ABSTRACT

Title of Dissertation: **An Alternative Measure to Detect Intentional Earnings Management through Discretionary Accruals**

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This study proposes an alternative measure of discretionary accruals that can be used in testing for intentional earnings management. Prior research has shown the prevalence of measurement error in all models used to estimate discretionary accruals (Healy (1985), DeAngelo (1986), Jones (1991) and modified Jones models (Dechow et al., 1995). The alternative measure proposed relies on the premise that managers use one or more components of accruals (accounts receivable, inventories, accounts payable, other working capital and depreciation) to manipulate bottom-line income in a given direction, consistent with their incentives. In other words, components of discretionary accruals are expected to be positively correlated. If they are not, this is an indication of high measurement error in the models estimating them. The alternative measure is tested in terms of its power (type II error) and specification (type I error) and compared to the

traditional discretionary accruals measure. The power of the tests is measured in random samples with added accrual manipulation as well as a sample of firms targeted by the Securities and Exchange Commission for alleged fraud and a sample of firms that violated their debt covenants. The results indicate that the power of this alternative discretionary measure is higher than that of the traditional discretionary accruals measure. The specification (specificity) is tested in random samples chosen from the full sample as well as random samples chosen from extreme income and cash from operations observations and a sample in which discretionary accruals is a noisy measure of the estimated discretionary accruals. The results indicate that the specification of detecting earnings management behavior is improved by using the alternative discretionary accruals measure.

AN ALTERNATIVE MEASURE TO DETECT INTENTIONAL EARNINGS MANAGEMENT THROUGH DISCRETIONARY ACCRUALS

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2005

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Definitions

DAR = Increase (Decrease) in accounts receivable from the cash flow statement,

DINV = Increase (Decrease) in inventories from the cash flow statement,

DAP = Decrease (Increase) in accounts payable from the cash flow statement,

DOWC = Change in other working capital from the cash flow statement,

DEP = Depreciation expense,

TAC = Total operating accruals = *DAR* + *DINV* + *DAP* + *DOWC* + *DEP*,

EDAC = Estimated discretionary accruals using one of the following models: Healy (1985), DeAngelo (1986), Jones (1991), or modified Jones (Dechow et al., 1995),

RATIO = Measure of consistency between components of discretionary accruals, and

$EDAC^{C}$ = Alternative estimated discretionary accruals using one of the following models: Healy, DeAngelo, Jones, or modified Jones.

Acknowledgments

I would like to thank first and foremost all my committee members for their valuable help, especially my advisor, Dr. Oliver Kim, for his seasoned guidance, for helping me through the tough parts, and for always motivating me to keep going, whether directly or indirectly.

A special thanks goes to Dr. Partha Sengupta for his constructive critique throughout the phases of this study, as well as proof reading several versions of the manuscript.

I would like to thank my colleague Myojung Cho for her comments and proof reading.

I would never have come so far without the moral support of my parents, my sister and brother back in Egypt. My children, Dana, Mareya and Tymour deserve a lot of credit. They kept me smiling when I felt it was too overwhelming.

I would like to thank my father-in-law, Mohamed Saba, for his help in modeling and mathematical techniques and my mother-in-law for her moral support and advice.

Lastly, I would like to thank my husband, Magdi. He was always there when I needed him. He was eager to review what I had done and provide constructive remarks. I would never be where I am today without him.

"It is difficult to get a man to understand something

when his salary depends on his not understanding it."

Upton Sinclair

Chapter 1: Introduction and Literature Review

1.1 Introduction

Earnings management has become a well-researched topic in the accounting literature, especially in recent years after the many accounting scandals in prominent companies such as Enron and WorldCom[1]. These scandals were even a catalyst for the passage of the U.S. Sarbanes-Oxley act of 2002, which has changed the accounting environment tremendously. In the context of the study, earnings management refers to the intentional manipulation of accruals in order to maximize the managers' utility and/or the market value of the firm. The next section provides a more detailed definition. Healy (1985) was the first to consider earnings management using what he termed "discretionary accruals". These are the accruals that are under the discretion of management and are considered a proxy for earnings management behavior. Since then, there has been much research using discretionary accruals considering diverse research questions. However, modeling techniques to estimate discretionary accruals have not improved much since the seminal Jones model (1991), in which a regression-type model is used with the change in sales and the level of gross property, plant, and equipment as independent variables that explain the non-discretionary level of accruals. Dechow et al. (1995) and others have shown that these models estimating discretionary accruals suffer from the existence of measurement error that can be significant and may affect the research results. The measurement error in these models arises because variables that

[1] For example, see: Stewart (2003) and Scott (2002).

explain non-discretionary accruals have been omitted from the expectation models and so wind up on the residual term, which represents discretionary accruals.

Until now, there has been no formal modeling dealing with the way managers manipulate earnings using the various tools under their discretion. This study fills the gap in the literature by modeling, albeit simplistically, managers' decisions to manipulate earnings in a specific case. This model shows that managers are expected to manipulate one or more components of accruals in the same direction (positive manipulation to increase income and negative manipulation to decrease income). Based on this expectation, an alternative measure of discretionary accruals is proposed that utilizes the information about the consistency between the components of accruals. This alternative measure discounts the traditional discretionary accruals measure when components of accruals do not behave as expected, thus creating a measure that suffers from less measurement error than the current measure. The testable hypotheses of the study relate to the improvement in power (type II error) and specificity or specification (type I error) of the alternative model in the detection of earnings management behavior. Type II error refers to not rejecting the null hypothesis of no earnings management when it is false i.e. the ability to detect earnings management when it is in the sample. Type I error refers to rejecting the null hypothesis of no earnings management when it is true.

Section 1.2. presents the literature review related to earning management research.

1.2 Literature Review

I begin by defining earnings management (EM), which is not an easy task. There are numerous definitions ranging from situations in which earnings is fraudulently manipulated to harm investors, to situations in which earnings is manipulated non-fraudulently to signal to the shareholders the firm's financial future. The following exhibit is extracted from Mulford and Comiskey (2002) and presents some alternative definitions of EM.

Defining Earnings Management
Earnings management is the active manipulation of accounting results for the purpose of creating an altered impression of business performance.[a] Given that managers can choose accounting policies from a set (e.g. GAAP), it is natural to expect that they will choose policies so as to maximize their own utility and/or the market value of the firm. This is called earnings management.[b] During 1999 we focused on financial reporting problems attributable to earnings management by public companies. Abusive earnings management involves the use of various forms of gimmickry to distort a company's true financial performance in order to achieve a desired result.[c]
[a]C. Mulford and E. Comiskey, Financial Warnings (New York: John Wiley & Sons, 1996), p.360. [b]W. Scott, Financial Accounting Theory (Englewood Cliffs, NJ: Prentice-Hall, 1997), p.295. [c]Securities and Exchange Commission, Annual Report (Washington, DC: Securities and Exchange Commission, 1999), p.84.

Exhibit 3.1 as appearing in Charles W. Mulford and Eugene E. Comiskey (2002), p.59.

The first definition does not specify how earnings are managed. In reality, managers can choose to manipulate earnings through actual operations such as the timing of capital expenditures or asset sales. Alternatively, they can use accrual manipulations, which are adjustments made to the accounts. This second type of manipulation is more common and is the subject of this study. Also, this first definition does not stipulate whether EM is harmful or beneficial to investors. The second definition refers to the incentives of managers. They choose accounting policies that maximize their utility and/or market value of the firm. This definition indicates that it is important to consider managerial incentives that cause the manipulation behavior. The third definition by the Securities and Exchange Commission (SEC) is the harshest, treating EM as fraudulent behavior aimed at distorting the true financial performance of the firm. In the context of this study, I refer to earnings management as manipulation in earnings that is designed to serve management's purposes. Whether it is fraudulent is not a consideration. Also, whether it is harmful to investors and others is not a consideration.

Healy (1985) was the first to test for EM in the accounting literature using what is termed "discretionary accruals". In his paper, he tests the bonus-maximizing hypothesis of managerial behavior.[2] By using actual parameters and definitions of bonus contracts in 94 sample firms, he finds that accrual policies of managers are linked to income-reporting incentives of their bonus contracts, and that changes in accounting procedures by managers are linked to adoption or modification of their bonus plan. He proposes "discretionary" accruals as a proxy for EM behavior. This discretionary component of

[2] The bonus-maximizing hypothesis was first introduced by Watts and Zimmerman (1986). It states that managers of firms with bonus plans are more likely to choose accounting procedures that shift reported earnings from future periods to the current period under certain conditions.

accruals is the component of accruals that is under the discretion of managers. The other component of accruals is the "non-discretionary" component, which is the expected level of accruals in the firm given no manipulation. Specifically, accruals can be defined as follows:

$$TAC_t = NDAC_t + DAC_t$$

where TAC_t = Total operating accruals in year t,

$NDAC_t$ = Non-discretionary Accruals in year t, and

DAC_t = Discretionary Accruals in year t.

The problem is that both components of accruals are not observable so the researcher has to make assumptions about one of the components. Healy assumes that the discretionary accruals component is the level of accruals in a given year and so effectively, he assumes that non-discretionary accruals are zero in expectation.

DeAngelo (1986) conducts a study of 64 companies whose managers propose to go private by purchasing all of the publicly held common stock. She uses discretionary accruals to test whether these managers systematically understate earnings in the period before the buyouts. The results indicate no such manipulation behavior. The proxy she uses for discretionary accruals is the change in total accruals. This effectively sets the prior year level of accruals as the expectation of non-discretionary accruals in the current year.

McNichols et al. (1988) examine whether managers manipulate earnings by focusing on a specific accrual, the provision for bad debts. They use Generally Accepted

Accounting Principles (GAAP) to formulate a model of the expected accrual in the absence of EM. The results show that the discretionary component of the provision for bad debts is income-decreasing for firms whose earnings are unusually high or low. Even though their methodology is more powerful in detecting EM than the previous methodology using total accruals, the total accrual approach is preferred because of its comprehensiveness.

Jones (1991) tests EM behavior during import relief investigations by the U.S. International Trade Commission (ITC). She finds that discretionary accruals are more income-decreasing during the year the ITC completed its investigation than would otherwise be expected. She uses a regression-type model to estimate non-discretionary accruals in a given year based on the change in economic conditions. Specifically she expects that working capital accruals are related to the change in sales and that depreciation is related to the level of gross property, plant, and equipment. The model used to estimate non-discretionary accruals is as follows:

$$\frac{TAC_t}{A_{t-1}} = a\ (\frac{1}{A_{t-1}}) + b_1(\frac{\Delta S_t}{A_{t-1}}) + b_2(\frac{PPE_t}{A_{t-1}}) + e_t \qquad \textbf{(1.1)}$$

where TAC_t = Total operating accruals in year t,

A_{t-1} = Total assets at the beginning of year t,

ΔS_t = Change in sales from year $t-1$ to year t, and

PPE_t = Gross Property, Plant, and Equipment.

In the previous model, all variables are divided by the beginning level of total assets to adjust for heteroscedasticity.

The discretionary accrual component is estimated as the difference between total accruals and the non-discretionary component using the coefficients from the above regression.

$$DAC_t = \frac{TAC_t}{A_{t-1}} - (a * \frac{1}{A_{t-1}} - b_1 * \frac{\Delta S_t}{A_{t-1}} - b_2 \frac{PPE_t}{A_{t-1}}) \qquad \textbf{(1.2)}$$

where a, b_1 and b_2 are the coefficients estimated in (1.1) and all other variables are as previously defined.[3]

Dechow et al. (1995) test several models estimating discretionary accruals including those discussed above in terms of their power (type II error) and specification (type I error). They introduce the modified Jones model in which the change in receivables is deducted from change in sales in the estimation model (1.1) to eliminate the conjectured tendency of the Jones model to measure discretionary accruals with error when discretion is exercised over revenues. They conclude that all models appear well specified when applied to a random sample of firm-years with no expectation of EM. However, all models generate tests of low power for EM of plausible magnitude (one to five percent of assets). All models reject the null hypothesis of no EM at rates exceeding the test levels when applied to samples of firms with extreme financial performance. Finally, the modified Jones model exhibits the most power in detecting EM. This confirms the existence of measurement error in the existing models.

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[3] Jones uses a time-series specification to estimate regression (1.1) on a firm-by-firm basis. However, recently, this regression has been estimated cross-sectionally over industry groups to improve the power of the model e.g. Subramanyam (1996).

Thomas and Zhang (2000) also test six models of estimating expected accruals for forecast accuracy using three different methods and conclude that these models are not accurate. They demonstrate that a naïve model that assumes that non-current accruals equal -5% of prior year total assets and current accruals equal 0% of prior year total assets frequently outperformed these models.

Kang and Sivaramakrishnan (1995) put forward a model to detect EM using the balance of accruals rather than the more common change in the accounts used in other papers. They discuss accruals related to sales (accounts receivable), accruals related to expenses (inventories, other current assets, and current liabilities), and accruals related to property, plant and equipment (depreciation). Their model relies on the instrumental variable approach and provides stronger results. However, it has not caught on in later research as a method of testing for EM.

The review thus far has alluded to the fact that, to date, the models used to estimate discretionary accruals for the purpose of testing for EM suffer from the existence of measurement error. This measurement error arises because variables that explain non-discretionary accruals have been omitted from the expectation models and so wind up on the residual term, which represents discretionary accruals. Following are some papers that specifically deal with the measurement error that exists in these models.

Guay et al. (1996) provide evidence consistent with models estimating non-discretionary accruals having considerable imprecision or misspecification. This measurement error or imprecision in the model occurs due to the unobservable nature of the manipulation and the inadequate job of modeling the non-discretionary accruals. McNichols and Wilson (1988) characterize the measurement error and state that "the non-discretionary component can be large in mean and variation relative to the discretionary accrual. If so, the proxy will be too noisy to detect EM in situations where it exists". This means that if models estimating non-discretionary accruals are not well specified, and omit important variables that are correlated with these non-discretionary accruals, then the residual of the model (discretionary accruals) will consist mainly of non-discretionary accruals, rendering tests of EM biased.

As Hansen (1999) notes "models of discretionary accruals are actually of expected and unexpected accruals. Therefore, for most earnings management studies, unexpected accruals that arise for reasons other than managerial discretion over financial reporting represent measurement error in discretionary accruals." Measurement error in discretionary accruals estimates arise because variables that explain non-discretionary accruals have been omitted from the expectation model and so wind up on the residual term, which represents discretionary accruals.

Young (1999) states that studies of discretionary accruals activity have generally failed to document consistent evidence of EM, e.g. Healy (1985), Gaver et al. (1995), and Holthausen et al. (1995) find inconsistent results for management compensation contracts. Measurement error in the discretionary accruals estimate is one explanation for these inconsistent findings.

Studies of EM that use aggregate accruals in order to detect earnings do not distinguish between the separate components of accruals. Accruals consist of components that can behave differently under different economic conditions. If we look at the R^2 from a modified Jones regression, they are quite low across all industries (as will be shown in the empirical section of the study). Given the fact that a manager who wishes to change the bottom-line earnings will probably do so through accrual accounts, as it is the least likely to be detected, I propose that it will be beneficial to disaggregate the Jones model into its components and look separately at the discretionary accruals of each component. When the separate components are considered, this provides the opportunity to consider the differential manipulation behavior in these components. The next chapter shows that managers' incentives lead them to manipulate one or more components of accruals in the direction that affects bottom-line income consistently. This avoids dilution that occurs when components are not consistently managed. Given this expected behavior, the discretionary accruals components can be used to infer the presence of measurement error in the models that estimate these components.

The literature provides incentives for managers to engage in EM such as during initial public offerings, seasoned equity offerings, and government investigations. Other factors that induce EM are the executive's compensation, and closeness to debt-covenant violation. Beneish (2001) provides a good perspective on EM research and the incentives for increasing income (e.g. compensation agreements, security equity offerings, insider trading, and debt covenants) and incentives for reducing income (e.g. regulation and cookie-jar reserves). Some of these situations are used to test for EM using the proposed measure developed in this study. These appear in the empirical section in chapter 4.

1.3 Chapter Summary

Models for detecting EM set forth in the literature concentrate on operating accruals as a tool of EM. The Jones model and its later modifications use aggregate accruals and their relationship to economic factors (change in sales) and the level of property, plant, and equipment to estimate non-discretionary accruals. Review of the literature that deals with testing for EM reveals the presence of measurement error in all models estimating non-discretionary accruals. This fact provides an avenue for research, which is followed in this study. I propose to separately estimate discretionary components of accruals (accounts receivable, inventories, accounts payable, other working capital, and depreciation) then measure the consistency between them. Any inconsistency between the discretionary components is an indication of measurement error in the estimation models. The following chapter presents the hypotheses development of the study. Chapter 3 presents the sample selection and methodology, followed by the empirical results in chapter 4. Chapter 5 concludes.

Chapter 2: Hypotheses Development

The purpose of the study is to improve the power and specification of existing methods of estimating discretionary accruals. This is done through a measure that takes into account the consistency between the components of accruals. This chapter deals with the development of this measure. First, the source of bias or measurement error in existing models is presented, followed by a detailed description of the existing models used in the literature. An optimization model of manipulation by managers is then introduced when the manager has two components of accruals that he can choose from to manipulate earnings. Finally, the measure of consistency proposed in the study is introduced and the testable hypotheses based on this measure are presented.

2.1 Bias in Tests of Earnings Management Using Aggregate Accruals

Accruals are the differences that are created in the accounting system between earnings in a year and cash flow from operations. Operating accruals are calculated as follows:[4]

$$TAC_t = \Delta AR_t + \Delta INV_t + \Delta AP_t + \Delta OWC_t + DEP_t$$

where TAC_t = Total operating accruals in year t,

DAR_t = Increase (Decrease) in accounts receivable from year t-1 to year t,

$DINV_t$ = Increase (Decrease) in inventories from year t-1 to year t,

DAP_t = Decrease (Increase) in accounts payable from year t-1 to year t,

[4] Note all liabilities and expenses are the negative of the true values to simplify calculations. This is followed in the remainder of the study.

$DOWC_t$ = Change in other working capital from year t-1 to year t, and

DEP_t = Depreciation expense in year t,

Following Healy (1985), researchers use a measure of discretionary accruals as a proxy for EM behavior. Specifically, researchers divide total accruals into a non-discretionary component (normal level of accruals to maintain the operations) and a discretionary component (abnormal level that is under the discretion of managers).

$$TAC_t = NDAC_t + DAC_t$$

where TAC_t = Total accruals,

$NDAC_t$ = Non-discretionary accruals, and

DAC_t = Discretionary accruals.

