-year observations with restated earnings data	142
Total number of fraud-year observations with restated data to estimate the various measures of discretionary accruals	118-142

TABLE 2
Type of Alleged Accounting Fraud

Accounts and Other Factors Involved in Income Overstatement	Number of Firms	Percentage of Fraud Sample
Revenues	89	75%
Accounts Receivable	72	61%
Expenses	49	42%
Other Assets	37	31%
Inventory	28	24%
Accounts Payable and Other Accrued Expenses	17	14%
Cost of Sales	14	12%
Debt	9	8%
Other Gaines/Losses	3	3%
Related Parties	6	5%
Acquisitions and Mergers	5	4%
Total	329*	

Notes: * Does not sum to the number of firms in the sample because of the dual-entry nature of accounting (i.e. early revenue recognition generates fraudulent credit to revenue and debit to accounts receivable) and several firms are accused of engaging in multiple types of fraudulent behavior.

TABLE 3
Frequency of Fraud Observations Across Industries and Years

Panel A

SIC Code	Industry	Number	Percent
1300-1399	Oil and Gas Extraction	1	0.5%
1500-1599	Building Construction, General Contractors, and Operative Builders	1	0.5%
1600-1699	Heavy Construction	1	0.5%
1700-1799	Construction: Special Trade Contractors	1	0.5%
2000-2099	Food and Kindred Products	7	3.7%
2300-2399	Apparel and other Finished Products	8	4.3%
2700-2799	Printing, Publishing and Allied Industries	1	0.5%
2800-2899	Chemicals and Allied Products	6	3.2%
3300-3399	Primary Metal Industries	4	2.1%
3400-3499	Fabricated Metal Products	3	1.6%
3500-3599	Industrial and Commercial Machinery and Computer Equipment	24	12.8%
3600-3699	Electronic and other Electrical Equipment and Components	12	6.4%
3700-3799	Transportation Equipment	6	3.2%
3800-3899	Measuring, Analyzing, and Controlling Instruments	19	10.1%
4800-4899	Communications	3	1.6%
4900-4999	Electric, Gas, and Sanitary Services	13	6.9%
5000-5099	Wholesale Trade - durable goods	6	3.2%
5100-5199	Wholesale Trade - non-durable goods	4	21%
5600-5699	Apparel and Accessory Stores	1	0.5%
5700-5799	Home Furniture, Furnishings, and Equipment Stores	1	0.5%
5900-5999	Miscellaneous Retail	9	4.8%
7300-7399	Business Services	40	21.3%
7900-7999	Amusement and Recreation Services	2	1.1%
8000-8099	Health Services	7	3.7%
8200-8299	Educational Services	3	1.6%
8700-8799	Engineering, Accounting, Research, Management, and Related Services	2	1.1%
9900-9999	Other	3	1.6%
		188	100%

	Panel B	
Year	Number	Percent
1988	5	2.6%
1989	10	5.2%
1990	9	4.8%
1991	15	8.0%
1992	12	6.4%
1993	8	4.3%
1994	13	6.9%
1995	11	5.9%
1996	13	6.9%
1997	18	9.6%
1998	22	11.7%
1999	23	12.2%
2000	21	11.2%
2001	8	4.3%
	188	100%