In the measurement of discretionary accruals, researchers use proxies for this component of accruals since neither the discretionary nor the non-discretionary components are observable. Previous research has shown that the discretionary accruals using the Jones method and other methods contain measurement error, which may be significant and can bias the research results. McNichols and Wilson (1988) characterize the measurement error and show that the coefficient of discretionary accruals on a variable, *PART* (dummy variable that partitions the data into two groups for which EM are specified)[5] is biased when the partitioning variable, *PART*, and the measurement error

[5] "For example, *PART* could indicate where earnings are above or below target. *PART* can be extended to a vector without loss of generality" McNichols and Wilson (1988).

in the proxy of discretionary accruals are correlated. If discretionary accruals were observable then tests of EM could be done using the following regression:

$$DAC = b_0 + b_1 PART + e \tag{2.1}$$

In the previous regression, b_0 represents the average value of *DAC* (discretionary accruals) when the variable *PART* is equal to zero, and b_0+b_1 is the average value of *DAC* when the variable PART equals one (observations in which EM is being tested). The researcher rejects the null hypothesis of no EM if the coefficient on the dummy variable, b_1, has the proper sign and is statistically significant.

Since true discretionary accruals are not observed, researchers rely on a proxy of estimated discretionary accruals, *EDAC*, which contains measurement error, h. This measurement error arises due to poor estimation of non-discretionary accruals:

$$EDAC = DAC + h$$

The test of EM using the proxy is then:

$$EDAC = g_0 + g_1 PART + n \tag{2.2}$$

where $g_1 = b_1 + r_{PART,h} * \frac{s_h}{s_{PART}}$

It is apparent from the above discussion that the bias in the coefficient g_1 will be affected by the degree of correlation between the partitioning variable and the measurement error ($r_{PART,h}$) as well as the standard deviation of the measurement error

(s_h) and that of the partitioning variable (s_{PART}). The standard deviation of the measurement error (s_h) arises from the poor estimation of the non-discretionary accruals. The larger the variance, the more the noise in the residual and so "discretionary accruals" contains significant "non-discretionary" components. Even if the correlation between *PART* and h is zero (unbiased coefficient), this can lead to an inflated standard error for the estimated coefficient on *PART* which will increase the probability of a type II error.

The goal of this study is to try to reduce the measurement error inherent in all models of discretionary accruals by relying on the information contained in the separate components of discretionary accruals. Rather than estimating discretionary accruals (*DAC*) in the aggregate, it is possible to estimate components of accruals separately such as accounts receivable, inventories, accounts payable, other working capital, and depreciation. The sum of these discretionary components equals the aggregate discretionary accruals obtained from one single regression such as the Jones model.

$$EDAR_t = DAR_t + e_{1t},$$

$$EDINV_t = DINV_t + e_{2t},$$

$$EDAP_t = DAP_t + e_{3t},$$

$$EDOWC_t = DOWC_t + e_{4t},$$

$$EDDEP_t = DDEP_t + e_{5t},$$

where $EDAC_t = EDAR_t + EDINV_t + EDAP_t + EDOWC_t + EDDEP_t$.

$EDAR_t$ = Discretionary Accounts Receivable,

$EDINV_t$ = Discretionary Inventories,

$EDAP_t$ = Discretionary Accounts Payable,

$EDOWC_t$ = Discretionary Other Working Capital, and

$EDDEP_t$ = Discretionary Depreciation.

Noise in the discretionary accruals ($EDAC_t$) estimate is reduced when the model specification is improved. This is possible when the components are separately modeled since the researcher can add whatever variables are related to the specific components. The goal is to improve the specification of the model but not reduce the signal (*DAC* in the residual). The *EDAC* will contain less noise from "non-discretionary accruals" which means that the correlation between *PART* and the measurement error will most likely be reduced[6] and so the tests are expected to be more powerful (lower type II error) as well as more specific (lower type I error). However, this is not the focus of the study. I propose that the relationship between the components of discretionary accruals can provide insightful information into the prevalence of measurement error in these components. I propose a measure that captures the consistency between the components and use this measure to provide an alternative discretionary accruals measure that eliminates some of the measurement error discussed so far.

[6] Since variables that were previously omitted have been included in the model estimating normal accruals, the abnormal accruals will contain less of the normal component. This omitted variable problem was the cause of the correlation between *PART* and the measurement error (whether positive or negative).

2.2 Models of Discretionary Accruals in the Literature

This section discusses the most common models that have been used in the literature to estimate non-discretionary accruals. They were discussed briefly in the literature review. They are presented one more time in this section to explain the source of measurement error in each one of them. All these models will be used in this study in the empirical section.

1) Healy model

In this model, Healy (1985) defines estimated discretionary accruals in a period as total accruals scaled by lagged total assets. This implies that non-discretionary accruals are expected to be zero.

$$EDAC_{it} = TAC_{it} / A_{it-1}$$

i refers to the firm or the industry depending on whether the analysis is time series or cross-sectional. This is the simplest of all the models discussed and is expected to contain the highest measurement error since it does not take into account the normal operations that would require some level of accruals. Dechow et al. (1995) test the Healy model compared to other models but define discretionary accruals as the deviation of *total* accruals in the event period from the mean total accruals during the estimation period.

$$EDAC_{it} = (TAC_{it} - \frac{\sum_t TAC_{it}}{N}) / A_{it-1} \qquad \textbf{(2.3)}$$

where $EDAC_{it}$ = Estimated discretionary accruals for firm i in year t,

TAC_{it} = Total accruals for firm i in year t,

A_{it-1} = Total assets for firm i at beginning of year t,

N = number of years in estimation period.

The source of measurement error in the Healy model comes from the omitted variables in estimating discretionary accruals that are affected by factors in the current year. For example, any change in the economic factors in the current year will affect the level of accruals without changing the estimate of the discretionary accruals.

2) *DeAngelo model*

In this model, DeAngelo (1986) assumes that non-discretionary accruals follow a random walk and uses the change in the aggregate accruals from year *t-1* to year *t* to represent the discretionary component.

$$EDAC_{it} = (TAC_{it} - TAC_{it-1}) / A_{it-1} \qquad \textbf{(2.4)}$$

where $EDAC_{it}$ = Estimated discretionary accruals for firm i in year t,

TAC_{it} = Total accruals for firm i in year t,

A_{it-1} = Total assets for firm i at beginning of year t.

Similar to the Healy model, the source of measurement error in this model comes from omitted variables affecting accruals in the current year. However, this model is expected to contain less measurement error than the Healy model if non-discretionary accruals follow a random walk.

3) *Jones model*

Jones (1991) uses a regression-type model to estimate discretionary accruals. She estimates non-discretionary accruals using the following regression:

$$TAC_{it} / A_{it-1} = a_{i1} (1/A_{it-1}) + b_{i1} (DREV_{it}/A_{it-1}) + b_{i2} (PPE_{it}/A_{it-1}) + e_{it}$$

where TAC_{it} = Total accruals for firm i in year t,

A_{it-1} = Total assets for firm i at beginning of year t,

$DREV_{it}$ = Change in revenue for firm i from year t-1 to year t, and

PPE_{it} = Gross property, plant, and equipment for firm i in year t.

All variables are deflated by beginning total assets to adjust for heteroscedasticity.

The residual from this regression represents discretionary accruals under the Jones methodology.

$$EDAC_{it} = TAC_{it} / A_{it-1} - [a_{i1}\ (1/A_{it-1}) + b_{i1}\ (DREV_{it}/A_{it-1}) + b_{i2}\ (PPE_{it}/A_{it-1})] \quad \textbf{(2.5)}$$

where the coefficients used are those estimated from the prior least square regression.

The source of measurement error in this model comes from omitted variables not captured by sales and the level of PPE such as the change in the credit standing of clients. However, it is expected (and shown in Dechow et al., 1995) that this model will capture more non-discretionary accruals than the prior two models.

4) *Modified Jones model*

The modified version of the Jones model proposed by Dechow et al. (1995) deducts the change in receivables from the change in revenue to account for manipulation to non-cash revenue in the tested period of manipulation. In prior research testing all the previous models the modified Jones model exhibited the highest power and specification. It is the one with the least measurement error when manipulation occurs through accounts receivable (non-cash revenues).

$$EDAC_{it} = TAC_{it} / A_{it-1} - [a_{i1}\ (1/A_{it-1}) + b_{i1}\ ((DREV_{it} - DAR_{it})/A_{it-1}) + b_{i2}\ (PPE_{it}/A_{it-1})] \quad \textbf{(2.6)}$$

where $EDAC_{it}$ = Estimated discretionary accruals for firm i in year t,

TAC_{it} = Total accruals for firm i in year t,

A_{it-1} = Total assets for firm i at beginning of year t,

$DREV_{it}$ = Change in revenue for firm i from year t-1 to year t,

DAR_{it} = Change in accounts receivable for firm i from year t-1 to year t, and

PPE_{it} = Gross property, plant, and equipment for firm i in year t.

The above four different models are used to estimate discretionary accruals in the empirical section, with the expectation that the Healy and DeAngelo models are inherently more misspecified than the Jones and modified Jones models.

2.3 Manager's Manipulation Decision

In order to proceed in the study, there has to be some expectation about how managers manipulate the different components under their discretion when faced with their specific incentives. Watts & Zimmerman (1986) talk about the accounting role in contracting, specifically in compensation plan contracts and debt contracts. In regards to compensation plans, there are two types of plans that reward management based on accounting numbers (usually earnings), which are bonus plans and performance plans. Watts & Zimmerman stipulate that if managers controlled the calculation of earnings to the extent that they could report any number they wished, then earnings-based bonus plans would not exist. However, in practice, these plans do exist and are quite common in the remuneration packages of managers. It is true that managers cannot manipulate earnings to whatever number they wish but evidence of earnings management exists and so the compensation packages are not working as intended in favor of the principal (the investors). There is evidence in the literature that EM is influenced by the compensation package. For example, Healy (1985) finds that accrual policies of managers are linked to income-reporting incentives of their bonus contracts, and that changes in accounting procedures by managers are linked to adoption or modification of their bonus plan. Bergstresser and Philippon (2004) provide evidence of the use of discretionary accruals to manipulate earnings in firms where the CEO's potential compensation is more closely tied to the value of stock and option holdings.

In this section, I analyze the manager's manipulation decision when his earnings-based compensation plan is based on meeting a specific benchmark such as analyst expectations, prior year earnings, or a budgeted level of earnings[7]. It is expected that monitoring and contracting is costly for the principal so not all manipulation will be eliminated. Since there are different components that the manager can use to manipulate earnings, I first discuss the costs and benefits of manipulating these different accounts.

2.3.1 Costs and Benefits of Manipulating Components of Accruals

The next section introduces an optimization model to show how managers manipulate different components to maximize their utility. An important consideration in the model is what it costs to manipulate the different components of accruals as well as what are the benefits from this manipulation. There have not been many papers on the subject. Marquardt and Wiedman (2004) discuss the costs of manipulating different accrual accounts in the context of three EM incentives: seasoned equity offerings,

[7] Burgstahler and Dichev (1997) document significant discontinuities around zero in earnings, earnings changes, and analyst forecast error distributions. This provides evidence that firms manage earnings to exceed three thresholds: zero earnings, last period's earnings, and consensus analysts' forecasts of earnings.

management buyouts, and avoidance of earnings decreases. They divide the costs of EM into two categories:

- Costs of detected EM
- Costs of undetected EM

Costs that are incurred when EM is detected include market price devaluation, loss of managerial reputation, loss of future employment opportunities, or penalties. In addition, there are intrinsic costs such as the managers' dislike of lying. Detection could be through SEC enforcement actions, earnings restatements, shareholder litigation, qualified audit reports, or negative coverage in the press. Marquardt et al. state that the empirical evidence suggests that EM involving recurring items, specifically revenue recognition, increase the probability of detection and are associated with higher negative price consequences.[8]

Costs of undetected EM include inevitable reversal of manipulation and reduced reporting flexibility in firms with bloated balance sheets. In addition, audit costs may be higher and perceived earnings quality lower. These costs also are expected to be higher for recurring than non-recurring items.

The costs of manipulation that is detected exceed those from manipulation that goes undetected. These costs are expected to increase at an increasing rate since it gets easier to detect manipulation when larger (material) amounts are manipulated. Also, auditors will be more willing to accept immaterial discrepancies than large material ones.

The above discussion provides some insights into the costs of manipulation but does not show exactly which specific accounts are expected to have high costs and which

[8] See Feroz et al. (1991) and Dechow et al. (1996).

are expected to have low costs. In general, revenue manipulation (and accounts receivable manipulation) is expected to have a higher cost of manipulation than other types of manipulation.[9] The working capital accounts are expected to have the next highest costs since they will require faster reversal. Depreciation will probably have the lowest cost but it is not very flexible. I expect different industries will have different cost functions for the specific accounts. Firms with a larger client base may have lower costs when manipulating revenues than firms with a smaller client base, since detection will be less probable.

Marquardt and Wiedman (2004) discuss the benefits of manipulation and propose that they depend on the context. They present three contexts namely EM before seasoned-equity offerings, before management buyouts, and in order to avoid earnings decreases. However, they do not discuss the benefits of using a specific accrual. Ertimur et al. (2003) investigate investors' reactions to revenue and expense surprises around earnings announcements. They show that investors value more highly a dollar of revenue surprise than a dollar of expense surprise. They also show that this differential reaction varies systematically between growth and value firms (based on the market-to-book value) and depend on the proportion of variable to total costs, the relative persistence of sales and expenses, and the proportion of operating to total expenses. I expect that the benefits pattern follow the costs pattern closely. Revenue manipulation (and accounts receivables) will have the highest benefit from manipulation since it gives the impression of a higher level of operations. Other working capital accounts will have the next highest benefit. Depreciation manipulation will have the lowest benefit since it is well known that this is

[9] Ertimur et al. (2003) argue that accounting manipulation of expenses may be more difficult to detect than manipulation of sales.

under managerial discretion. In addition, I do not expect that the benefits increase at a decreasing rate but rather follow a linear pattern.

From the above discussion, it appears that the costs of detection of a specific accrual will increase with the *probability of detection*. I propose that the probability of detection is related to two factors:

- *The magnitude of the component:*

  I expect the probability of detection to be positively related to the magnitude of the component used to manipulate earnings. Barton and Simko (2002) show that the level of net operating assets (total operating assets less operating liabilities) relative to sales is associated with the ability to meet/beat analyst forecasts. Specifically, firms that have bloated balance sheets with a large amount of prior EM cannot manipulate earnings in the current period. This means that larger components may have reached the limit of manipulation and any additional manipulation is easily detected.

- *The volatility of the component:*

  I expect the probability of detection to be positively related to the volatility of the component used to manipulate earnings. More volatile components are more scrutinized by auditors and require a higher level of verification before the auditor signs off on the financial statements. This volatility is captured by the variance of the component.

In addition, the benefit of manipulation of a specific component is proportional to the improvement in market value that results from that particular component. This is expected to depend on the following factor:

- *The persistence of the component:*

  More persistent components are preferred to less persistent components since they give an impression of sustained improvement in earnings.

I expect that there is a trade-off between costs and benefits of components. The components of accruals that provide the highest benefit also have the highest cost. The above measures are presented in the empirical section. However, it is not directly testable whether these above factors are related to the costs and benefits of manipulating specific components, and so the results are only suggestive.

2.3.2 Modeling Manipulation with Two Components of Accruals

Suppose the manager has two choices that can be used to manipulate earnings. Denote x_1 as the manipulation related to the first variable and x_2 as the manipulation related to the second variable. For example, x_1 could be the amount of accounts receivable (and revenue) manipulation while x_2 could be the amount of accounts payable manipulation. The desired manipulation in any given period depends on the true earnings. If earnings fall short of the benchmark that the manager uses then he will have the incentive to manipulate earnings to reach this benchmark. The benchmark could be the prior period earnings or the level of earnings below which he receives no bonus. Denote D as the deviation of true earnings from the benchmark, which represents the targeted manipulation. Denote by b_1 and b_2 the benefit from x_1 and x_2, respectively. Without loss of generality, assume that $b_1 > b_2$. Denote by c_1 and c_2 the costs associated with x_1 and x_2, respectively. Assume that $c_1 > c_2$. There is a trade-off between the costs and benefits of both components. The component that provides the highest benefit from manipulation is also associated with the highest cost.

Furthermore, the manager cannot manipulate earnings at any desired amount. He sets a cost threshold for himself. If the costs of manipulation exceed this threshold then he will not manipulate beyond that point. This represents his willingness to accept the costs created by the manipulation. The threshold changes with the context such as equity issuance versus preventing a decrease after a string of earnings increases. Denote this threshold by T.

In the event that the manager cannot manipulate enough to cover the deviation D then there will be a shortfall from the benchmark. This shortfall is costly to the manager. As the former SEC chairman Arthur Levitt commented in his 1998 speech, there can be a tremendous drop in share price associated with even a "one penny" shortfall from expectations. Denote by z the shortfall from expectations (the remaining amount that cannot be manipulated) and denote by f the cost of this shortfall in the manager's objective function. The manager's problem can be modeled as follows[10]:

$$\max_{x_1, x_2} \quad b_1 x_1 + b_2 x_2 - fz \tag{2.7}$$

$$\text{s.t.} \quad c_1 x_1^2 + c_2 x_2^2 \le T \tag{2.8}$$

$$x_1 + x_2 + z = D \tag{2.9}$$

[10] Assuming that managers have a short-horizon, they only care about maximizing current earnings without regard to future earnings.

The objective function (2.7) is a function of only earnings, which is affected by x_1, x_2, and z. This objective function is consistent with maximization of compensation, given that this is a function of earnings. The cost function is represented in (2.8). Notice that the cost constraint uses the square values of the x_1 and x_2 variables to account for the fact that costs increase at an increasing rate. The final constraint (2.9) represents the fact that the desired manipulation equals the deviation from the benchmark, D.

The Lagrangian takes the following form:

$$L = b_1 x_1 + b_2 x_2 - fz + l[T - c_1 x_1^2 - c_2 x_2^2] + m[D - x_1 - x_2 - z]$$

The f.o.c.'s are:

$$\frac{\partial L}{\partial x_1} = b_1 - 2lc_1 x_1 - m \le 0 \qquad x_1 \ge 0 \qquad (1)$$

$$\frac{\partial L}{\partial x_2} = b_2 - 2lc_2 x_2 - m \le 0 \qquad x_2 \ge 0 \qquad (2)$$

$$\frac{\partial L}{\partial z} = -f - m \le 0 \qquad z \ge 0 \qquad (3)$$

$$\frac{\partial L}{\partial l} = T - c_1 x_1^2 - c_2 x_2^2 \le 0 \qquad l \ge 0 \qquad (4)$$

with complementary slackness, and finally,

$$\frac{\partial L}{\partial m} = D - x_1 - x_2 - z = 0 \qquad m > 0 \qquad (5)$$

By examining the above f.o.c.'s, (5) need always hold as an equality. The solution to the above formulation will depend on the magnitude of D. When D is not too large and can be fully manipulated by x_1 and x_2, then z will equal to zero and so (3) will not be binding. (1) is always binding i.e. $x_1 > 0$. However (2) is not binding at first until a certain point.

When D is too large to be manipulated z will take a non-zero value and so the f.o.c. (3) holds as an equality. In summary, the solution to the above formulation is:

1) If $D \le \sqrt{\frac{T}{c_1}}$ then $x_1 = D, x_2 = 0, z = 0$;

2) If $D > \sqrt{\frac{T}{c_1}}$ and $D \le \frac{(c_1 + c_2)T}{c_1 c_2}$, then

$$x_1 = \frac{c_2 D + \sqrt{(c_1 + c_2)T - c_1 c_2 D^2}}{c_1 + c_2}, x_2 = \frac{c_1 D - \sqrt{(c_1 + c_2)T - c_1 c_2 D^2}}{c_1 + c_2}, z = 0$$

3) If $D > \frac{(c_1 + c_2)T}{c_1 c_2}$, then

$$x_1 = \frac{c_2 (b_1 + f)^2 T}{c_1 c_2 (b_1 + f)^2 + c_1^2 (b_2 + f)^2}, x_2 = \frac{c_1 (b_2 + f)^2 T}{c_2^2 (b_1 + f)^2 + c_1 c_2 (b_2 + f)^2},$$

$$z = D - \frac{c_2^2 (b_1 + f)^2 + c_1^2 (b_2 + f)^2}{c_1 c_2^2 (b_1 + f)^2 + c_1^2 c_2 (b_2 + f)^2}$$

The previous model shows that when the deviation is not too large, the manager chooses to manipulate earnings using the choice with the highest benefit even though it is costlier, so in (1) the manager chooses to cover the shortfall in earnings by setting $x_1 = D$

(manipulation of the first component equal to full deviation from benchmark). When the deviation from the benchmark increases, there is a need to manipulate both choices so $x_1 > 0$ and $x_2 > 0$. This continues up to a limit when the cost threshold is met and then it is not feasible for the manager to manipulate any more. At this point the manager may decide to take a "big bath" and create "cookie-jar" reserves to avoid similar situations in the future. There is no expectation in this model that one component will be increased while the other component is decreased. This makes sense, as that will dilute the total effect on earnings.

Academic research on the subject of manipulating different components of accruals includes Plummer and Mest (2001), who examine the distribution of different components of earnings and find that firms that manage earnings upwards do so by managing sales (and current assets) upwards and managing operating expenses (and current liabilities) downwards. Thus it is reasonable to assume that components of abnormal accruals will be used simultaneously in the direction that increases, or decreases, earnings depending on the incentives of managers.

If reversal of prior year initiated discretionary accruals occurs during the year, it is unlikely that managers will actively manipulate other components to achieve the earnings benchmark, especially if the reversal is a large amount. This is true because the cost of managing accruals increases at an increasing rate.

The following exhibit, extracted from Mulford & Comiskey (2002), confirms the above results. These are examples of firms that manipulated earnings fraudulently through different mechanisms. The firms achieved the desired manipulation through one or more component of accruals in the direction that affected earnings consistently.

Examples of Abusive Earnings Management	
Company	**Nature of Abusive Earnings Management**
Advanced Medical Products, Inc. AAER[a] No. 812, Sept. 5, 1996	• Improperly recognized revenue upon shipments to field representatives • Improperly held open its accounting periods and continued to book sales • Recognized sales without shipping the goods actually ordered • Recognized full sale amount on partial shipments
Cendant Corporation AAER No. 1272, June 14, 2000	• Both understated reserves and reverses reserves into earnings • Overstated acquisition-related reserves and then reversed portions into earnings • Failed to record membership charge-backs and cancellations • Improperly charged asset write-offs against acquisition reserves
Chambers Development AAER No.767, March 5, 1996	• Improper cost capitalization, especially interest capitalization
First Merchant Accep. Corp. AAER No.1166, Sept 28,1999	• Understated its allowance for credit losses by misrepresenting the payment status of accounts
Hybrid/Ikon Corp. AAER No.1281, June29, 2000	• Improperly recognized as a sale a transaction that provided an absolute right of return through side letter
Informix Corp.	• Recognized revenue on transactions with reseller customers who were not creditworthy • Recognized revenue on disputed claims against customers • Recognized revenue on transactions granting rights to refunds and other concessions
Intile Designs, Inc. AAER No.1259, May23, 2000	• Underreported value of ending inventory so as to decrease property taxes
Pepsi-Cola P.R. AAER No.1171, Sept28, 1999	• Understated allowances for sales discounts
System Software Associates, Inc. AAER No.1285, July 14, 2000	• Recognized revenue on sales with significant uncertainties about customer acceptance of the product and collectibility of the contract price and significant vendor obligations remained
[a]AAER refers to the Securities and Exchange Commission's Accounting and Auditing Enforcement Release for the indicated date	

Exhibit 3.5 as appearing in Charles W. Mulford and Eugene E. Comiskey (2002), p.67.

2.4 Measure of Consistency between Components (RATIO)

2.4.1 The Case of Two Components of Discretionary Accruals

Given the previous discussion that managers will use one or more components in the same direction to achieve the desired earnings manipulation, a measure that captures this effect is devised. This measure is expected to be helpful in eliminating some of the measurement error in the aggregate discretionary accruals.

Suppose as before that there are two discretionary components of accruals x_1 and x_2, which are linearly related such that $x_2 = ax_1$ where $a \geq 0$.

The variables x_1 and x_2 are normally distributed with zero mean and variance s_x^2 and $a^2 s_x^2$, respectively.

The researcher does not observe x_1 and x_2 but observes the variables y_1 and y_2 such that $y_1 = x_1 + e_1$ and $y_2 = ax_1 + e_2$. The error terms represent model misspecification in estimating discretionary components. Assume that e_1 and e_2 are normally distributed with zero mean and variance s_1^2 and s_2^2, respectively.

Under these assumptions, $y_1 \sim N(0, s_x^2 + s_1^2)$ and $y_2 \sim N(0, a^2 s_x^2 + s_2^2)$. In addition, assume that the error terms are uncorrelated with any of the variables but they are correlated with each other with $Cov(e_1, e_2) = s_{12}$, then $Cov(y_1, y_2) = a s_x^2 + s_{12}$.

Consider the following measure that utilizes the variance of the observed components.

$$RATIO = \frac{Var(y_1 + y_2)}{Var(y_1) + Var(y_2)} = \frac{Var(y_1) + Var(y_2) + 2Cov(y_1, y_2)}{Var(y_1) + Var(y_2)}$$

$$= 1 + 2\frac{Cov(y_1, y_2)}{Var(y_1) + Var(y_2)} = 1 + 2\frac{Cov(x_1, x_2) + Cov(e_1, e_2)}{Var(x_1) + Var(x_2) + Var(e_1) + Var(e_2)}$$

$$= 1 + 2\frac{a s_x^2 + s_{12}}{s_x^2(1 + a^2) + s_1^2 + s_2^2}$$

The variance term s_x^2 appears in the numerator and denominator with different multiples. When $0 < a \leq 1$, as was shown in the discussion in the previous section, then the multiple in the denominator is more than double that of the numerator and it drops out if $a = 0$.

This measure is inversely related to the variance of the error terms and positively related to the covariance of the error terms. Assuming that the covariance between the error terms is negligible[11] or does not systematically differ between firms, this measure provides information about the magnitude of measurement error in the observed discretionary accruals. Large values of this measure are indicative of low variance in the error terms. However, small values of the measure are indicative of high variance in the error terms and so the aggregate discretionary accruals are contaminated with high uncertainty.

A disadvantage with this measure is that it uses the variance of the observed components, which requires a large number of observations. In addition it will not

[11] This assumption was used by Kirschenheiter (1997) in estimating the reliability of accounting signals.

pinpoint the year in which the observation is contaminated but will capture the firms that, on average, are subject to uncertainty (high measurement error).

An alternative measure that captures the essence of the above but that can be used for each observation individually, whether annual, quarterly, or for some other sub-period, uses the absolute values of the components. Recall that $|x| = \sqrt{x^2}$. Given that the components of accruals have zero mean, the measure can be modified as follows:

$$RATIO = \frac{|y_1 + y_2|}{|y_1| + |y_2|} = \frac{|x_1 + ax_1 + e_1 + e_2|}{|x_1 + e_1| + |ax_1 + e_2|}$$

The measure is the absolute value of the sum of the components of discretionary accruals over the sum of their absolute values. This measure is restricted to values between zero and one. It tends to zero as the error terms increase and tends to one as the error terms decrease.

In essence this measure captures the signs and magnitudes of the components of discretionary accruals. It is high when the components have consistent signs. It is low when the components have inconsistent signs and magnitudes. When the discretionary accruals measure is represented by one component with a large magnitude and the remaining components have small magnitudes then the ratio, *R*, will still be high even if the signs are inconsistent, representing the high magnitude of that particular component. The above measure can be easily extended to include more than two components of accruals under certain assumptions as shown in the next section.

2.4.2 Extension to n Components of Discretionary Accruals

Suppose that there are n components of accruals x_1, x_2 and $x_3, \ldots., x_n$ which are linearly related such that $x_2 = a_1 x_1$ and $x_3 = a_2 x_1, \ldots\ldots, x_n = a_{n-1} x_1$ where $a_n \geq 0$[12].

The x_i's are normally distributed with zero mean and variance $a_i^2 s_x^2$, given that $a_1 = 1$.

The researcher does not observe the x_i's but observes the variables y_i such that:

$$y_1 = x_1 + e_1,$$

$$y_2 = a_2 x_1 + e_2,$$

.

.

.

$$y_n = a_n x_1 + e_n.$$

The error terms represent measurement error in estimating non-discretionary accruals. Discretionary accruals with larger measurement error are less reliable and discretionary accruals with smaller error are more reliable so the e_i's represent the degree of bias in the measurement of these accruals. Assume that the e_i's are normally distributed with zero mean and variance s_i^2.

---

[12] This linear correlation could be due to the correlation of all of the components of accruals to a common variable such as sales.

Under these assumptions, $y_1 \sim N(0, s_x^2 + s_1^2)$, $y_2 \sim N(0, a_2{}^2 s_x^2 + s_2^2)$, ……….. $y_n \sim N(0, a_n^2 s_x^2 + s_n^2)$. In addition, assume that the error terms are uncorrelated with any of the variables but they are correlated with each other with $Cov(e_i, e_j) = s_{ij}$ for i,j = 1, 2,…..n. The covariances of the observed components of accruals are then:

$$Cov(y_1, y_2) = a_2 s_x^2 + s_{12},$$

$$Cov(y_1, y_3) = a_3 s_x^2 + s_{13},$$

$$Cov(y_2, y_3) = a_2 a_3 s_x^2 + s_{23},$$

.

.

$$Cov(y_i, y_j) = a_i a_j s_x^2 + s_{ij} \qquad \text{for } i \neq j \text{, given that } a_1 = 1$$

Consider the following measure that utilizes the variance of the observed components.

$$RATIO = \frac{Var(\sum_{i=1}^{n} y_i)}{\sum_{i=1}^{n} Var(y_i)} = \frac{Var(y_1 + y_2 + \ldots\ldots + y_n)}{Var(y_1) + Var(y_2) + \ldots\ldots + Var(y_n)} \qquad \text{for } i \neq j$$

$$= \frac{\sum_{i=1}^{n} Var(y_i) + \sum_{i=1}^{n} \sum_{j=1}^{n} Cov(y_i, y_j)}{\sum_{i=1}^{n} Var(y_i)}$$

$$= 1 + \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (a_i a_j s_x^2 + s_{ij})}{\sum_{i=1}^{n} Var(y_i)}$$

$$= 1 + \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (a_i a_j s_x^2 + s_{ij})}{\sum_{i=1}^{n} (a_i^2 s_x^2 + s_i^2)}$$

This measure is inversely related to the variance of the error terms (s_i^2's) and positively related to the covariance between the error terms. Assuming that these covariances are negligible, then large values of this measure are indicative of low variance in the error terms (low noise). On the other hand, small values of the measure are indicative of high variance in the error terms and so accruals are contaminated with high uncertainty.

As before, an alternative measure that captures the essence of the above but that can be used for each observation individually, is as follows:

$$RATIO = \frac{|y_1 + y_2 + ... + y_n|}{|y_1| + |y_2| + ... + |y_n|}$$

$$= \frac{|x_1 + a_2 x_1 + ... + a_n x_1 + e_1 + e_2 + ... + e_n|}{|x_1 + e_1| + |a_2 x_1 + e_2| + ... + |a_n x_1 + e_n|} \qquad \textbf{(2.10)}$$

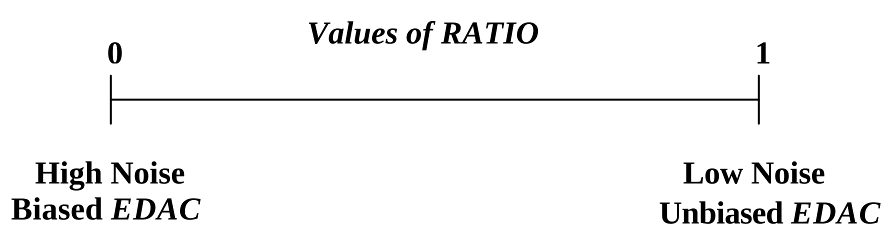
The measure is the absolute value of the sum of the discretionary components of accruals over the sum of their absolute values. This measure is restricted to values between zero and one. It tends to zero as the error terms increase and tends to one as the error terms decrease.

In essence this measure captures the signs and magnitudes of the discretionary components of accruals. It is high when the components have consistent signs. It is low when the components have inconsistent signs and magnitudes.

2.4.3 Alternative Measure of Discretionary Accruals

Since it is impossible to distinguish between what is attributable to true discretionary accrual signals and the measurement error or noise from observing discretionary accruals, then the relationship between the various components can provide useful information that can distinguish between cases with “intentional” EM and cases with low likelihood of EM.

As was established in the last section, using the information from the components of the discretionary accruals provides a measure of consistency, *RATIO*, that is an indicator of noise in the aggregate discretionary accruals (the sum of the discretionary components). *RATIO* is a measure that is, by construction, limited to values between zero and one. Since it is inversely related to the variance in the error terms, then as the values of *RATIO* increase (and tend to one) this is an indication of low error variance. As values of *RATIO* decrease (and tend to zero) this is an indication of high error variance. The following chart illustrates this concept.



The above measure can be used in conjunction with the traditional discretionary accruals to provide a measure of EM, which is less noisy. The alternative discretionary accruals, $EDAC_t^C$ is calculated as follows:

$$EDAC_t^C = EDAC_t * RATIO_t \quad \textbf{(2.11)}$$

The correction in the above measure is the degree of uncertainty in discretionary accruals, given the expectation that components of discretionary accruals are positively related. As was shown in the previous section, *RATIO* is a measure that is inversely related to the variance of the error terms or the measurement error in the model estimating discretionary accruals. If there is no measurement error in the discretionary accruals measure, then *RATIO* will equal to one and the alternative discretionary accruals will equal to the uncorrected discretionary accruals. If, however, there is a high degree of measurement error in the discretionary accruals measure then *RATIO* will be close to zero and the alternative discretionary accruals will be discounted towards zero. It is expected that this alternative measure will produce more powerful tests of EM (less type II error when there exists earnings management) and will be more specific (less type I error when there is no earnings management). The following chart illustrates the relationship between *EDAC* and $EDAC^C$.

Values of EDAC and $\boldsymbol{EDAC^C}$

where *EDAC* = Estimated discretionary accruals measure using the Healy, DeAngelo, Jones or modified Jones methods, and

$EDAC^C$ = Estimated alternative discretionary accruals measure using the Healy, DeAngelo, Jones or modified Jones methods.

The following table presents examples of values of *EDAC* and $EDAC^C$ when there are only two components of discretionary accruals (accounts receivable and accounts payable).

Examples of values of *EDAC* and $EDAC^C$:

	EDAR	*EDAP*	*RATIO*	*EDAC*	$EDAC^C$
Example 1	0.06	0.01	1.00	0.07	0.07
Example 2	-0.09	0.01	0.80	-0.08	-0.06
Example 3	0.08	-0.03	0.45	0.05	0.02
Example 4	0.05	-0.01	0.67	0.04	0.03
Example 5	0.04	-0.02	0.33	0.02	0.01
Example 6	0.09	-0.05	0.04	0.04	0.00
Example 7	0.06	-0.06	0.00	0.00	0.00

From the table, several observations can be made:

Observation 1: *Both the mean and standard deviation of* $EDAC^C$ *is lower than that of EDAC.*

The above observation follows from the fact that *RATIO* is constrained to take on values between zero and one. Essentially, if components of discretionary accruals follow the expected pattern (as in example 1 where both components are positive), then the aggregate discretionary accruals measure is not adjusted in calculating the alternative discretionary accruals, $EDAC^C$. However, if the components do not follow the expected pattern (examples 2 through 7), then *EDAC* is discounted towards zero to calculate $EDAC^C$. Since *RATIO* cannot be negative, then $EDAC^C$ will have a smaller variance and standard deviation. This observation is confirmed in the empirical section.

The smaller mean works against finding EM in samples so if there are significant results in testing for EM, this is construed as evidence of EM with greater reliability.

Observation 2: The order of *EDAC* does not carry over to $EDAC^C$.

The values of *EDAC* are dependent on the magnitude of *RATIO* so it is possible that large values of *EDAC* are associated with small values of $EDAC^C$ and vice versa. This can be seen in examples 3 and 4. The value of *EDAC* is higher in example 2 than in example 3 whereas the value of $EDAC^C$ is smaller.

Observation 3: The difference in magnitude between *EDAC* and $EDAC^C$ represents the magnitude of *RATIO*, which is dependent on the magnitude of each of the components and their signs.

If *EDAC* is dominated by one large component, then *RATIO* will be high even if the relationship between the components is not compatible with intentional EM, e.g. example 2. This shows that even if there is inconsistency between the components, this will only slightly be apparent in *RATIO* if there is one large discretionary accrual component. Whether this represents intentional EM or simple misspecification is not apparent but the likelihood of misspecification is less when the magnitude of discretionary accruals is higher.

2.5 Testable Hypotheses of the Study

In the previous section, I propose an alternative discretionary accruals measure that takes into account the degree of consistency between the separate discretionary components.