TABLE 4
Descriptive Statistics for the Fraud and the Control Samples

Variables	Control Firms						Fraud Firms						Mean Diff.	Median Diff
	N	Mean	Median	Std.	Min.	Max.	N	Mean	Median	Std.	Min.	Max.		
AT	89,571	1,593.498	87.354	10,219.880	0.001	750,330.000	188	3,531.028	126.196	10,758.188	1.362	73,781.000	1,937.530[b]	38.842[c]
CFO	89,571	-0.021	0.057	0.350	-2.194	0.481	188	-0.039	0.021	0.289	-2.034	0.481	-0.018[c]	-0.036[c]
TA	89,571	-0.112	-0.060	0.344	-2.932	0.603	188	-0.013	-0.004	0.313	-2.256	0.603	0.099[c]	0.056[c]
ROA	89,571	-0.147	0.019	0.687	-6.109	0.467	188	-0.046	0.045	0.363	-2.034	0.467	0.101[c]	0.025[c]
LEVERAGE	89,571	0.562	0.205	14.032	0.000	2,226.500	188	0.261	0.260	0.189	0.000	0.803	-0.301[c]	0.055[a]
BIG4	89,571	0.805	1.000	0.396	0.000	1.000	188	0.830	1.000	0.377	0.000	1.000	0.024[a]	0.000[c]
JONES	89,571	0.005	0.027	0.301	-3.137	3.870	188	0.073	0.069	0.299	-1.796	1.025	0.068[b]	0.042[c]
MJONES	89,571	0.005	0.026	0.302	-3.173	3.920	188	0.079	0.072	0.302	-1.818	0.875	0.074[c]	0.046[c]
MJONES2	89,571	0.002	0.013	0.266	-3.088	2.919	188	0.054	0.049	0.314	-2.030	1.194	0.053[a]	0.037[c]
PMATCHC	89,571	-0.003	-0.004	0.186	-2.799	3.414	188	0.038	0.029	0.229	-1.331	1.100	0.040[a]	0.033[c]
PMATCHP	89,571	0.000	0.020	0.285	-3.042	3.279	188	0.074	0.066	0.281	-1.848	0.891	0.074[c]	0.046[c]
PMATCH	89,571	0.001	-0.001	0.345	-5.714	5.714	188	0.052	0.049	0.325	-1.367	1.595	0.051[a]	0.050[c]
DD	61,257	0.000	-0.002	0.100	-0.932	0.836	146	0.080	0.040	0.155	-0.418	0.632	0.080[c]	0.042[c]
MDD	61,448	-0.003	0.001	0.204	-23.864	4.400	147	0.061	0.043	0.126	-0.415	0.594	0.064[c]	0.043[c]
BPROB	66,805	0.076	0.006	0.211	0.000	1.000	157	0.149	0.020	0.276	0.000	1.000	0.073[c]	0.015[c]
BPROBW	66,805	0.047	0.001	0.177	0.000	1.000	157	0.086	0.005	0.224	0.000	1.000	0.040[a]	0.004[c]
AMTRESTAT							142	0.140	0.044	0.337	0.001	2.887		
% Positive *TA*						23.7%						49.4%	25.7%[c]	
% Positive *JONES*						60.6%						73.4%	12.8%[c]	
% Positive *MJONES*						60.3%						71.8%	11.5%[b]	
% Positive *MJONES2*						55.9%						68.6%	12.7%[c]	
% Positive *PMATCHC*						48.2%						63.8%	15.6%[c]	
% Positive *PMATCHP*						58.7%						72.9%	14.2%[c]	
% Positive *PMATCH*						50.0%						61.2%	11.7%[b]	

[a, b, and c] indicate, respectively, statistical significance at the 0.05, 0.01, and 0.001 levels for a two-tailed test. We use *t*-test for test of differences in means and Wilcoxon test for test of median differences.

AT = assets in the year of manipulation in millions;
CFO = cash flows in the year of manipulation scaled by AT_{t-1};
TA = total accruals in the year of manipulation scaled by AT_{t-1};
ROA = return on assets in the year of the manipulation defined as net income/beginning total assets;
LEVERAGE = long-term debt plus debt in current liabilities over total assets in the year of manipulation;
BIG4 = equals 1 for clients of Big4 auditors and 0 otherwise;
JONES = discretionary accruals in the year of manipulation from model (1);
MJONES = discretionary accruals in the year of manipulation from model (2);
MJONES2 = discretionary accruals in the year of manipulation from model (3);
PMATCHC = discretionary accruals in the year of manipulation from model (4);
PMATCHP = discretionary accruals in the year of manipulation from model (5);
PMATCH = performance matched discretionary accruals from model (2) as in Kothari et al. (2005);
DD = accrual estimation errors from model (6);
MDD = accrual estimation errors from model (7);
BPROB = Probability of earnings manipulation estimated from unweighted probit model (8);
BPROBW = Probability of earnings manipulation estimated from weighted probit model;
AMTRESTAT = the difference between actual reported earnings and the restated earnings scaled by $AT_{t-1;}$

TABLE 5
Correlations

Panel A: Correlations with FRAUD

	TA	*JONES*	*MJONES*	*MJONES2*	*PMATCHC*	*PMATCHP*	*PMATCH*	*DD*	*MDD*	*BPROB*	*BPROBW*
Pearson	0.013	0.010	0.011	0.009	0.010	0.012	0.007	0.039	0.015	0.017	0.011
prob. Value	<.0001	0.002	0.001	0.007	0.003	0.000	0.043	<.0001	0.000	<.0001	0.005
Spearman	0.024	0.015	0.017	0.016	0.016	0.018	0.011	0.031	0.030	0.029	0.029
prob. Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.001	<.0001	<.0001	<.0001	<.0001