The correction in the alternative discretionary accruals measure, $EDAC^C$, is the degree of uncertainty given the expectation that components of discretionary accruals are positively related. If there is no measurement error in the discretionary accruals measure, then *RATIO* will equal one and the alternative discretionary accruals will equal to the uncorrected discretionary accruals. If, however, there is a high degree of measurement error in the discretionary accruals measure then *RATIO* will be close to zero and the alternative discretionary accruals will be discounted towards zero. It is expected that this alternative measure will produce more powerful tests of EM (type II error when there exists earnings management) and will be more specific (less type I error when there is no earnings management). This leads us to the hypotheses of the study stated in the alternative form:

H_1: The alternative measure of discretionary accruals, $EDAC^C$, has more power than the traditional discretionary accruals measure, EDAC, in the detection of earnings management.

H_2: The alternative measure of discretionary accruals, $EDAC^C$, is more specific than the traditional discretionary accruals measure, EDAC, in the detection of earnings management.

Furthermore, the improvement in the alternative discretionary accruals will be higher when the measure used for uncorrected discretionary accruals contains more measurement error, ceteris paribus. Discretionary accruals measured using the Healy and DeAngelo models have been shown (Dechow et al., 1995) to contain more measurement error than those using the Jones and modified Jones models. This leads us to two sub-hypotheses of the main hypotheses:

H_{1a}: The improvement in the power of the tests using the alternative measure of discretionary accruals, $EDAC^C$, is higher when the discretionary accruals measure, EDAC, is a noisier signal.

H_{2a}: The improvement in the specification of the tests using the alternative measure of discretionary accruals, $EDAC^C$, is higher when the discretionary accruals measure, EDAC, is a noisier signal.

The discretionary accruals, *EDAC*, are noisier signals when the model used to estimate them is less specified e.g. the Healy and DeAngelo models. I expect that the improvement from using $EDAC^C$ will be less prominent if the models used to estimate discretionary accruals are the Jones and modified Jones models, than when the models used are the Healy and DeAngelo models.

These hypotheses are tested in the following two chapters.

2.6 Chapter Summary

This chapter explains the motivation and hypotheses of the study. I show that managers are expected to manipulate one or more component of accruals and that these accruals will change in the direction that affects earnings in the same way. Thus, the signs and magnitude of the components of accruals are expected to provide incremental information over the magnitude of the aggregate discretionary accruals. Using the separate components of discretionary accruals, a measure *RATIO* is proposed that considers the relationship between these components. High values of *RATIO* are expected to be associated with intentional EM whereas low values of *RATIO* are expected to represent misspecification in the discretionary accrual model used.

An alternative measure of discretionary accruals is proposed ($EDAC^C$), which is the product of *RATIO* and the uncorrected or traditional measure of discretionary accruals (*EDAC* using Healy, DeAngelo, Jones and modified Jones models). I expect that the $EDAC^C$ will provide better results than *EDAC* in terms of the power and specification of the detection of EM. Furthermore, I expect the improvement in testing for EM is higher when the models used to measure discretionary accruals are noisier models such as the Healy and DeAngelo models.

Chapter 3: Sample Selection and Methodology

3.1 Sample Selection and Descriptive Statistics

Following Hribar and Collins (2002), I use the cash flow statement data to measure total accruals and its components rather than calculate accruals from the balance sheet data. I obtain the data from the Standard & Poor's Compustat database for the years 1988-2003. I use all active and research firms in the database. The sample is reduced when I delete firms with missing observations and extreme values (those in the highest and lowest 1% of the distribution) of accruals, earnings (income before extraordinary items), cash from operations, change in revenue, gross property, plant, and equipment, change in accounts receivable, change in inventory, change in accounts payable, change in other working capital, and depreciation. Firms in the financial sector are also eliminated (SIC between 6000 and 6999). This results in a total of 46,783 firm-year observations. I divide the full sample into industrial groupings based on four-digit SIC code classifications with adequate data (≥30 observations) to conduct the empirical analysis. Table 1 shows the industries used in the empirical work (based on the two-digit SIC codes for simplification) and the number of observations in each industry. The sample used is broad and encompasses most industries.

((Table 1))

Operating accruals are calculated directly from the cash flow statement as follows:[13]

$$TAC_t = -(DAR_t + DINV_t + DAP_t + DTAX_t + DOTH_t + DEP_t)/ A_{t-1}$$

where TAC_t = Total accruals in year t,

DAR_t = Decrease (increase) in accounts receivable (Compustat #302),

$DINV_t$ = Decrease (increase) in inventories (Compustat #303),

DAP_t = Increase (decrease) in accounts payable and accrued liabilities (Compustat #304),

$DTAX_t$ = Increase (decrease) in taxes payable (Compustat # 305),

$DOTH_t$ = Net change in other current assets and liabilities (Compustat #307),

DEP_t = Depreciation expense (Compustat #125), and

A_{t-1} = Lagged total assets (Compustat #6).

The industry subscript has been dropped for simplification. The components of accruals used are accounts receivable, inventory, accounts payable, other working capital, and depreciation, which are measured as follows:

$$\Delta AR_t = -\Delta AR_t / A_{t-1}$$

$$\Delta INV_t = -\Delta INV_t / A_{t-1}$$

$$\Delta AP_t = -\Delta AP_t / A_{t-1}$$

$$\Delta OWC_t = -(\Delta OTH_t + \Delta TAX_t)/ A_{t-1}$$

[13] Hribar and Collins (2002) show that using the balance sheet approach to calculate accruals results in numbers that have measurement error that may be high in some cases, especially in periods of structural changes.

$$DEP_t = -DEP_t / A_{t-1}$$

Note that the variables are set up so that asset accounts are represented by positive amounts and liability accounts are represented by negative amounts. This enables the simple addition of the components to reach total accruals. Table 2, panel A, provides descriptive statistics for the full sample of firms for the period 1989-2003. The mean income is negative for this period (-0.044). The means of accruals and cash from operations are -0.047 and 0.003, respectively. The negative accruals follow from the inclusion of depreciation expense. The means of the components of accruals: *DAR*, *DINV*, *DAP*, *DOWC*, and *DEP* are 0.018, 0.009, -0.013, 0.0006, and -0.061, respectively. Depreciation is the largest of the components of accruals with a negative sign. All variables are deflated by beginning assets to correct for heteroscedasticity. Panel B provides Pearson correlations between some of the variables. This shows that the correlation between accruals and cash from operations is negative (-0.078).

((Table 2))

The methodology used to measure discretionary accruals follows Healy (1985), DeAngelo (1986), Jones (1991) and Dechow et al. (1995). Using the Healy methodology components of discretionary accruals are measured as follows:

$$EDAR_t = (\Delta AR_t - \sum_{t=1}^{N} \frac{\Delta AR_t}{N}) / A_{t-1}$$

$$EDINV_t = (\Delta INV_t - \sum_{t=1}^{N} \frac{\Delta INV_t}{N}) / A_{t-1}$$

$$EDAP_t = (\Delta AP_t - \sum_{t=1}^{N} \frac{\Delta AP_t}{N}) / A_{t-1}$$

$$EDOWC_t = (\Delta OWC_t - \sum_{t=1}^{N} \frac{\Delta OWC_t}{N}) / A_{t-1}$$

$$EDDEP_t = (DEP_t - \sum_{t=1}^{N} \frac{\Delta DEP_t}{N}) / A_{t-1}$$

Using the DeAngelo methodology, components of accruals are measured as follows:

$$EDAR_t = (\Delta AR_t - \Delta AR_{t-1}) / A_{t-1}$$

$$EDINV_t = (\Delta INV_t - \Delta INV_{t-1}) / A_{t-1}$$

$$EDAP_t = (\Delta AP_t - \Delta AP_{t-1}) / A_{t-1}$$

$$EDOWC_t = (\Delta OWC_t - \Delta OWC_{t-1}) / A_{t-1}$$

$$EDDEP_t = (DEP_t - DEP_{t-1}) / A_{t-1}$$

Using the Jones methodology while disaggregating accruals into its components is achieved through the following five regressions:

$$DAR_t/A_{t-1} = a_{11} (1/A_{t-1}) + b_{11} (DREV_t /A_{t-1}) + b_{21} (PPE/AA_{t-1}) + EDAR_t$$

$$DINV_t/A_{t-1} = a_{12} (1/A_{t-1}) + b_{12} (DREV_t /A_{t-1}) + b_{22} (PPE/AA_{t-1}) + EDINV_t$$

$$DAP_t/A_{t-1} = a_{13} (1/A_{t-1}) + b_{13} (DREV_t /A_{t-1}) + b_{23} (PPE/AA_{t-1}) + EDAP_t$$

$$DOWC_t/A_{t-1} = a_{14}\,(1/A_{t-1}) + b_{14}\,(DREV_t\,/A_{t-1}) + b_{24}\,(PPE/AA_{t-1}) + EDOWC_t$$

$$DEP_t/A_{t-1} = a_{15}\,(1/A_{t-1}) + b_{15}\,(DREV_t\,/A_{t-1}) + b_{25}\,(PPE_t/A_{t-1}) + EDDEP_t$$

Finally, using the modified Jones model while disaggregating accruals into its components is achieved through the following five regressions:

$$DAR_t/A_{t-1} = a_{11}\,(1/A_{t-1}) + b_{11}\,(DREV_t\text{-}DAR_t/A_{t-1}) + b_{21}\,(PPE/AA_{t-1}) + EDAR_t$$

$$DINV_t/A_{t-1} = a_{12}\,(1/A_{t-1}) + b_{12}\,(DREV_t\text{-}DAR_t/A_{t-1}) + b_{22}\,(PPE/AA_{t-1}) + EDINV_t$$

$$DAP_t/A_{t-1} = a_{13}\,(1/A_{t-1}) + b_{13}\,(DREV_t\text{-}DAR_t/A_{t-1}) + b_{23}\,(PPE/AA_{t-1}) + EDAP_t$$

$$DOWC_t/A_{t-1} = a_{14}\,(1/A_{t-1}) + b_{14}\,(DREV_t\text{-}DAR_t/A_{t-1}) + b_{24}\,(PPE/AA_{t-1}) + EDOWC_t$$

$$DEP_t/A_{t-1} = a_{15}\,(1/A_{t-1}) + b_{15}\,(DREV_t\text{-}DAR_t/A_{t-1}) + b_{25}\,(PPE_t/A_{t-1}) + EDDEP_t$$

where *EDAR*, *EDINV*, *EDAP*, *EDOWC*, and *EDDEP* are the proxies used for discretionary accounts receivable, inventory, accounts payable, other working capital and depreciation, respectively and all other variables are as previously defined. Notice that one benefit from disaggregating accruals is that it is possible to use different independent variables for each component. This is not attempted in this study since I am interested in isolating the benefit of the measure $RATIO_{t,}$ given the current discretionary accruals measures. The predicted values from the previous regressions are the non-discretionary components, while the residuals from these regressions represent the discretionary components. The previous regressions are estimated cross-sectionally across four-digit SIC codes for the entire period 1989-2003. The results in tables 2 and 3 are presented using the modified Jones method only for convenience.

The results of the disaggregated regressions appear in table 3.

((Table 3))

From examining the coefficients in table 3, we see that *DAR*, *DINV*, *DAP*, are more correlated with the proxy for the change in economic condition (change in revenues less change in receivables) as expected but the main effect that appears in the total accruals regression is diluted since assets and liabilities have similar coefficients but are of opposite signs. The regression of *DOWC* is weak with a mean R^2 of 7.8%. *DEP* has the highest explanatory power with a mean R^2 of 83.3%.

The measure $RATIO_t$ is calculated from the discretionary components from the above regressions. As shown before, $RATIO_t$ is the ratio of the absolute value of the sum of the discretionary components to the sum of the absolute value of the components. This translates to the following given the five components of accruals:

$$RATIO_t = \frac{\left|EDAR_t + EDINV_t + EDAP_t + EDOWC_t + EDDEP_t\right|}{\left|EDAR_t\right| + \left|EDINV_t\right| + \left|EDAP_t\right| + \left|EDOWC_t\right| + \left|EDDEP_t\right|} \qquad \textbf{(3.1)}$$

Table 2 provides descriptive statistics for the variable $RATIO_t$. As shown in the previous section $RATIO_t$ take on values between zero and one. Its mean in the full sample is 0.454. In the absence of any earnings management or measurement error in the proxies of abnormal components, the value of $RATIO_t$ should equal zero. So the sample contains either earnings management or measurement error or both. Panel B presents the correlation of $RATIO_t$ with other variables. It is negatively correlated with total accruals

(TAC_t), earnings (INC_t) and cash from operations (CFO_t) as well as all components of accruals at 1% or less.

The alternative measure of discretionary accruals, $EDAC^C$, takes into account the measurement error that is contained in the estimated discretionary accruals, *EDAC*. It discounts *EDAC* when there is high measurement error (when *RATIO* is close to zero) and leaves *EDAC* intact when measurement error is low (when *RATIO* is close to one). Panel A of table 2 shows that both *EDAC* and $EDAC^C$ have the same mean of –0.004 but the alternative measure $EDAC^C$ has a smaller standard deviation of 0.068 as compared to that of *EDAC* of 0.089. Panel B of table 2 shows that $EDAC^C$ is less correlated than *EDAC* with *TAC*, *INC*, and *CFO*. This is an improvement on the discretionary accruals measure since one of the disadvantages cited in previous work is the high correlation between *EDAC* and *CFO* and *INC*, which are used as partitioning variables to test for EM. Figure 2 plots the values of *EDAC* against the values of $EDAC^C$.

((Figure 2))

As we can see from figure 2, the values of $EDAC^C$ are higher than those of *EDAC* (below the 45 degree line) for negative values of *EDAC*. Values of $EDAC^C$ are lower than those of *EDAC* (above the 45 degree line) for positive values of *EDAC*. In general, $EDAC^C$ has a tighter distribution than *EDAC* since the mean is similar but the standard deviation is smaller.

As shown in the previous chapter, managers have under their discretion several components of accruals, which they can use to achieve the desired earnings manipulation.

The literature proposes that the costs of manipulation are higher for recurring items and specifically for revenue manipulation because these types of manipulation have the highest likelihood of detection. On the other hand, firms prefer revenue manipulation because it provides a better picture of the financial position. This creates a tension for the managers, as there is a trade-off between the costs and benefits of manipulating the specific components. To confirm this, I investigate the factors that I propose are related to the costs and benefits of manipulation, namely:

- Magnitude of components
- Volatility of components
- Persistence of components

I expect the costs of manipulation to be positively related to the magnitude and volatility of components whereas I expect the benefits of manipulation to be positively related to the persistence of components. Table 4 provides an analysis of the magnitude and volatility of the specific components of accruals in the full sample and for the different industrial groupings.

((Table 4))

Panel A presents the mean of each component as an indicator of its magnitude and the standard deviation of each component as an indicator of its volatility. These descriptives are provided for each two-digit SIC group as well as in the whole sample. The results show that there are differences between the industries with respect to the magnitude and volatility of the components of accruals. Depreciation has the largest magnitude, considering that it is the only component that is not a difference from year t-1 to year t. Other than depreciation, accounts receivable has the highest magnitude in both the non-durable and durable manufacturing industries (SIC 20-39), the transportation and public utilities industry (SIC 40-49), the wholesale trade industry (SIC 50-51) and the services industry (SIC 70-89). Inventories have the highest magnitude in the agriculture, forestry and fishing industry (SIC 01-09) and the retail trade industry (SIC 52-59). The accounts payable component is the highest in the mining and construction industry (SIC 10-17). In the full sample, accounts receivable have the largest magnitude (in components other than depreciation) followed by accounts payable, then inventories, and then other working capital. There is a similar pattern with respect to the volatility of the components.

The statistics in panel A do not provide a true picture of the manipulation flexibility or the likelihood of detection in different components. It is more important to examine the balance of the accrual accounts from the balance sheet. This is provided in panel B. The data in panel B confirm what was shown in panel A. Accounts receivable have the highest magnitude in most industries (SIC 10-17, 20-29, 20-39, 40-49, 70-89, 99) followed by inventory levels (SIC 01-09, 20-29, 50-51, 52-59). Other components of accruals have a smaller magnitude and volatility.

In the full sample, accounts receivable has the highest magnitude whereas inventories have the highest volatility.

Table 5 presents the results of persistence of the components of accruals. The persistence is estimated through autocorrelation coefficients estimated from the regression of each component of accruals on its lagged counterpart as follows.

$$\Delta AR_t = a_1 + b_1 * \Delta AR_{t-1}$$

$$\Delta INV_t = a_2 + b_2 * \Delta INV_{t-1}$$

$$\Delta AP_t = a_3 + b_3 * \Delta AP_{t-1}$$

$$\Delta OWC_t = a_4 + b_4 * \Delta OWC_{t-1}$$

$$DEP_t = a_5 + b_5 * DEP_{t-1}$$

((Table 5))

The results in table 5 show that the accounts receivable component is significantly auto-correlated in all industries except the mining and construction industry (SIC 10-17) as well as both durable and non-durable manufacturing industries (SIC 30-49). Inventories are highly persistent in all industries except durable manufacturing. The other working capital component has a high negative autocorrelation coefficient in most industries, which indicates mean reversion. This confirms that the components that are the most costly to manipulate provide the least benefit since they are not persistent. These tables indicate that there is a trade-off between the costs and benefits of manipulating different components of accruals.

3.2 Methodology for Hypotheses Testing

Dechow et al. (1995) test EM by regressing the estimated discretionary accruals on a partitioning variable, *PART*. This variable takes on the value of one if the observation is from the event period (in which EM is being tested) and the value of zero if the observation is from the estimation period. The regression is as follows:

$$EDAC_t = a + b * PART_t + e_t \qquad \textbf{(3.2)}$$

The null hypothesis of no EM is tested by applying a t-test that the coefficient $b = 0$ when there is no a priori expectation in the direction of earnings manipulation. The coefficient "*a*" in the regression represents discretionary accruals, *EDAC*, when the variable *PART* is equal to zero i.e. it is the average level of *EDAC*. When the variable *PART* equals one, i.e. there is expectation of earnings manipulation, then *EDAC* equals the sum of the coefficients *a* and *b*. When there is an expectation of earnings manipulation in a certain direction (e.g. income-increasing manipulation) then there is an expectation as to the sign of the variable *PART* $(b > 0)$. Using the alternative measure described in this paper, the test of EM is achieved through the following regression:

$$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t} \qquad \textbf{(3.3)}$$

The results from (3.2) are compared to (3.3) in terms of their R^2, the significance of the coefficient on *PART*, as well as their standard errors. The regressions are estimated cross-sectionally across four-digit SIC codes. A Z-statistic is calculated using the individual t-statistics from these regressions to test the significance of the coefficient on *PART* as follows:

$$Z - statistic = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{t_i}{\sqrt{k_i/(k_i - 2)}}$$

where t_i = t-statistic for industry *i* (four-digit SIC code) or firm *i*,

k_i = Degrees of freedom for regression of industry *i* or firm *i*.