Panel B: Correlations with AMTRESTAT

	AMTRESTAT	*TA*	*JONES*	*MJONES*	*MJONES2*	*PMATCHC*	*PMATCHP*	*PMATCH*	*DD*	*MDD*	*BPROB*	*BPROBW*
AMTRESTAT		-0.067	0.088	0.082	0.017	0.073	0.082	0.269	0.189	0.235	0.477	0.372
		0.426	0.295	0.330	0.843	0.386	0.332	0.001	0.040	0.010	<.0001	<.0001
TA	0.132		0.851	0.855	0.749	0.537	0.829	0.402	0.445	0.196	-0.037	-0.081
	0.117		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
JONES	0.283	0.699		0.996	0.868	0.619	0.942	0.551	0.402	0.198	-0.002	-0.039
	0.001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.674	<.0001
MJONES	0.289	0.706	0.990		0.872	0.622	0.946	0.554	0.416	0.198	0.003	-0.036
	0.001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.369	<.0001
MJONES2	0.252	0.684	0.806	0.812		0.786	0.847	0.574	0.427	0.200	0.061	0.024
	0.003	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
PMATCHC	0.283	0.654	0.663	0.667	0.745		0.632	0.547	0.403	0.190	0.140	0.102
	0.001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
PMATCHP	0.253	0.712	0.918	0.925	0.784	0.696		0.528	0.421	0.200	0.019	-0.021
	0.002	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001
PMATCH	0.326	0.465	0.554	0.556	0.535	0.540	0.540		0.244	0.117	0.065	0.044
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001
DD	0.266	0.534	0.436	0.453	0.494	0.423	0.467	0.291		0.919	0.146	0.066
	0.004	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001
MDD	0.322	0.501	0.463	0.461	0.502	0.435	0.475	0.308	0.881		0.039	0.013
	0.000	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	0.005
BPROB	0.394	0.420	0.290	0.307	0.313	0.283	0.314	0.205	0.406	0.300		0.939
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
BPROBW	0.383	0.424	0.293	0.309	0.317	0.291	0.316	0.209	0.405	0.305	0.995	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

In panel A, *FRAUD* = 1 for fraud firms and 0 for control firms. See Table 4 for definitions of other variables. In panel B, Pearson (Spearman) correlations are above (below) the diagonal. *DACC* refers to the various discretionary accrual measures or the Beneish measures.

TABLE 6
Logistic Regressions of *FRAUD* on Measures of Discretionary Accruals

	A	B	C	D	E	F	G	H	I	J	K
Intercept	-5.820[d]	-5.842[d]	-5.865[d]	-5.825[d]	-5.855[d]	-5.881[d]	-5.849[d]	-6.108[d]	-5.883[d]	-5.849[d]	-5.774[d]
AT	0.000[b]	0.000[b]	0.000[b]	0.000[b]	0.000[b]	0.000[b]	0.000[b]	0.000[c]	0.000[c]	0.000[a]	0.000[a]
CFO	-0.435	-1.232[d]	-1.122[c]	-1.349[d]	-1.014[d]	-1.026[c]	-1.149[d]	0.280	-0.930[a]	-1.476[d]	-1.632[d]
ROA	0.339	1.179[d]	1.069[c]	1.276[d]	1.109[d]	0.987[c]	1.159[d]	-0.055	0.849[a]	1.299[d]	1.366[d]
LEVERAGE	-0.077	-0.108	-0.105	-0.106	-0.100	-0.102	-0.106	0.011	0.006	-0.097	-0.101
BIG 4	-0.310[a]	-0.311[a]	-0.304[a]	-0.316[a]	-0.313[a]	-0.300[a]	-0.308[a]	-0.168	-0.211	-0.287	-0.308[a]
TA	1.561[c]										
JONES		0.034									
MJONES			0.255								
MJONES2				-0.192							
PMATCHC					0.609						
PMATCHP						0.459					
PMATCH							0.233				
DD								5.443[d]			
MDD									2.515[c]		
BPROB										0.844[c]	
BPROBW											0.561
No of fraud obs.	188	188	188	188	188	188	188	146	147	157	157
No of control obs.	89,569	89,569	89,569	89,569	89,569	89,569	89,569	61,256	61,447	66,804	66,804
χ^2	37.162	31.324	31.617	31.537	32.335	32.228	31.817	77.714	35.742	40.191	35.228
pseudo R^2	0.014	0.012	0.012	0.012	0.012	0.012	0.012	0.038	0.018	0.018	0.016
Odds ratio for *DACC*	4.764	1.035	1.291	0.825	1.838	1.582	1.262	231.098	12.364	2.326	1.753

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.

TABLE 7
Logistic Regressions of *FRAUD* on Measures of Discretionary Accruals after Controlling for Total Accruals

	A	B	C	D	E	F	G	H	I	J	K
Intercept	-5.820[d]	-5.722[d]	-5.752[d]	-5.739[d]	-5.788[d]	-5.788[d]	-5.813[d]	-6.124[d]	-5.878[d]	-5.835[d]	-5.764[d]
AT	0.000[b]	0.000[c]	0.000[c]	0.000[c]	0.000[b]	0.000[b]	0.000[b]	0.000[c]	0.000[c]	0.000[a]	0.000[a]
CFO	-0.435	-0.481	-0.473	-0.519	-0.481	-0.459	-0.437	-0.444	-0.640	-0.571	-0.648
ROA	0.339	0.334	0.339	0.280	0.161	0.337	0.300	0.647	0.554	0.347	0.344
LEVERAGE	-0.077	-0.074	-0.076	-0.059	-0.076	-0.076	-0.075	0.011	0.006	-0.070	-0.073
BIG 4	-0.310[a]	-0.330[b]	-0.324[b]	-0.329[b]	-0.305[a]	-0.316[a]	-0.311[a]	-0.161	-0.212	-0.282	-0.299[a]
TA	1.561[c]	2.341[c]	2.093[c]	2.379[d]	2.182[c]	1.826[c]	1.669[c]	-0.834	0.356	1.520[c]	1.673[c]
JONES		-0.960									
MJONES			-0.638								
MJONES2				-1.031[a]							
PMATCHC					-0.875						
PMATCHP						-0.333					
PMATCH							-0.128				
DD								5.547[d]			
MDD									2.463[c]		
BPROB										0.791[c]	
BPROBW											0.532
No of fraud obs.	188	188	188	188	188	188	188	146	147	157	157
No of control obs.	89,569	89,569	89,569	89,569	89,569	89,569	89,569	61,256	61,447	66,804	66,804
χ^2	37.162	39.669	38.242	41.067	38.388	37.445	37.287	78.477	35.805	44.123	39.943
Pseudo R^2	0.014	0.015	0.014	0.016	0.015	0.014	0.014	0.039	0.018	0.020	0.018
Odds ratio for *DACC*		0.383	0.528	0.357	0.417	0.717	0.880	256.376	11.743	2.205	1.702

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.

TABLE 8
Logistic Regressions of *FRAUD* on Measures of Discretionary Accruals Using Data from the Year Prior to the Year of Manipulation

	A	B	C	D	E	F	G	H	I	J	K
Intercept	-6.617[d]	-6.502[d]	-6.531[d]	-6.577[d]	-6.642[d]	-6.561[d]	-6.653[d]	-6.916[d]	-6.792[d]	-6.482[d]	-6.375[d]
AT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CFO	0.365	-2.087[c]	-1.874[b]	-1.739[b]	-1.011	-1.761[b]	-0.973	0.359	-0.342	-1.360[a]	-1.609[b]
ROA	0.213	2.804[d]	2.585[c]	2.377[c]	1.826[b]	2.443[c]	1.799[b]	0.396	1.104	1.554[b]	1.659[b]
LEVERAGE	-0.218	-0.265	-0.259	-0.249	-0.240	-0.246	-0.244	-0.160	-0.195	-0.911	-0.918
BIG 4	-0.107	-0.136	-0.132	-0.120	-0.114	-0.125	-0.104	-0.039	-0.069	-0.161	-0.195
TA	2.200										
JONES		-1.515									
MJONES			-1.065								
MJONES2				-0.703							
PMATCHC					0.534						
PMATCHP						-0.848					
PMATCH							0.502				
DD								4.767[d]			
MDD									3.865[c]		
BPROB										0.973[a]	
BPROBW											0.442
No of fraud obs.	65	65	65	65	65	65	65	65	65	54	54
No of non-fraud obs.	61,337	61,337	61,337	61,337	61,337	61,337	61,337	61,337	61,337	47,527	47,527
χ^2	9.735	10.821	9.695	9.170	8.804	9.243	9.139	25.462	16.459	11.238	8.682
Pseudo R^2	0.010	0.011	0.010	0.009	0.009	0.009	0.009	0.025	0.016	0.014	0.010
Odds ratio for *DACC*	9.022	0.220	0.345	0.495	1.706	0.428	1.653	117.593	47.718	2.646	1.556