The Z-statistic is asymptotically distributed unit normal if the t's are cross-sectionally independent.

To directly test the significance of the alternative discretionary accruals measure, $EDAC^C$, in the power of detecting EM, I employ the following logistic regression:

$$PART_t = c + d*Log(EDAC_t) + f*Log(RATIO_t) + e_t \qquad \textbf{(3.4)}$$

Since the alternative discretionary accruals, $EDAC^C$, is the result of the multiplication of the discretionary accruals, *EDAC*, and *RATIO*, the log of *EDAC* and *RATIO* are used to transform $EDAC^C$ from the multiplication format into the addition format to directly test the improvement from using $EDAC^C$. The above regression uses *PART*, a binary variable, as the dependent variable and so the least square method cannot be used.

Testing for earnings management is performed mainly in six different samples:

(1) Randomly selected samples of 1000 firm-years in which a fixed and known amount of accrual manipulation has been artificially introduced,

(2) A sample of firms that were targeted by the SEC for alleged accounting fraud,

(3) A sample of firms that have violated their debt covenants,

(4) Randomly selected samples of 1000 firm-years from the full sample,

(5) Randomly selected samples from sub-samples of extreme earnings and cash from operations performance.

(6) Randomly selected sample of 1000 firm-years in which noise has been introduced.

The first three samples are used to test the power of the measure $EDAC_t^C$. Since these samples contain manipulation, $EDAC_t^C$ is expected to detect EM better than the uncorrected $EDAC_t$. In the context of EM, the power of the tests is more important than the specification since it is of paramount importance to discover manipulation behavior when it occurs. However, if manipulation is suspected, further tests can be made to be sure that actual EM has occurred and thus reduce the type I error.

The first random sample of 1000 firm-year observations is selected from the 46,783 firm-year observations in the full sample that have positive *EDAC* (using the modified Jones method) to alleviate the dilution that can occur in the observations that have negative *EDAC* when manipulated with positive amounts. The random selection process is done without replacement. After the selection process, these 1000 observations are assigned a value of one for the variable *PART*. The variable *PART* is assigned the value of zero for the remaining firm-year observations. Once the firm-year is chosen, I artificially add accrual manipulation to these observations. The amount of manipulation I add is 5%, 10%, and 20% of total assets. These amounts seem reasonable since Jones (1991) reports mean abnormal accruals of 6% of total assets ranging from 0.6% to 16.1% (however, it was negative in her paper since her sample was chosen with incentives for income-decreasing management). Also, Dechow et al. reported that all discretionary accruals models were not powerful enough to detect manipulation of economically plausible magnitudes (1% to 5% of total assets). I assume that full reversal of the discretionary accruals occurs within one year. In the event year, I add the same amount of manipulation to accounts receivable and revenue, with the remaining manipulation in accounts payable. For example, in the 5% manipulation case, 2% manipulation is added to accounts receivables and revenues, while 3% is added to accounts payable. This manipulation effectively adds 0.02 to accounts receivable and 0.03 to accounts payable since they are deflated by lagged assets. In the 10% manipulation scenario, I add 5% manipulation to accounts receivable and 5% to accounts payable. Finally, in the 20% manipulation scenario, I add 16% to accounts receivable and 4% to accounts payable. The relative manipulation in the components is changed in each scenario to assess the incremental usefulness of the alternative discretionary accruals measure under different assumptions.

Another way to test the power of the models detecting EM is to look at firms that were subject to litigation by the SEC. 142 firms were identified from the Accounting and Auditing Enforcement Releases (AAER's) made by the SEC during the years 2000-2004 (up till October 2004). Table 6 presents the specific manipulation that these firms made as alleged by the SEC. Nine observations were dropped because the allegation by the SEC did not include manipulation in any accrual account.

((Table 6))

The table shows that about 34% of the sample (45 firms out of total 133 firms) had manipulation in more than one component of accruals. Out of these, 39 firms had manipulation of revenue (accounts receivable) in addition to some other components, whereas only 6 firms manipulated components other than revenue. The remaining 66% of the sample (88 firms) manipulated only one component, with the bulk (56 firms) manipulating revenues only.

Out of this sample, there were 10 firms that had no Cusip number identified from the Compustat Active and Research firms so they were dropped. A further 104 firms were dropped due to insufficient data on the Compustat database. The final sample consists of 19 firms (249 firm-year observations). The sample is small and so the results may not be strong. The AAER's identified the years in which these firms had allegedly inflated earnings and so these years are used as the test years in which the *PART* variable is assigned the value of one. These firms allegedly inflated earnings over periods ranging from 1 year to 5 years and most were in the later years 2000-2001.

The third sample relies on positive accounting theory, which predicts that firms approaching debt covenant violation will make income-increasing accounting choices to loosen their debt constraints (Watts and Zimmerman, 1986, DeFond and Jiambalvo, 1994). The literature has presented inconsistent results when tackling this issue. For example, DeFond and Jiambalvo (1994) show that in the year prior to debt covenant violation, discretionary accruals are significantly income-increasing, whereas in the year of violation, they show only evidence of income-increasing discretionary working capital accruals, after controlling for management changes and auditor going concern qualifications. Jaggi and Lee (2002) show that managers of financially distressed firms use income-increasing discretionary accruals if they are able to obtain waivers for debt covenant violations, and use income-decreasing discretionary accruals if debt restructuring takes place or debts are renegotiated because waivers are denied. I obtain a sample of firms that have violated their debt covenants directly from the Lexis-Nexis database (Disclosure Reports in year 2005). This results in a sample of 67 firms. I check all existing annual reports (10K) that are available on the EDGAR database to see if these firms had any more periods of violations. This results in 137 firm-year observations of debt covenant violations. I consider the year prior to violation a violation period also to test for manipulation made in that period. This results in a sample of 141 firm-year observations. Matching these observations with the available data on Compustat results in a sample of 161 firm-year observations (69 firm-year observations in which there was violation).[14] This sample is used to test the differences between discretionary accruals in the violation period vs. the non-violation period using the same regressions discussed above.

The specificity or specification of the discretionary accruals measure is tested in the last three samples. Since there is no expectation of EM in the fourth sample then the variable *PART* should be insignificant and the null hypothesis of no EM should not be rejected. The specification of the models is measured by the rejection rates of the null hypothesis of no EM in this sample. The sample used is a random sample selected as in (1) but with no artificially added accrual manipulation.

Sample five uses random samples chosen from observations that are in the highest and lowest deciles of cash from operations and income. These observations represent firm-years that are experiencing extreme financial performance. This sampling method is

[14] Firms that have less than 5 observations in non-violation periods are deleted.

meant to test the specification of the models when the variable *PART* is correlated with firm performance since the EM stimulus in many existing studies are correlated with firm performance.

The final sample is a random sample chosen as in (5) form the highest and lowest decile of income. However, once the sample of 1000 observations is chosen, I replace the discretionary accrual estimates (for the components) with random numbers drawn from a normal distribution with the same mean and standard deviation as the vector of modified Jones model estimates. This approach was used in Elgers et al. (2003) to test for measurement error. This effectively creates a noisy measure of discretionary accruals. The rejection rates using *EDAC* and $EDAC^C$ are compared.

3.3 Chapter Summary

This chapter explains the methodology used to test the power and specification of the measures of discretionary accruals in the next chapter. Three samples are chosen to test the power of the discretionary accruals measures: a random sample with added accrual manipulation, a sample of firms targeted by the SEC for alleged fraud, and a sample of firms that violated their debt covenants.

Three samples are used to test the specification of the measures of discretionary accruals: a random sample with no expectation of EM, random samples chosen from extreme income and cash from operations sub-samples, and a random sample with added noise.

Chapter 4: Empirical Results

4.1 Testing Power of Discretionary Accruals Models

The power of the tests refers to type II error. This type of error occurs when the null hypothesis of no EM is not rejected when it is false. This means that the sample contains actual EM but the models are not powerful enough to detect this. This is tested in a random sample in which I add accrual manipulation as well as a sample of firms that were targeted by the SEC for income-increasing manipulation and a sample of firms that violated their debt covenants. The following regressions are used to test the power of the discretionary accruals measure, $EDAC_t$, against the alternative discretionary accruals measure, $EDAC_t^C$.

$$EDAC_t = a + b * PART_t + e_t \qquad \textbf{(4.1)}$$

$$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t} \qquad \textbf{(4.2)}$$

$$PART_t = c + d*Log(EDAC_t) + f* Log(RATIO_t) + e_t \qquad \textbf{(4.3)}$$

4.1.1 Random Sample with Added Accrual Manipulation

Hypothesis 1 of the study states that the power of $EDAC^C$ will be higher than that of *EDAC*. This is tested first in a random sample with artificially added accrual manipulation.

Table 7 provides the results of the above regressions (4.1) and (4.2) using *EDAC* and $EDAC^C$ as the dependent variable in the first sample. The added accrual manipulation used is 5%, 10%, and 20% of total assets. The regressions are estimated across four-digit SIC codes. The results presented are the means and standard deviation of the coefficients and t-values from these regressions. *EDAC* and $EDAC^C$ are calculated using the Healy, DeAngelo, Jones, and modified Jones methodology.

Hypothesis 1 predicts that using $EDAC^C$ as the dependent variable will improve the power of the tests. This means that the t-values of the *PART* variable will be higher and the R^2 of the regressions will be higher when using $EDAC^C$.

Hypothesis 1a predicts that this improvement will be higher when the signal *EDAC* is noisier. The Healy and DeAngelo models have been shown to contain more measurement error than the Jones and modified Jones model and so the improvement is expected to be higher for these two models.

((Table 7))

From inspection of the results in table 7, we see that the power of all models is improved when using $EDAC^C$. The t-values of the *PART* variable increase and the coefficients on *PART* are closer to the actual manipulation using $EDAC^C$. The manipulation in the table is 5% (2% to *DAR* and 3% to *DAP*), 10% (5% to *DAR* and 5% to *DAP*) and 20% (16% to *DAR* and 4% to *DAP*). The improvement in the results is higher when the amount of manipulation is higher. So hypothesis 1 of the paper is accepted.

Hypothesis 1a predicts that the improvement in the power of the tests will be higher when the Healy and DeAngelo models are used. There is some evidence of this, especially under the 20% manipulation. For example, the z-statistic under the 20% manipulation (average t-statistic for all four-digit code regressions) increases by 8.52 using the Healy method and 8.82 using the DeAngelo method, whereas the increase is only 4.62 using the Jones method and 4.89 using the modified Jones method. The same pattern holds when comparing the mean R^2 from these regressions. These R^2's under the 20% manipulation increase by 2.33% using the Healy method and 2.52% using the DeAngelo method, whereas the increase is only 1.39% using the Jones method and 1.45% using the modified Jones method. Examination of the standard errors of all regressions reveal that these are lower using $EDAC^C$ than when using $EDAC$, which is the reason for the improved power of the models.

To directly test the significance of $EDAC^C$ I employ the logistic regression in (4.3). This directly tests the significance of $EDAC^C$ by testing the significance of *Log(RATIO)*. If the coefficient on *Log(RATIO)* is significant even in the presence of *Log(EDAC)* then there is a significant improvement in the power of the model from using $EDAC^C$. Panel B of table 7 presents the results from regression (4.3) using the modified Jones method. Both *Log(EDAC)* and *Log(RATIO)* are significant at less than 1% for all amounts of manipulation.

4.1.2 SEC Litigation Sample

The second sample used to test the power of the models is the sample of firms that were targeted by the SEC for alleged accounting fraud. The sample consists of 19 firms (249 observations). The regressions (4.1) and (4.2) are estimated on a firm-by-firm basis rather than by SIC codes. Table 8 presents the results of these regressions (mean and standard deviation of coefficients and t-values). From examining the Z-statistics, we see that $EDAC^C$ is an improvement using all methods to estimate discretionary accruals. Under the modified Jones method, the Z-statistic becomes significant at the 1% level using $EDAC^C$ (2.454) although it is not significant when using *EDAC* (1.950). The standard errors are lower when using $EDAC^C$ for all discretionary accruals models and the R^2 from these regressions are higher (except when using the DeAngelo method). Hypothesis 1 is thus accepted. However, there is no support for hypothesis 1a.

((Table 8))

Panel B provides the results of the logistic regression with *Log(EDAC)* and *Log(RATIO)* as the independent variables. Even though *Log(EDAC)* is not significant, the variable *Log(RATIO)* is significant at less than 5%, which corroborates the improvement in the power of the model using $EDAC^C$. This regression is provided only using the modified Jones method.

4.1.3 Debt-Covenant Violation Sample

Positive accounting theory predicts that firms approaching debt covenant violation will make income-increasing accounting choices to loosen their debt constraints (Watts and Zimmerman, 1986, DeFond and Jiambalvo, 1994). The literature has presented inconsistent results when tackling this issue. For example, DeFond and Jiambalvo (1994) show that in the year prior to debt covenant violation, discretionary accruals are significantly income-increasing, whereas in the year of violation, they show only evidence of income-increasing discretionary working capital accruals, after controlling for management changes and auditor going concern qualifications. Jaggi and Lee (2002) show that managers of financially distressed firms use income-increasing discretionary accruals if they are able to obtain waivers for debt covenant violations, and use income-decreasing discretionary accruals if debt restructuring takes place or debts are renegotiated because waivers are denied.

Empirical results for the sample of firms that violated their debt covenants are presented in table 9. In the regressions (4.1), (4.2) and (4.3), the variable *PART* is set to 1 in the period of violation and the prior year of violation (year 0 and –1) and set to 0 in the remaining periods. The regressions are on a firm-by-firm basis as in the SEC litigation sample.

((Table 9))

Panel A of table 9 presents the results of (4.2) and (4.3) using the Healy, DeAngelo, Jones and modified Jones models to estimate discretionary accruals. The results provide some evidence of income-decreasing EM in the year of covenant violation. *PART* has a negative coefficient using all models. However, these coefficients are mostly insignificant at conventional test level (probably due to the small sample size). There appears to be only an improvement when using $EDAC^C$ using the modified Jones model. There is also an increase in the R^2 of the regressions when using the Jones and modified Jones models.

Panel B of table 9 presents the results from regression (4.3). This provides evidence of the incremental significance of $EDAC^C$ over *EDAC*. The sample is smaller since the log of negative numbers is not defined. The results indicate that even though *EDAC* is not significantly different between violation and non-violation periods, $EDAC^C$

is incrementally significant since the coefficient on *RATIO* is significant at the 10% level. This provides direct supporting evidence of the usefulness of considering the interaction between the discretionary components of accruals when using the modified Jones model.

The analysis was repeated with *PART* equaling 1 in the period of violation alone (Year 0), and 0 otherwise. There were no significant results using either *EDAC* or $EDAC^C$.

To further test for the usefulness of *RATIO* in this sample, a 2X2 frequency table is provided in which the actual and expected frequency of observations with values of *RATIO* above (or equal to) and below the median in periods of violation and non-violation are compared. The median value of *RATIO* is calculated for each firm in all periods excluding year 0 and –1.

((Table 10))

The two-way test statistics performed test the null hypothesis of no association between the row variable and the column variable. When the sample size *n* is large, these test statistics are distributed approximately as Chi-square when the null hypothesis is true. When the sample size is not large, exact tests may be useful. The results indicate that the actual frequency of observations in violation periods that are **above** the median exceed expectation (29 vs. 23.21) whereas the actual frequency of observations in non-violation periods that are **below** the median exceed expectation (55 vs. 49.21). Using Fisher's exact test, the Chi square value of the table is 4.460, which indicates the null hypothesis of no association between the rows and columns is rejected at the 5% test level. This table shows that the components of discretionary accruals are consistent in periods of no-violation (*RATIO* > median).

The results in tables 7 through 10 confirm the improvement of the alternative measure of discretionary accruals, $EDAC^C$, to the power of all models. The next section discusses the specification or specificity of the models.

4.2 Testing Specification of Discretionary Accruals Models

The specification of the models is harder to test since all models are expected to return insignificant results. Specification, also referred to as specificity, relates to type I error, which means the null hypothesis of no EM is rejected in favor of the alternative hypothesis when the null is true. This is tested in several ways. First, a random sample is chosen in the same manner as above. Since this is a random sample from the whole population, there is no expectation of EM in either direction and the null should not be rejected.

4.2.1 Random Sample

Following Dechow et al. (1995), I test specification by calculating the rejection rates of regressions (4.1) and (4.2) in random samples chosen in the same manner as above (in 4.1.1) but with no artificially added manipulation.

Table 11 presents the results in the random samples from the regressions estimated over the four-digit SIC codes. Ten different iterations are estimated and the mean and median values of the rejection rates are presented. The rejection rates are given separately for significance of the *PART* coefficient at the 1% and 5% levels for one-tailed tests (Coefficient > 0 and coefficient < 0). No pattern emerges from the rejection rates. All models tested are similar in their rejection rates using *EDAC* and $EDAC^C$ as the dependent variables. All models appear well specified as reported in Dechow et al. whether using *EDAC* or $EDAC^C$.

((Table 11))

4.2.2 Extreme Performance Samples

Tables 12 and 13 provide rejection rates of regressions (4.2) and (4.3) in samples chosen in the highest and lowest deciles of income and cash from operations, respectively. These sub-samples represent extreme earnings and cash from operations performance. Panel A of table 12 provides results for the sample chosen from the lowest decile of income.

((Table 12))

The results document the same pattern as in Dechow et al. All models tend to reject the null hypothesis of no EM against the alternative hypothesis that EM is income-decreasing (i.e. actual rejection rates are higher than the expected rejection rates in a random sample at the conventional test levels of 1% and 5% when the alternative hypothesis is that EM < 0). This result occurs because observations with low earnings tend to have low accruals and all the models attribute this to negative discretionary accruals. The improvement in specification from using $EDAC^C$ is only slight (ranging from 0.94% reduction in mean rejection rates using the Healy method to 2.56% using the Jones method) when the test level is 5%, except when using the DeAngelo method. Reduction in rejection rates is less prominent at the 1% test level and there is even a 0.53% increase in rejection rates using the modified Jones method.

Panel B provides the results for the sample chosen from the highest decile of income. The pattern is opposite to the results in Panel A. Here, the rejection rates tend to exceed the test levels when the alternative hypothesis tested is that EM is income-increasing. The improvement from using $EDAC^C$ ranges from 0.05% reduction in mean rejection rates using the DeAngelo method to 3.48% using the Healy method at the 5% level. There is only improvement when using the Healy method (2.25% reduction in mean rejection rates) and when using the modified Jones method (0.24% reduction in mean rejection rates) at the 1% test level.

Table 13 provides the results for the samples chosen from the highest and lowest deciles of cash from operations. The pattern of rejection rates are expected to be opposite to that using the extreme income samples since there is a negative correlation between cash flow and accruals.