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for definitions.

TABLE 9
Regressions of *AMTRESTAT* on Measures of Discretionary Accruals

	A	B	C	D	E	F	G	H	I	J	K
Intercept	0.236[c]	0.221[c]	0.203[b]	0.227[c]	0.234[c]	0.200[b]	0.077[a]	0.148[c]	0.143[c]	0.092	0.153[a]
ASSETS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CFO	-0.110	0.266	0.342[a]	0.041	0.203	0.426[b]	0.152[d]	0.180[a]	0.232[b]	0.057	-0.093
ROA	-0.224	-0.557[d]	-0.637[d]	-0.344[a]	-0.408[b]	-0.716	0.115[d]	-0.449[d]	-0.449[d]	0.071	0.122
LEVERAGE	-0.228	-0.224	-0.216	-0.222	-0.219	-0.180	0.136	-0.015	-0.021	-0.015	-0.121
BIG4	-0.036	-0.068	-0.064	-0.041	-0.055	-0.070[d]	0.073	-0.085[a]	-0.084[a]	-0.034	-0.026
TA	0.029										
JONES		0.522[c]									
MJONES			0.602[c]								
MJONES2				0.191							
PMATCHC					0.439						
PMATCHP						0.703[c]					
PMATCH							0.150[d]				
DD								0.345[c]			
MDD									0.509[c]		
BPROB										0.656[d]	
BPROBW											0.585[c]
N	142	142	142	142	142	142	142	118	119	120	120
F-Value	2.28	3.69	3.90	2.42	2.58	4.10	8.85	11.97	12.88	5.90	3.52
Adjusted R^2	0.052	0.103	0.110	0.057	0.063	0.117	0.251	0.360	0.377	0.198	0.113

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 variable definitions.

TABLE 10
Regressions of *AMTRESTAT* on Measures of Discretionary Accruals After Controlling for Total Accruals for a Common Sample

	A	B	C	D	E	F	G	H	I	J	K
Intercept	0.200[d]	0.192[d]	0.178[d]	0.176[d]	0.191[d]	0.173[d]	0.040[d]	0.169[d]	0.157[d]	0.144[d]	0.147[d]
ASSETS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CFO	1.338	-0.056	-0.347	-0.732	1.193	-1.235	5.052	-1.316	-1.503	-0.444	-0.263
ROA	-1.586	-0.059	0.241	0.694	-1.178	1.141	5.064	1.129	1.363	0.353	0.174
LEVERAGE	-0.063	-0.051	-0.042	-0.013	-0.045	-0.038	0.081	-0.039	-0.030	0.011	0.007
BIG4	-0.107[c]	-0.134[c]	-0.132[d]	-0.130[c]	-0.132[c]	-0.124[c]	0.039[c]	-0.098[b]	-0.095[b]	-0.096[b]	-0.090[b]
TA	1.435	-0.336	-0.723	-1.220	0.702	-1.634	5.057	-1.305	-1.549	-0.502	-0.309
JONES		0.325[b]									
MJONES			0.419[c]								
MJONES2				0.446[c]							
PMATCHC					0.606[c]						
PMATCHP						0.430[b]					
PMATCH							0.108[a]				
DD								0.194			
MDD									0.345[b]		
BPROB										0.241[d]	
BPROBW											0.347[d]
N	101	101	101	101	101	101	101	101	101	101	101
F-Value	4.63	5.16	5.72	5.71	5.41	5.19	4.55	4.42	4.86	6.30	7.49
Adjusted R^2	0.179	0.226	0.248	0.248	0.236	0.227	0.199	0.193	0.213	0.271	0.312

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.

TABLE 11
Descriptive Statistics for the Restatement and Control Samples

	No Restatement						Restatement							
	N	Mean	Median	Std.	Min.	Max.	N	Mean	Median	Std.	Min.	Max.	Mean Diff.	Median Diff.
AT	89,743	1597.640	87.414	10222.210	0.001	750330.000	25	984.890	377.885	2290.120	8.072	11702.800	-612.750	897.476[c]
CFO	89,743	-0.021	0.057	0.350	-2.194	0.481	25	0.006	0.032	0.123	-0.280	0.199	0.028	-0.051
TA	89,743	-0.112	-0.060	0.344	-2.932	0.603	25	-0.036	-0.028	0.144	-0.406	0.386	0.077[a]	0.025
ROA	89,743	-0.147	0.019	0.687	-6.109	0.467	25	-0.029	0.023	0.163	-0.513	0.155	0.118[b]	-0.049
LEVERAGE	89,743	0.561	0.205	14.019	0.000	2226.500	25	0.186	0.142	0.172	0.000	0.507	-0.375[c]	-0.019
BIG 4	89,743	0.788	1.000	0.409	0.000	1.000	25	0.840	1.000	0.374	0.000	1.000	0.052	-0.160
JONES	89,743	0.005	0.027	0.301	-3.133	3.870	25	0.072	0.046	0.130	-0.166	0.377	0.067[a]	0.045
MJONES	89,743	0.005	0.026	0.302	-3.173	3.920	25	0.063	0.045	0.131	-0.171	0.394	0.058[a]	0.037
MJONES2	89,743	0.002	0.013	0.267	-3.088	2.918	25	0.040	0.001	0.123	-0.186	0.357	0.039	0.028
PMATCHC	89,743	-0.003	-0.004	0.186	-2.799	3.414	25	0.028	0.011	0.100	-0.136	0.282	0.030	0.031
PMATCHP	89,743	0.000	0.020	0.285	-3.042	3.279	25	0.037	0.034	0.137	-0.333	0.345	0.036	0.016
PMATCH	89,743	-0.001	0.000	0.307	-5.714	5.714	25	-0.051	-0.039	0.185	-0.545	0.304	-0.050	-0.051
DD	61,369	0.000	-0.002	0.101	-0.932	0.836	22	0.052	0.012	0.112	-0.074	0.389	0.052[a]	0.054
MDD	61,562	-0.003	0.001	0.204	-23.864	4.400	22	0.046	0.024	0.096	-0.068	0.359	0.048[a]	0.045[a]
BPROB	66,941	0.076	0.006	0.211	0.000	1.000	23	0.088	0.009	0.216	0.000	0.998	0.012	0.082
BPROBW	66,941	0.047	0.001	0.177	0.000	1.000	23	0.053	0.002	0.190	0.000	0.915	0.006	0.051
AMTRESTAT2							17	0.014	0.009	0.015	0.001	0.058		

AMTRESTAT2 = the difference between actual reported earnings and the voluntarily restated earnings scaled by AT_{t-1};
[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.

TABLE 12
Logistic Regressions of *RESTATE* on Measures of Discretionary Accruals

	A	B	C	D	E	F	G	H	I	J	K
Intercept	-8.045[d]	-8.153[d]	-8.099[d]	-8.063[d]	-8.099[d]	-8.012[d]	-8.082[d]	-7.780[d]	-7.649[d]	-7.752[d]	-7.748[d]
AT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CFO	-0.020	-0.328	-0.598	-0.799	-0.052	-1.162	-1.362[a]	0.067	-0.895	-1.209	-1.219
ROA	0.172	0.525	0.768	0.963	0.611	1.319	1.403[a]	0.258	1.143	0.919	0.925
LEVERAGE	-1.168	-1.145	-1.168	-1.186	-1.193	-1.207	-1.149	-1.224	-1.310	-1.539	-1.541
BIG 4	0.269	0.295	0.281	0.273	0.268	0.266	0.289	0.097	0.097	0.197	0.196
TA	1.136										
JONES		0.777									
MJONES			0.338								
MJONES2				0.006							
PMATCHC					1.313						
PMATCHP						-0.671					
PMATCH							-1.293[a]				
DD								3.757[b]			
MDD									1.424[b]		
BPROB										0.087	
BPROBW											0.079
Number of restating obs.	25	25	25	25	25	25	25	22	22	23	23
Number of control obs.	89,743	89,743	89,743	89,743	89,743	89,743	89,743	61,369	61,562	66,941	66,941
χ^2	4.422	4.469	4.212	4.160	4.614	4.354	6.645	7.691	6.005	4.273	4.270
pseudo R^2	0.010	0.010	0.009	0.009	0.010	0.010	0.015	0.020	0.015	0.010	0.010
Odds ratio for *DACC*	3.114	2.175	1.402	1.006	3.718	0.511	0.274	42.829	4.155	1.091	1.082