((Table 13))

Panel A presents the results in the lowest decile of cash from operations. The alternative hypothesis of income-increasing EM tends to be rejected more often than the alternative of income-decreasing EM, even though the rejection rates are similar. $EDAC^C$ shows improvement in specification, ranging from 1.22% reduction in mean rejection rates using the DeAngelo method to 2.04% using the Jones method at the 5%, and ranging from about 0.21% reduction in mean rejection rates using the DeAngelo method to 1.31% using the Healy method at the 1% test level for the alternative hypothesis of positive EM. There is less significant improvement for the alternative hypothesis of negative EM.

Panel B presents the results in the highest decile of cash from operations. The alternative hypothesis of income-decreasing EM tends to be rejected more frequently than the alternative hypothesis of income-increasing EM. $EDAC^C$ shows improvement at the 5% level using the all methods except DeAngelo (ranging from 2.44% reduction in mean rejection rates using the Jones method to 2.88% using the modified Jones method).

The results of the specification of the models using *EDAC* and $EDAC^C$ are mixed. However, there is not much improvement using the alternative measure of discretionary accruals. These results could be attributed to the sampling procedure. The extreme performance samples may contain a higher incidence of observations that truly are managing earnings and so in reality the rejection rates do not represent type I errors. Also, empirically, the improvement in testing for EM using $EDAC^C$ may not be significant in homogeneous groups. The specification tests were conducted on homogenous groups with extreme performance. In this case, *RATIO* may not be able to extract the noise from the discretionary accruals measure. The benefit from using the alternative discretionary accruals is expected to be higher in heterogeneous samples. This creates a problem in testing for specification issues. In the next section, I create a noisy signal of discretionary accruals to test the improvement in specification using $EDAC^C$. In section 4.2.4., I provide some determinants of measurement error in discretionary accruals and relate them to both $EDAC$ and $EDAC^C$ to show that there is a reduction in measurement error when $EDAC^C$ is used.

4.2.3 Noise Sample

To further test the specification of the alternative discretionary accruals measure, I calculate the rejection rates of regressions (4.1) and (4.2) in a random sample compared to a random sample that has artificial discretionary accruals. I choose a random sample from extreme income deciles then replace the discretionary accruals components with random numbers drawn from a normal distribution with the same mean and standard deviation as the vector of modified Jones model estimates. This effectively creates a noisy measure of discretionary accruals. The results appear in table 14.

((Table 14))

The first portion of the table presents the results from the samples chosen from the lowest decile of income. As seen in the previous section all models tend to reject the null hypothesis of no EM against the alternative hypothesis of negative or income-decreasing manipulation. This is because the discretionary accruals tend to associate low levels of accruals (in low income deciles) with income-decreasing manipulation. In the random sample, the alternative discretionary accruals measure shows some improvement in the rejection rates at both the 1% and 5% test levels. The noise sample is the same random sample with replaced discretionary accruals. The rejection rates are similar to those in the random sample with unchanged discretionary accruals. The alternative discretionary accruals measure, $EDAC^C$, is able to reduce rejection rates by over 5% at the 5% test level and over 2% at the 1% test level. These are quite significant numbers when dealing with large samples.

The second portion of the table deals with rejection results in samples chosen from the highest decile of income. All models tend to reject the null hypothesis of no EM against the alternative of positive or income-increasing manipulation. This is because the models tend to associate high levels of accruals (present in high income deciles) with income-increasing manipulation. In the random sample, $EDAC^C$ shows some improvement in rejection rates as compared to $EDAC$. In the noise sample, the rejection rates show only slight improvement when using $EDAC^C$ at the 5% test level. Collectively, these results indicate that there is some improvement in specification from using $EDAC^C$. However, there is no support for the improvement in specification using the Healy and DeAngelo methods compared to the Jones and modified Jones methods. Hypothesis 2a is thus rejected.

4.2.4 Determinants of Measurement Error

To further test whether $EDAC^C$ reduces the measurement error contained in $EDAC$, I follow the analysis in Young (1999). Young quantifies the measurement error in alternative models of discretionary accruals and presents four possible determinants of the non-discretionary component in the discretionary accruals measures. These determinants are:

(i) *Cash flow performance*: Failure to adequately control for the association between accruals and cash flow when estimating discretionary accruals will cause part of the positive non-discretionary accruals associated with extreme negative cash flows to be incorrectly attributed to income-increasing manipulation,

(ii) *Growth rate*: Growth firms tend to experience large increases in working capital accounts while the opposite is true for firms in decline. Failure to control for this relation will cause part of the positive non-discretionary accruals associated with high growth to be incorrectly attributed to income-increasing manipulation,

(iii) *Fixed asset intensity*: Even in the absence of earnings management, firms with a large asset base tend to have large depreciation expenses. The magnitude of the depreciation accrual is expected to be positively associated with fixed asset intensity.

(iv) *Fixed asset life*: The magnitude of the depreciation accrual is expected to be negatively associated with average fixed asset life.

The following regressions are used to test the presence of measurement error in models of discretionary accruals:

$$EDAC_t = a + b*CFO_t + c*Growth_t + d*Intensity_t + e*Life_t + e_t \qquad \textbf{(4.4)}$$

$$EDAC_t^C = a_1 + b_1*CFO_t + c_1*Growth_t + d_1*Intensity_t + e_1*Life_t + e_{1t} \qquad \textbf{(4.5)}$$

where CFO_t = Cash from operations in year t,

$Growth_t = REV_t – REV_{t-1} / REV_{t-1}$,

$Intensity_t = Net\ PPE_t / A_t$, and

$Life_t = Gross\ PPE_t / DEP_t$.

The presence of measurement error in the discretionary accruals measures is established from the significance of the coefficients in the above regressions. Table 15 presents the results from the above regressions estimated over four-digit SIC codes.

((Table 15))

From inspection of the R^2 of all regressions using *EDAC*, the model with most measurement error captured in the discretionary accruals measure is the Healy model with an R^2 of 31.85%. The modified Jones and Jones models follow closely while the DeAngelo surprisingly has the lowest R^2 of 13.99%. Using $EDAC^C$ provides slight improvement in all models with the largest improvement using the Healy model (Reduction of 4.75% in R^2). The t-values using $EDAC^C$ are also smaller than when using *EDAC* as the dependent variable. This analysis supports the assertion that the alternative measure of discretionary accruals alleviates some of the measurement error present in the discretionary accruals measures.

4.2.5 Further analysis

To further test the specification of the alternative discretionary accruals and whether it is able to reduce the measurement error, I follow the methodology in Elgers et al. (2003). Their analysis reassesses the evidence of anticipatory income smoothing reported in DeFond and Park (1997). They show that the methodology followed by DeFond and Park, in which they use unmanaged earnings calculated as income less the discretionary portion estimated, provides identical results when a random assignment of discretionary accruals to firm-year observations is used in place of the actual discretionary accruals numbers. This means that the results in DeFond and Park are representative of measurement error in the discretionary accruals measure.

I use the I/B/E/S Summary History Data to obtain the consensus analysts' forecast of earnings in year $t+1$ as of March (and the first 10 days of April) of year $t+1$ for all December fiscal year firms. I assume these forecasts are management's expectation of future period unmanaged earnings as of the time they are making their discretionary accruals decision for year t. In each year, "unmanaged earnings" are calculated as earnings before extraordinary items less estimated discretionary accruals. Unmanaged earnings are then are classified as "good" or "poor" relative to the two-digit SIC code industry median unmanaged earnings. The resulting sample is 7,796 observations that have forecasts of future earnings.

Future earnings are also coded as "good" or "poor" relative to the two-digit SIC code industry median forecasted earnings. The above classification results in four samples that appear in table 16. Panel A contains the analysis that uses *EDAC* to estimate unmanaged earnings, while Panel B presents the results using $EDAC^C$. I focus on groups (ii) and (iii) in table 16. Group (ii) represents the group that has "good" current earnings performance (unmanaged earnings higher than the industry median) but "poor" expected earnings performance in the next year (income forecast less than the industry median). In this case, DeFond and Park postulate that the manager will extend some of the current good earnings performance in year t to the next year $t+1$ by using negative income-decreasing accruals. Thus I expect that the mean discretionary accruals will be negative in that sub-sample. Group (iii) represents the group that has "poor" current performance but “good” future performance. In this case, the manager is expected to borrow some of the good performance from next year and so I expect that discretionary accruals are positive in this sub-sample. However, the methodology of backing out the discretionary accruals from earnings to calculate unmanaged earnings is not able to distinguish between the null hypotheses proposed and the presence of measurement error in discretionary accruals as shown in Elgers et al. (2003).

((Table 16))

The results in table 16 indicate that group (ii) has a negative mean for both *EDAC* and $EDAC^C$. However, $EDAC^C$ is able to eliminate some measurement error since its mean is lower than *EDAC* as shown in Panel B (–0.019 vs. –0.03). As for group (iii), mean *EDAC* and $EDAC^C$ are both positive but $EDAC^C$ has a lower mean (0.36 vs. 0.55). These results corroborate that the methodology used in DeFond and Park represents measurement error in discretionary accruals and shows that $EDAC^C$ is able to eliminate some of this measurement error.

4.3 Chapter Summary

The empirical results of the study are presented in this chapter. Both the power (type II error) and specification of testing for EM are compared when using the discretionary accruals measure, *EDAC*, vs. when using the alternative discretionary accruals measure, $EDAC^C$. The results indicate that there is an improvement in power using $EDAC^C$ for all samples in which there is added accrual manipulation (5%, 10%, and

20% manipulation). The improvement is proportional to the amount of manipulation i.e. the larger the manipulation, the more the improvement from using the alternative discretionary accruals measure. Also, there is more improvement when using more noisy methods to estimate discretionary accruals (Healy and DeAngelo methods) than when using less noisy methods (Jones and modified Jones).

The results in the SEC litigation sample and debt-covenant violation sample are less significant, probably due to the small sample. However, there is incremental significance from using $EDAC^C$ as shown by the significant coefficient on *Log(RATIO)* in the logistic regressions when using the modified Jones method.

Results of the specification or specificity of the models show improvement in the rejection rates of the alternative hypotheses of income-increasing and income-decreasing EM in samples chosen from extreme income and cash from operations deciles. However, the rejection rates still exceed the test levels in most cases.

Other samples used include noise samples chosen from extreme income deciles in which I replace discretionary accruals with random numbers with the same mean and standard deviation assuming a normal distribution. The results indicate a reduction in rejection rates from using the alternative discretionary accruals measure.

Regressions of proxies of measurement error contained in discretionary accruals reveal that the alternative discretionary accruals measure reduces some of this measurement error.

Overall, the results indicate that $EDAC^C$ is an improvement in testing for EM in most samples.

Chapter 5: Summary and Conclusion

Models for detecting EM set forth in the literature include simple models such as the Healy and DeAngelo models. Dechow et al. (1995) and others have shown the prevalence of measurement error in all models estimating non-discretionary accruals. I propose to separately estimate discretionary components of accruals (accounts receivable, inventories, accounts payable, other working capital and depreciation), and then measure the consistency between them. Any inconsistency is an indication of measurement error in the estimation models. This measurement error arises from misspecification of models estimating non-discretionary accruals and this carries onto the residual or discretionary accruals estimates.

Chapter 2 shows that managers are expected to manipulate one or more component of accruals in the direction that affects income consistently. Thus, the signs and magnitude of the components of accruals are expected to provide incremental information over the magnitude of the aggregate discretionary accruals. Using the separate components of discretionary accruals, I propose a measure, *RATIO*, which captures the relationship between these components. High values of *RATIO* are associated with intentional EM whereas low values of *RATIO* represent misspecification in the discretionary accruals model used.

I propose an alternative measure of discretionary accruals ($EDAC^C$), which is the product of *RATIO* and the traditional measure of discretionary accruals (*EDAC* using Healy (1985), DeAngelo (1986), Jones (1991) and modified Jones models (Dechow et al. (1995)). I expect that the $EDAC^C$ will provide better results than *EDAC* in testing for EM in terms of the power and specification of the detection of EM. Furthermore, I expect the improvement in testing for EM is higher when the models used to measure discretionary accruals are more misspecified such as the Healy and DeAngelo models.

To test the improvement in the power using $EDAC^C$, I use three different samples with expectation of EM. The first is a random sample chosen from the full sample in which I add accrual manipulation to both accounts receivable and accounts payable. I use manipulation of 5%, 10% and 20%. Furthermore, I test the power of $EDAC^C$ in a sample of firms targeted by the SEC for alleged fraud, and a sample of firms that violated their debt covenants. The results appearing in chapter 4 indicate that there is an improvement in power using *EDAC* for all samples in which there is added accrual manipulation (5%, 10%, and 20% manipulation). The improvement is proportional to the amount of manipulation. Also, there is more improvement when using more noisy methods to estimate discretionary accruals (Healy and DeAngelo methods). The results in the SEC litigation sample and debt-covenant violation sample are less significant, probably due to the small sample. However, there is incremental significance from using $EDAC^C$ as shown by the significant coefficient on *Log(RATIO)* in the logistic regressions.

To test the specification of the tests using $EDAC^C$, I use three samples with no expectation of EM. First, I choose a random sample in which I add no manipulation. Next, I choose random samples from extreme income and cash from operations sub-samples. Lastly, I use a random sample with added noise.

Results of the specification or specificity of the models are less straightforward. There is some improvement in the rejection rates of the alternative hypotheses of income-increasing and income-decreasing EM in the samples chosen from extreme income and cash from operations deciles. However, the improvements are not across the board and are not enough to reduce the rejection rates to the expected rejection rates at the specific test levels.

Other samples used include noise samples chosen from extreme income deciles in which I replace discretionary accruals with random numbers with the same mean and standard deviation assuming a normal distribution. The results indicate a reduction in rejection rates.

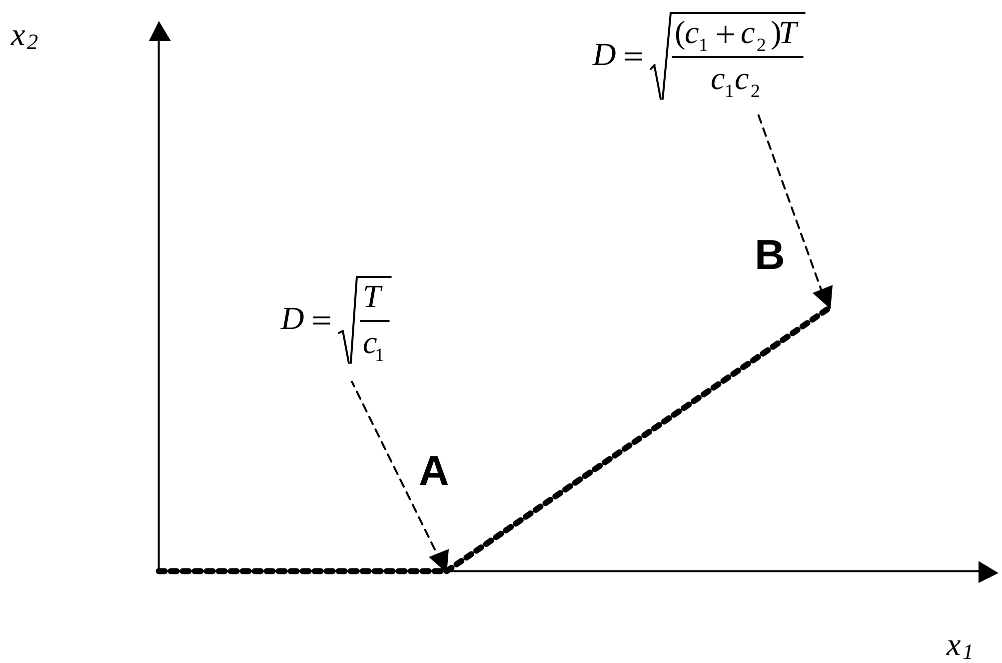
Regressions of proxies of measurement error contained in discretionary accruals reveal that the alternative discretionary accruals measure reduces some of this measurement error.

Overall, the results in the study indicate that $EDAC^C$ is an improvement in testing for EM. The improvement in both power and specification, even though at times not significant, is an indication that it is important to consider the relationship between the specific components of discretionary accruals.

Further research can be done in specific industries in which there is a prior expectation about which components are used to manipulate bottom-line income.

The results may be tampered by the fact that some of the expectation models of the specific components of accruals do not capture the true nature of the component. For example, under the modified Jones methodology, non-discretionary accounts receivable is a function of change is sales less accounts receivables and the level of property, plant, and equipment, which is unlikely to capture this component. This is left as an avenue for future research.

Figure 1: Graphical Representation of Manipulation by Manager Using Two Components of Accruals (x_1 and x_2) Given a Deviation from Benchmark, D (All Remaining Factors are Constant):



As can be seen from the graphical representation, manipulation by the manager begins with only one component (x_1) until the deviation from the benchmark reaches a certain level (A) after which both components are used in the manipulation. At the point B, the manipulation using both components cannot increase. In practice, this is probably the point where the decision to take a "Big Bath" is made. The above graphical representation assumes the only factor changing is the deviation D.

c_1 = Cost of manipulating x_1,

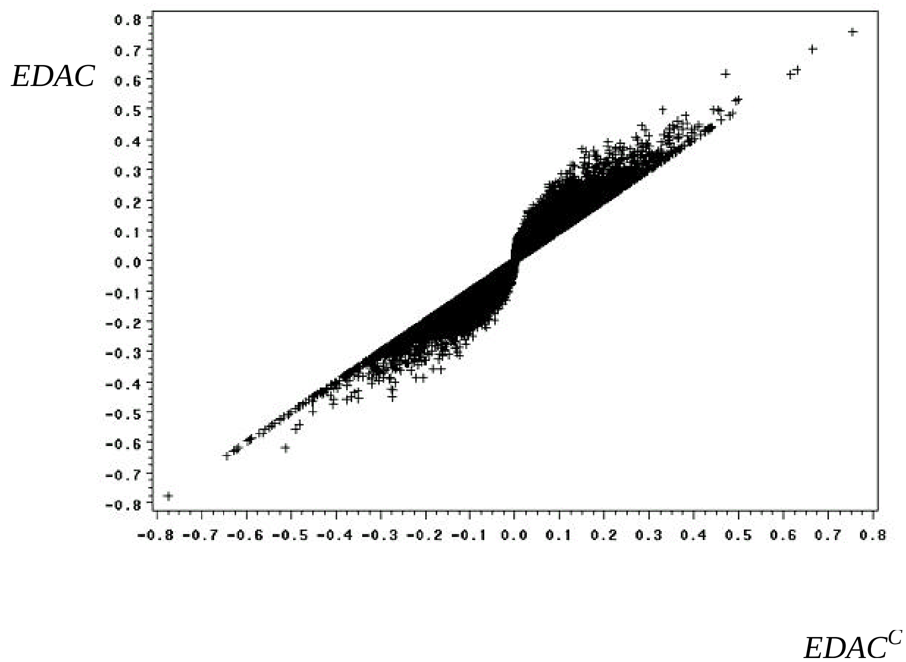
c_2 = Cost of manipulating x_2,

T = Cost threshold acceptable to manager,

D = Deviation of earnings from benchmark e.g. prior year earnings.