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.

TABLE 13
Logistic Regressions of *RESTATE* on Measures of Discretionary Accruals After Controlling for Total Accruals

	A	B	C	D	E	F	G	H	I	J	K
Intercept	-8.045[d]	-8.117[d]	-8.033[d]	-7.999[d]	-8.097[d]	-7.887[d]	-8.033[d]	-7.782[d]	-7.643	-7.737	-7.735
AT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CFO	-0.020	-0.010	-0.023	-0.069	-0.030	-0.124	-0.252	-0.122	-0.004	-0.447	-0.448
ROA	0.172	0.202	0.169	0.137	0.573	0.163	0.204	0.445	0.240	0.155	0.156
LEVERAGE	-1.168	-1.144	-1.172	-1.181	-1.192	-1.207	-1.103	-1.225	-1.306	-1.523	-1.524
BIG 4	0.269	0.286	0.267	0.261	0.268	0.247	0.271	0.098	0.095	0.195	0.195
TA	1.136	0.651	1.222	1.562	0.076	2.559	2.078	-0.208	1.020	1.070	1.075
JONES		0.562									
MJONES			-0.101								
MJONES2				-0.518							
PMATCHC					1.260						
PMATCHP						-1.810					
PMATCH							-1.545[b]				
DD								3.779[b]			
MDD									1.414[b]		
BPROB										0.058	
BPROBW											0.067
Number of restating obs.	25	25	25	25	25	25	25	22	22	23	23
Number of control obs.	89,743	89,743	89,743	89,743	89,743	89,743	89,743	61,369	61,562	66,941	66,941
χ^2	4.422	4.539	4.425	4.511	4.614	5.247	7.849	7.695	6.065	4.475	4.475
pseudo R^2	0.010	0.010	0.010	0.010	0.010	0.012	0.017	0.020	0.016	0.011	0.011
Odds ratio for *DACC*		1.755	0.904	0.596	3.524	0.164	0.213	43.755	4.111	1.060	1.070

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.

TABLE 14
Regressions of *AMTRESTAT2* on Measures of Discretionary Accruals for a Common Sample

	A	B	C	D	E	F	G	H	I	J	K
Intercept	0.041[b]	0.041[a]	0.035	0.053[a]	0.052[b]	0.039[b]	0.016[b]	0.035[a]	0.038[b]	0.058[b]	0.055[c]
ASSETS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CFO	0.039	0.002	0.016	-0.069	-0.172	-0.004	0.070	0.039	0.052	-0.028	-0.027
ROA	0.039	0.038	0.004	0.074	0.108	-0.011	0.037	0.036	0.022	0.002	0.010
LEVERAGE	-0.024	-0.024	-0.017	-0.017	-0.008	-0.011	0.029	-0.023	-0.011	-0.012	-0.011
BIG4	-0.025	-0.025	-0.025	-0.031	-0.026	-0.030	0.020	-0.023	-0.031	-0.040[a]	-0.039[a]
TA	-0.003										
JONES		-0.002									
MJONES			0.049								
MJONES2				-0.087							
PMATCHC					-0.204						
PMATCHP						0.066					
PMATCH							0.039				
DD								0.061			
MDD									0.093		
BPROB										-0.050	
BPROBW											-0.050
N	14	14	14	14	14	14	14	14	14	14	14
F-Value	1.30	0.95	1.12	1.57	2.55	1.36	0.95	1.04	1.32	1.78	1.92
Adjusted R^2	0.104	-0.024	0.052	0.208	0.418	0.143	-0.021	0.020	0.130	0.264	0.299

[a, b, c, and d] indicate, respectively, statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels for a two-tailed test. See Table 4 for variable definitions.