This representation ignores the reversal of manipulation. The points between A and B are characterized by manipulation using both components.

Figure 2: Plot of *EDAC* against $EDAC^C$:



$EDAC_t$ = Discretionary accruals using modified Jones methodology
$RATIO_t$ = Measure of magnitude of measurement error in components of discretionary accruals (close to 0 when high measurement error and close to 1 when low measurement error)
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

Table 1: Industrial Sample Distribution:

Two-digit SIC Code	*Industry*	*N*	*%*
01-09	Agriculture, Forestry & Fishing	158	0.34
10-17	Mining & Construction	2,444	5.22
20-29	Manufacturing – Non-durables	8,055	17.22
30-39	Manufacturing – Durables	16,078	34.37
40-49	Transportation & Public Utilities	5,717	12.22
50-51	Wholesale Trade	2,097	4.48
52-59	Retail Trade	3,511	7.50
70-89	Services	8,376	17.90
99	Unidentified	347	0.74
Total		46,783	100.00

N = Number of observations in each industry;
% = Percentage of observations in each industry relative to full sample.

Table 2: Descriptive Statistics for Full Sample:
(N = 46,783) Panel A:

Variable	*Mean*	*Std Deviation*	*Minimum*	*Maximum*
TAC_t	-0.047	0.097	-0.819	0.744
INC_t	-0.044	0.249	-2.191	0.400
CFO_t	0.003	0.237	-1.916	0.478
DAR_t	0.018	0.067	-0.207	0.449
$DINV_t$	0.009	0.047	-0.166	0.286
DAP_t	-0.013	0.058	-0.449	0.197
$DOWC_t$	0.0006	0.035	-0.216	0.187
DEP_t	-0.061	0.040	-0.333	-0.005
A_t	1,007.60	2,834.44	0.100	54,548.00
Modified Jones:				
$EDAC_t$	-0.004	0.089	-0.778	0.754
$EDAR_t$	0.002	0.060	-0.349	0.521
$EDINV_t$	0.001	0.042	-0.341	0.302
$EDAP_t$	-0.0004	0.053	-0.446	0.294
$EDOWC_t$	0.0002	0.034	-0.215	0.215
$EDDEP_t$	-0.007	0.034	-0.319	0.318
$RATIO_t$	0.454	0.294	0.000	1.000
$EDAC_t^C$	-0.004	0.068	-0.776	0.754

$TAC_t = -(DAR_t + DINV_t + DAP_t + DTAX_t + DOTH_t + DEP_t)/A_{t-1}$
INC_t = Income before extraordinary items
$CFO_t = INC_t - TAC_t$
DAR_t = Change in accounts receivable
$DINV_t$ = Change in inventory
DAP_t = -Change in accounts payable
$DOWC_t$ = Change in other working capital accounts
DEP_t = -Depreciation from cash flow statement
$EDAC_t$ = Discretionary accruals using modified Jones methodology
$EDAR_t$ = Discretionary accounts receivable using modified Jones methodology
$EDINV_t$ = Discretionary inventory using modified Jones methodology
$EDAP_t$ = Discretionary accounts payable using modified Jones methodology
$EDOWC_t$ = Discretionary other working capital using modified Jones methodology
$EDEPP_t$ = Discretionary depreciation using modified Jones methodology

$RATIO_t$ = Measure of magnitude of measurement error in components of discretionary accruals (close to 0 when high measurement error and close to 1 when low measurement error)
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

Panel B: Pearson Correlation Coefficients:

	TAC_t	INC_t	CFO_t	DAR_t	$DINV_t$	DAP_t	$DOWC_t$	DEP_t	$EDAC_t$	$RATIO_t$	$EDAC_t^C$
TAC_t	1.000	0.317*	-0.078*	0.513*	0.487*	0.190*	0.327*	0.442*	0.891*	-0.066*	0.852*
INC_t		1.000	0.921*	0.128*	0.109*	0.120*	0.032*	0.228*	0.273*	-0.063*	0.271*
CFO_t			1.000	-0.076*	-0.086*	0.047*	-0.101*	0.057*	-0.079*	-0.039*	-0.065*
DAR_t				1.000	0.231*	-0.416*	-0.059*	-0.046*	0.479*	-0.017*	0.431*
$DINV_t$					1.000	-0.294*	0.016**	0.034*	0.428*	-0.014**	0.385*
DAP_t						1.000	-0.007	0.070*	0.217*	-0.028*	0.248*
$DOWC_t$							1.000	0.010***	0.340*	-0.037*	0.333*
DEP_t								1.000	0.254*	-0.043*	0.251*
$EDAC_t$									1.000	-0.072*	0.955*
$RATIO_t$										1.000	-0.088*

* Significant at less than 0.001
** Significant at 0.01 or less
***Significant at 0.05 or less

$TAC_t = -(DAR_t + DINV_t + DAP_t + DTAX_t + DOTH_t + DEP_t)/A_{t-1}$
INC_t = Income before extraordinary items
$CFO_t = INC_t - TAC_t$
DAR_t = Change in accounts receivable
$DINV_t$ = Change in inventory
DAP_t = -Change in accounts payable
$DOWC_t$ = Change in other working capital accounts
DEP_t = -Depreciation from cash flow statement

$EDAC_t$ = Discretionary accruals using modified Jones methodology
$RATIO_t$ = Measure of magnitude of measurement error in components of discretionary accruals (close to 0 when high measurement error and close to 1 when low measurement error)
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

Table 3: Results of Modified Jones Regressions of Components of Accruals:
Mean (Std Deviation) of Coefficients and t-values

Dep. Variable	*Intercept*	*t-value*	*$DREV_t$-DAR_t*	*t-value*	*PPE*	*t-value*	*R^2*
DAR_t	0.149	0.834	0.058	3.449	0.013	1.161	0.225
	(0.537)	(1.966)	(0.051)	(3.247)	(0.024)	(1.520)	(0.144)
$DINV_t$	0.083	0.301	0.051	3.302	0.007	0.737	0.191
	(0.418)	(1.716)	(0.047)	(2.636)	(0.016)	(1.286)	(0.143)
DAP_t	-0.125	-1.283	-0.043	-2.903	-0.008	-0.893	0.201
	(0.406)	(2.328)	(0.034)	(2.860)	(0.018)	(1.308)	(0.144)
$DOWC_t$	0.019	-0.161	0.0007	0.041	0.002	0.450	0.078
	(0.285)	(1.679)	(0.021)	(1.598)	(0.010)	(1.190)	(0.093)
DEP_t	-0.064	-1.850	-0.012	-1.385	-0.085	-21.127	0.833
	(0.787)	(3.129)	(0.023)	(1.757)	(0.032)	(12.865)	(0.111)
TAC_t	0.063	-0.781	0.053	1.285	-0.070	-6.057	0.351
	(1.208)	(2.578)	(0.071)	(2.262)	(0.045)	(6.111)	(0.194)

$TAC_t = -(DAR_t + DINV_t + DAP_t + DTAX_t + DOTH_t + DEP_t)/A_{t-1}$
DAR_t = Change in accounts receivable
$DINV_t$ = Change in inventory
DAP_t = -Change in accounts payable
$DOWC_t$ = Change in other working capital accounts
DEP_t = -Depreciation from cash flow statement
$DREV_t$ = Sales or revenues
PPE_t = Gross property, plant, and equipment
The coefficients are from pooled regressions using the modified Jones methodology across four-digit SIC codes over the period 1989-2003:
$DAR_t/A_{t-1} = a_{11}(1/A_{t-1}) + b_{11}(DREV_t\text{-}AR_t/A_{t-1}) + b_{21}(PPE/A_{t-1}) + EDAR_t$
$DINV_t/A_{t-1} = a_{12}(1/A_{t-1}) + b_{12}(DREV_t\text{-}AR_t/A_{t-1}) + b_{22}(PPE/A_{t-1}) + EDINV_t$
$DAP_t/A_{t-1} = a_{13}(1/A_{t-1}) + b_{13}(DREV_t\text{-}AR_t/A_{t-1}) + b_{22}(PPE/A_{t-1}) + EDAP_t$
$DAP_t/A_{t-1} = a_{14}(1/A_{t-1}) + b_{14}(DREV_t\text{-}AR_t/A_{t-1}) + b_{24}(PPE/A_{t-1}) + EDOWC_t$
$DEP_t/A_{t-1} = a_{15}(1/A_{t-1}) + b_{15}(DREV_t\text{-}AR_t/A_{t-1}) + b_{25}(PPE_t/A_{t-1}) + EDDEP_t$
$TAC_t/A_{t-1} = a_{16}(1/A_{t-1}) + b_{16}(DREV_t\text{-}AR_t/A_{t-1}) + b_{26}(PPE/A_{t-1}) + EDAC_t$

Table 4: Descriptive Statistics of Components of Accruals by Industry:

Panel A: Mean (Standard Deviation) of Components of Accruals by Industry:

Two-digit SIC Code	*N*	DAR_t	$DINV_t$	DAP_t	$DOWC_t$	DEP_t
01-09[a]	158	0.008	0.017	-0.007	-0.001	-0.041
		(0.036)	(0.039)	(0.041)	(0.025)	(0.015)
10-17[b]	2,444	0.010	0.004	-0.011	0.002	-0.086
		(0.055)	(0.031)	(0.049)	(0.032)	(0.056)
20-29[c]	8,055	0.012	0.009	-0.011	0.002	-0.052
		(0.049)	(0.043)	(0.049)	(0.031)	(0.027)
30-39[d]	16,078	0.018	0.012	-0.012	0.001	-0.054
		(0.071)	(0.058)	(0.060)	(0.035)	(0.032)
40-49[e]	5,717	0.012	0.002	-0.011	0.001	-0.066
		(0.043)	(0.016)	(0.043)	(0.027)	(0.042)
50-51[f]	2,097	0.026	0.018	-0.020	0.002	-0.037
		(0.074)	(0.065)	(0.072)	(0.030)	(0.029)
52-59[g]	3,511	0.010	0.020	-0.018	0.001	-0.062
		(0.040)	(0.057)	(0.054)	(0.031)	(0.031)
70-89[h]	8,376	0.032	0.002	-0.015	-0.003	-0.077
		(0.090)	(0.029)	(0.066)	(0.045)	(0.053)
99[i]	347	0.014	0.006	-0.030	0.005	-0.064
		(0.086)	(0.051)	(0.089)	(0.041)	(0.050)
All	46,783	0.018	0.009	-0.013	0.001	-0.061
		(0.067)	(0.047)	(0.058)	(0.035)	(0.040)

[a]Agriculture, Forestry & Fishing
[b]Mining & Construction
[c]Manufacturing – Non-durables
[d]Manufacturing – Durables
[e]Transportation & Public Utilities
[f]Wholesale Trade
[g]Retail Trade
[h]Services
[i]Unidentified

DAR_t = Increase (Decrease) in accounts receivable
$DINV_t$ = Increase (Decrease) in inventory

DAP_t = Decrease (Increase) in accounts payable
$DOWC_t$ = Change in other working capital accounts
DEP_t = – Depreciation expense from cash flow statement

Panel B: Mean (Standard Deviation) of Balances of Components of Accruals by Industry:

Two-digit SIC Code	*N*	AR_t	INV_t	AP_t	OWC_t	DEP_t
01-09[a]	158	0.139	0.189	-0.067	-0.089	-0.041
		(0.102)	(0.126)	(0.059)	(0.102)	(0.015)
10-17[b]	2,444	0.139	0.062	-0.094	-0.056	-0.086
		(0.151)	(0.140)	(0.093)	(0.136)	(0.056)
20-29[c]	8,055	0.165	0.165	-0.095	-0.069	-0.052
		(0.122)	(0.136)	(0.078)	(0.083)	(0.027)
30-39[d]	16,078	0.226	0.224	-0.107	-0.087	-0.054
		(0.132)	(0.141)	(0.088)	(0.118)	(0.032)
40-49[e]	5,717	0.112	0.027	-0.070	-0.059	-0.066
		(0.122)	(0.041)	(0.089)	(0.087)	(0.042)
50-51[f]	2,097	0.300	0.318	-0.216	-0.059	-0.037
		(0.178)	(0.197)	(0.153)	(0.089)	(0.029)
52-59[g]	3,511	0.097	0.278	-0.143	-0.077	-0.062
		(0.130)	(0.231)	(0.102)	(0.079)	(0.031)
70-89[h]	8,376	0.253	0.043	-0.089	-0.153	-0.077
		(0.206)	(0.092)	(0.106)	(0.444)	(0.053)
99[i]	347	0.232	0.133	-0.135	-0.111	-0.064
		(0.183)	(0.166)	(0.148)	(0.193)	(0.050)
All	46,783	0.195	0.157	-0.104	-0.089	-0.061
		(0.160)	(0.166)	(0.100)	(0.212)	(0.040)

[a]Agriculture, Forestry & Fishing
[b]Mining & Construction
[c]Manufacturing – Non-durables
[d]Manufacturing – Durables
[e]Transportation & Public Utilities
[f]Wholesale Trade
[g]Retail Trade
[h]Services
[i]Unidentified

AR_t = Accounts receivable,
INV_t = Inventories,
AP_t = Accounts payable,
OWC_t = Other working capital (other current assets minus other current liabilities),
DEP_t = Depreciation.

Table 5: Autocorrelation of Components of Accruals by Industry: Autocorrelation Coefficients (t-statistics)

Two-digit SIC Code	*N*	*DAR*	*DINV*	*DAP*	*DOWC*	*DEP*
01-09[a]	150	0.135	0.250	0.126	-2.233	0.703
		(3.562)	(4.816)	(2.703)	(-8.382)	(12.212)
10-17[b]	2,294	-0.006	0.052	-0.001	-0.158	0.004
		(-1.281)	(5.436)	(-0.442)	(-7.794)	(2.914)
20-29[c]	7,801	0.040	0.052	-0.008	-0.540	0.022
		(7.017)	(8.219)	(-5.915)	(-22.814)	(11.772)
30-39[d]	15,757	0.000	0.001	0.001	-0.033	0.001
		(0.049)	(1.616)	(1.299)	(-10.316)	(4.594)
40-49[e]	5,599	0.001	0.021	0.003	-0.429	0.057
		(0.679)	(5.104)	(10.674)	(-14.925)	(18.607)
50-51[f]	2,048	0.095	0.015	0.001	-0.184	0.180
		(8.148)	(3.686)	(0.168)	(-8.087)	(21.238)
52-59[g]	3,492	0.024	0.135	0.015	-0.127	0.243
		(6.139)	(14.984)	(3.316)	(-9.521)	(33.024)
70-89[h]	8,262	0.002	0.012	0.001	-0.065	0.002
		(3.763)	(4.114)	(1.872)	(-10.532)	(6.260)
99[i]	342	-0.001	0.001	0.000	-0.262	0.000
		(-0.413)	(2.853)	(0.261)	(-6.048)	(0.128)
All	45,745*	0.002	0.001	0.001	-0.056	0.002
		(5.199)	(5.747)	(5.291)	(-21.582)	(12.529)

[a]Agriculture, Forestry & Fishing
[b]Mining & Construction
[c]Manufacturing – Non-durables
[d]Manufacturing – Durables
[e]Transportation & Public Utilities
[f]Wholesale Trade
[g]Retail Trade
[h]Services
[i]Unidentified
*Sample excludes observations with missing data in year *t-1*.
Autocorrelation coefficients are the coefficients from the following regressions:

$$\Delta AR_t = a + b * AR_{t-1}$$

$$\Delta AP_t = a + b * AP_{t-1}$$

$$\Delta INV_t = a + b * INV_{t-1}$$

$\Delta OWC_t = a + b * OWC_{t-1}$

$DEP_t = a + b * DEP_{t-1}$

DAR_t = Increase (Decrease) in accounts receivable

$DINV_t$ = Increase (Decrease) in inventory

DAP_t = Decrease (Increase) in accounts payable

$DOWC_t$ = Change in other working capital accounts

DEP_t = – Depreciation expense from cash flow statement

Table 6: Type of Manipulation in Firms Subject to SEC Enforcement Actions in the Period 2000-2004:
N=133 firms

Type of manipulation	*Number of firms*
Manipulation in only one component:	
Manipulation of revenues (premature recognition or fictitious sales or misclassification)	56
Manipulation of inventories (failure to write down inventory or misclassification)	6
Manipulation of expenses (capitalization of expenses or manipulation of reserves)	25
Manipulation of other income	1
Subtotal	**88**
Manipulation in more than one component:	
Manipulation of revenues and inventories or expenses or depreciation	39
Manipulation of inventories or expenses or depreciation	6
Subtotal	**45**

Table 7: Results of Tests of Earnings Management for Random Sample with Artificially Added Accrual Manipulation:

Panel A: Mean (Std Deviation) of Regressions on *PART*:

	5% Manipulation				***10% Manipulation***				***20% Manipulation***			
Dep. Variable	*PART*	*Std Error*	*t-value*	R^2	*PART*	*Std Error*	*t-value*	R^2	*PART*	*Std Error*	*t-value*	R^2
Healy:												
$EDAC_t^C$	0.084	0.046	2.287	4.17%	0.123	0.046	3.359	7.79%	0.241	0.054	5.608	17.45%
	(0.070)	(0.035)	(1.604)	(5.04%)	(0.086)	(0.036)	(2.285)	(8.06%)	(0.148)	(0.040)	(3.540)	(15.34%)
Z-statistic			**34.98**				**51.49**				**86.63**	
$EDAC_t^C$	0.062	0.034	2.333	4.67%	0.100	0.035	3.701	9.50%	0.208	0.043	6.161	19.78%
	(0.059)	(0.027)	(1.819)	(6.46%)	(0.075)	(0.027)	(2.665)	(10.62%)	(0.136)	(0.032)	(3.994)	(17.72%)
Z-statistic			**35.68**				**56.72**				**95.15**	
DeAngelo:												
$EDAC_t$	0.092	0.111	1.327	2.46%	0.131	0.112	2.044	4.32%	0.239	0.112	3.925	11.32%
	(0.399)	(0.241)	(1.642)	(6.02%)	(0.403)	(0.241)	(2.131)	(7.32%)	(0.161)	(0.207)	(3.215)	(12.36%)
Z-statistic			**20.32**				**31.33**				**60.61**	
$EDAC_t^C$	0.067	0.074	1.415	2.78%	0.101	0.074	2.283	5.29%	0.203	0.075	4.496	13.84%
	(0.283)	(0.151)	(1.792)	(6.59%)	(0.288)	(0.151)	(2.435)	(8.29%)	(0.144)	(0.113)	(3.560)	(15.52%)
Z-statistic			**21.66**				**34.99**				**69.43**	
Jones:												
$EDAC_t$	0.083	0.041	2.492	4.69%	0.119	0.042	3.577	8.55%	0.220	0.049	5.518	17.10%
	(0.060)	(0.032)	(1.615)	(5.47%)	(0.077)	(0.032)	(2.033)	(8.63%)	(0.132)	(0.036)	(3.289)	(14.39%)
Z-statistic			**38.11**				**54.82**				**85.24**	
$EDAC_t^C$	0.062	0.031	2.517	5.17%	0.098	0.032	3.901	10.22%	0.184	0.039	5.817	18.49%
	(0.052)	(0.024)	(1.837)	(7.13%)	(0.068)	(0.025)	(2.689)	(11.30%)	(0.119)	(0.029)	(3.570)	(16.23%)
Z-statistic			**38.48**				**59.78**				**89.86**	

Table 7: Continued

Modified Jones:												
$EDAC_t$	0.085	0.042	2.485	4.67%	0.122	0.043	3.565	8.52%	0.222	0.050	5.455	16.83%
	(0.062)	(0.033)	(1.610)	(5.46%)	(0.079)	(0.033)	(2.300)	(8.62%)	(0.134)	(0.037)	(3.294)	(14.30%)
Z-statistic			**38.00**				**54.63**				**84.28**	
$EDAC_t^C$	0.063	0.032	2.515	5.17%	0.099	0.033	3.906	10.24%	0.186	0.040	5.772	18.28%
	(0.053)	(0.025)	(1.843)	(7.16%)	(0.069)	(0.025)	(2.701)	(11.37%)	(0.121)	(0.029)	(3.587)	(16.18%)
Z-statistic			**38.45**				**59.85**				**89.17**	

PART = Dummy variable that takes on the value of 1 in the test observations (with added accrual manipulation) and 0 otherwise
$EDAC_t$ = Discretionary accruals
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The results are from the regressions over four-digit SIC codes:
$EDAC_t = a + b * PART_t + e_t$
$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

$$Z-statistic = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{t_i}{\sqrt{k_i/(k_i-2)}}$$

Where t_i = t-statistic for industry i (four-digit SIC code),
k_i = Degrees of freedom for t-statistic of industry i,
N = Total number of industries in regressions.
The accrual manipulation is added to 1000 firm-year observations chosen randomly from the sample, with *EDAC* greater than zero to minimize dilution of manipulation.
20% manipulation is achieved by 16% manipulation of accounts receivable (and revenue) and 4% to accounts payable.
10% manipulation is achieved by 5% manipulation of accounts receivable (and revenue) and 5% to accounts payable.
5% manipulation is achieved by 2% manipulation of accounts receivable (and revenue) and 3% to accounts payable.

Panel B: Results of Logistic Regression for Random Sample with Artificially Added Accrual Manipulation:
Coefficient (Chi-square value) (p-value)

Dependent Variable	*Intercept*	*Log($EDAC_t$)*	*Log($RATIO_t$)*	*Likelihood Ratio*
5%				
Manipulation:	-0.415	0.675	1.144	1094.932
PART	(14.397)	(198.090)	(169.114)	
	(<.0001)	(<.0001)	(<.0001)	
10%				
Manipulation:	1.522	1.460	1.943	2306.113
PART	(154.035)	(586.091)	(236.503)	
	(<.0001)	(<.0001)	(<.0001)	
20%				
Manipulation:	5.312	4.425	-0.759	4515.147
PART	(847.736)	(1127.103)	(25.467)	
	(<.0001)	(<.0001)	(<.0001)	

The results are for the pooled logistic regression:
$PART_t = c + d*Log(EDAC_t) + f*Log(RATIO_t) + e_t$
$EDAC_t$ and $RATIO_t$ are calculated using the modified Jones method.
The accrual manipulation is added to 1000 firm-year observations chosen randomly from the sample, with *EDAC* greater than zero to minimize dilution of manipulation.
20% manipulation is achieved by 16% manipulation of accounts receivable (and revenue) and 4% to accounts payable.
10% manipulation is achieved by 5% manipulation of accounts receivable (and revenue) and 5% to accounts payable.
5% manipulation is achieved by 2% manipulation of accounts receivable (and revenue) and 3% to accounts payable.

Table 8: Results of Tests of Earnings Management for Firms Subject to SEC Litigation:

Panel A: Mean (Std Deviation) of Regressions on *PART*: N = 19 Firms, N = 249 Observations

Dependent Variable	*PART*	*Std. Error*	*t-value*	R^2
Healy:				
$EDAC_t$	0.025	0.097	0.575	8.71%
	(0.093)	(0.070)	(0.844)	(9.08%)
Z-statistic			**2.215**	
$EDAC_t^C$	0.018	0.069	0.588	9.76%
	(0.067)	(0.051)	(0.911)	(13.83%)
Z-statistic			**2.316**	
DeAngelo:				
$EDAC_t$	-0.006	0.139	0.211	10.95%
	(0.149)	(0.115)	(1.279)	(14.93%)
Z-statistic			**0.793**	
$EDAC_t^C$	0.003	0.091	0.207	8.57%
	(0.085)	(0.081)	(1.060)	(12.09%)
Z-statistic			**0.938**	
Jones:				
$EDAC_t$	0.020	0.094	0.492	9.45%
	(0.111)	(0.066)	(1.000)	(11.47%)
Z-statistic			**2.076**	
$EDAC_t^C$	0.020	0.069	0.584	10.78%
	(0.097)	(0.052)	(1.276)	(17.08%)
Z-Statistic			**2.422**	
Modified Jones:				
$EDAC_t$	0.019	0.097	0.499	9.11%
	(0.110)	(0.071)	(0.959)	(10.62%)
Z-statistic			**1.950**	
$EDAC_t^C$	0.019	0.070	0.593	11.09%
	(0.096)	(0.056)	(1.215)	(16.15%)
Z-statistic			**2.454**	

PART = Dummy variable that takes on the value of 1 in the test observations (with added accrual manipulation) and 0 otherwise.

$EDAC_t$ = Discretionary accruals

$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The results are from firm regressions with 10 or more observations:

$EDAC_{it} = a + b * PART_{it} + e_{it}$

$EDAC_{it}^C = a_1 + b_1 * PART_{it} + e_{1it}$

$$Z - statistic = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{t_i}{\sqrt{k_i / (k_i - 2)}}$$

Where t_i = t-statistic for industry i (four-digit SIC code),
k_i = Degrees of freedom for t-statistic of industry i,
N = Total number of industries in regressions.

Panel B: Results of Logistic Regression for Firms Subject to SEC Litigation: Coefficient (Chi-square value) (p-value), N = 130 observations

Dependent Variable	*Intercept*	*Log($EDAC_t$)*	*Log($RATIO_t$)*	*Likelihood Ratio*
PART	-2.044	-0.438	0.771	4.771
	(7.898)	(2.152)	(4.183)	
	(0.005)	(0.142)	(0.041)	

The results are for the pooled logistic regression:

$PART_t = c + d*Log(EDAC_t) + f* Log(RATIO_t) + e_t$

$EDAC_t$ and $RATIO_t$ are calculated using the modified Jones method.

Table 9: Results of Tests of Earnings Management for Sample with Debt Covenant Violation in Year 0 and –1:

Panel A: Mean (Standard Deviation) of Regressions on *PART*: N = 13 Firms, N = 161 Observations

Dependent Variable	*PART*	*Std. Error*	*t-value*	R^2
Healy:				
$EDAC_t$	-0.043	0.106	-0.532	4.41%
	(0.081)	(0.084)	(0.494)	(5.46%)
Z-statistic			**-1.729**	
$EDAC_t^C$	-0.020	0.066	-0.412	3.84%
	(0.052)	(0.050)	(0.536)	(5.05%)
Z-statistic			**-1.131**	
DeAngelo:				
$EDAC_t$	-0.031	0.155	-0.350	3.28%
	(0.065)	(0.141)	(0.509)	(3.93%)
Z-statistic			**-0.886**	
$EDAC_t^C$	-0.014	0.114	-0.212	2.71%
	(0.054)	(0.114)	(0.519)	(4.36%)
Z-statistic			**-0.714**	
Jones:				
$EDAC_t$	-0.025	0.080	-0.331	6.05%
	(0.060)	(0.045)	(0.806)	(5.95%)
Z-statistic			**-1.321**	
$EDAC_t^C$	-0.013	0.056	-0.196	6.43%
	(0.042)	(0.039)	(0.879)	(5.87%)
Z-statistic			**-0.938**	
Modified Jones:				
$EDAC_t$	-0.031	0.086	-0.305	5.37%
	(0.064)	(0.050)	(0.748)	(5.70%)
Z-statistic			**-0.722**	
$EDAC_t^C$	-0.015	0.056	-0.196	5.92%
	(0.045)	(0.040)	(0.841)	(6.33%)
Z-statistic			**-0.854**	

PART = Dummy variable that takes on the value of 1 in the year of violation and year prior to violation and 0 otherwise.

$EDAC_t$ = Discretionary accruals

$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The results are from firm regressions with 10 or more observations:

$EDAC_t = a + b * PART_t + e_t$

$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

$$Z-statistic = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{t_i}{\sqrt{k_i/(k_i-2)}}$$

Where t_i = t-statistic for industry i (four-digit SIC code),
k_i = Degrees of freedom for t-statistic of industry i,
N = Total number of industries in regressions.

Panel B: Results of Logistic Regression for Sample with Debt Covenant Violation in Year 0 and –1: N = 79 Observations
Coefficient (Chi-square value) (p-value)

Dependent Variable	*Intercept*	*Log(EDAC$_t$)*	*Log(RATIO$_t$)*	*Likelihood Ratio*
PART	-3.398	-1.220	1.487	8.219
	(8.987)	(6.180)	(5.971)	
	(0.003)	(0.013)	(0.015)	

The results are for the pooled logistic regression:
$PART_t = c + d*Log(EDAC_t) + f*Log(RATIO_t) + e_t$
$EDAC_t$ and $RATIO_t$ are calculated using the modified Jones method.

Table 10: 2X2 Chi Square Comparison of Violation vs. Non-Violation Periods with Values of *RATIO* Above and Below the Median:
Actual Frequency (Expected Frequency)

Dependent Variable	*RATIO > Median*	*RATIO < Median*	*Total*
Non-Violation	55	55	110
Periods	(60.79)	(49.21)	
Violation Periods	29	13	42
(Year 0 and –1)	(23.21)	(18.79)	
Total	84	68	152

Median *RATIO* is based violation period observations only and is measured by firm.
Chi-square value of table = 4.460, which is significant at 5% level.

Table 11: Rejection Rates of Null Hypothesis of No EM against Alternative Hypotheses of Positive and Negative EM in Random Sample with No Expectation of Earnings Management:
Mean (median) of 10 iterations

Alternative Hypothesis	*Earnings management >0*		*Earnings management <0*	
	5%	*1%*	*5%*	*1%*
Healy:				
$EDAC_t$	5.00%	1.38%	5.18%	1.88%
	(4.67%)	(1.39%)	(5.44%)	(1.80%)
$EDAC_t^C$	4.84%	2.05%	5.42%	2.27%
	(4.48%)	(1.97%)	(5.76%)	(2.42%)
DeAngelo:				
$EDAC_t$	3.52%	1.19%	4.37%	1.89%
	(2.94%)	(1.00%)	(4.55%)	(1.81%)
$EDAC_t^C$	3.72%	1.66%	4.25%	2.24%
	(3.30%)	(1.73%)	(4.49%)	(1.98%)
Jones:				
$EDAC_t$	4.91%	1.69%	5.10%	1.73%
	(4.27%)	(1.75%)	(4.74%)	(1.75%)
$EDAC_t^C$	4.71%	2.00%	5.70%	2.12%
	(4.55%)	(2.02%)	(5.33%)	(2.01%)
Modified Jones:				
$EDAC_t$	5.11%	1.61%	5.02%	1.69%
	(4.94%)	(1.62%)	(4.46%)	(1.59%)
$EDAC_t^C$	4.84%	2.19%	5.70%	2.12%
	(4.36%)	(2.20%)	(5.44%)	(1.95%)

PART = Dummy variable that takes on the value of 1 in the test observations (random sample of 1000 observations) and 0 otherwise.
$EDAC_t$ = Discretionary accruals
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The rejection rates represent percentage of regressions in which the variable *PART* is significant at the above levels. These regressions are over four-digit SIC codes:

$EDAC_t = a + b * PART_t + e_t$
$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

Table 12: Rejection Rates of Null Hypothesis of No EM against Alternative Hypotheses of Positive and Negative EM in Random Sample Chosen from Extreme Income Deciles:

Panel A: Lowest Decile of Income: Mean (Median) of 10 Iterations

Alternative Hypothesis	*Earnings management >0*		*Earnings management <0*	
	5%	*1%*	*5%*	*1%*
Healy:				
$EDAC_t$	2.47%	1.08%	47.75%	32.46%
	(2.80%)	(0.93%)	(48.72%)	(32.16%)
$EDAC_t^C$	1.83%	0.38%	46.81%	32.19%
	(1.89%)	(0.61%)	(46.58%)	(31.76%)
DeAngelo:				
$EDAC_t$	10.37%	7.59%	21.50%	14.42%
	(10.13%)	(6.96%)	(21.02%)	(14.78%)
$EDAC_t^C$	8.14%	6.24%	21.90%	14.38%
	(7.03%)	(6.38%)	(21.22%)	(14.15%)
Jones:				
$EDAC_t$	2.34%	0.82%	41.32%	26.37%
	(2.55%)	(0.93%)	(42.06%)	(25.95%)
$EDAC_t^C$	1.52%	0.64%	38.76%	26.21%
	(1.25%)	(0.63%)	(39.38%)	(25.88%)
Modified Jones:				
$EDAC_t$	2.27%	0.82%	40.95%	26.82%
	(2.48%)	(0.93%)	(41.14%)	(26.67%)
$EDAC_t^C$	1.65%	0.64%	39.78%	27.35%
	(1.83%)	(0.63%)	(40.51%)	(27.83%)

PART = Dummy variable that takes on the value of 1 in the test observations (random sample from lowest decile of income) and 0 otherwise.

$EDAC_t$ = Discretionary accruals

$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The rejection rates represent percentage of regressions in which the variable *PART* is significant at the above levels. These regressions are over four-digit SIC codes:

$EDAC_t = a + b * PART_t + e_t$
$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

Panel B: Highest Decile of Income: Mean (Median) of 10 Iterations

Alternative Hypothesis	*Earnings management >0*		*Earnings management <0*	
	5%	*1%*	*5%*	*1%*
Healy:				
$EDAC_t$	24.02%	13.45%	1.43%	0.51%
	(23.58%)	(13.11%)	(1.37%)	(0.46%)
$EDAC_t^C$	20.54%	11.20%	1.30%	0.60%
	(19.45%)	(10.88%)	(1.19%)	(0.47%)
DeAngelo:				
$EDAC_t$	7.05%	2.86%	2.98%	1.49%
	(6.71%)	(2.76%)	(2.82%)	(1.34%)
$EDAC_t^C$	7.00%	3.31%	2.89%	1.58%
	(6.38%)	(3.54%)	(2.83%)	(1.57%)
Jones:				
$EDAC_t$	16.02%	6.98%	2.73%	0.74%
	(14.83%)	(6.85%)	(2.84%)	(0.49%)
$EDAC_t^C$	14.44%	7.35%	2.88%	1.30%
	(13.84%)	(7.59%)	(3.17%)	(1.17%)
Modified Jones:				
$EDAC_t$	19.53%	8.93%	2.18%	0.61%
	(19.42%)	(8.56%)	(2.29%)	(0.49%)
$EDAC_t^C$	17.52%	8.69%	2.13%	0.93%
	(16.44%)	(9.15%)	(2.07%)	(0.92%)

PART = Dummy variable that takes on the value of 1 in the test observations (random sample from highest decile of income) and 0 otherwise.
$EDAC_t$ = Discretionary accruals
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The rejection rates represent percentage of regressions in which the variable *PART* is significant at the above levels. These regressions are over four-digit SIC codes:

$EDAC_t = a + b * PART_t + e_t$

$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

Table 13: Rejection Rates of Null Hypothesis of No EM against Alternative Hypotheses of Positive and Negative EM in Random Sample Chosen from Extreme Cash from Operations Deciles:
Panel A: Lowest Decile of Cash from Operations: Mean (Median) of 10 Iterations

Alternative Hypothesis	*Earnings management >0*		*Earnings management <0*	
	5%	*1%*	*5%*	*1%*
Healy:				
$EDAC_t$	16.37%	10.55%	16.39%	9.06%
	(16.82%)	(10.72%)	(16.79%)	(9.23%)
$EDAC_t^C$	14.37%	9.21%	16.32%	9.18%
	(14.42%)	(9.35%)	(16.51%)	(9.88%)
DeAngelo:				
$EDAC_t$	17.70%	11.17%	10.79%	7.48%
	(17.58%)	(11.53%)	(10.38%)	(7.30%)
$EDAC_t^C$	16.48%	10.96%	10.72%	6.62%
	(16.82%)	(11.22%)	(10.70%)	(6.44%)
Jones:				
$EDAC_t$	16.55%	9.83%	13.88%	6.75%
	(16.21%)	(10. 42%)	(14.11%)	(7.05%)
$EDAC_t^C$	14.51%	9.53%	12.49%	7.12%
	(14.41%)	(9.96%)	(13.06%)	(7.23%)
Modified				
Jones:				
$EDAC_t$	16.67%	9.70%	13.99%	6.75%
	(16.82%)	(10.26%)	(14.11%)	(7.14%)
$EDAC_t^C$	14.87%	8.84%	13.17%	7.00%
	(14.94%)	(9.01%)	(14.24%)	(6.69%)

PART = Dummy variable that takes on the value of 1 in the test observations (random sample from lowest decile of CFO) and 0 otherwise.
$EDAC_t$ = Discretionary accruals
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The rejection rates represent percentage of regressions in which the variable *PART* is significant at the above levels. These regressions are over four-digit SIC codes:

$EDAC_t = a + b * PART_t + e_t$

$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

Panel B: Highest Decile of Cash from Operations:
Mean (Median) of 10 Iterations

Alternative Hypothesis	*Earnings management >0*		*Earnings management <0*	
	5%	*1%*	*5%*	*1%*
Healy:				
$EDAC_t$	0.24%	0.04%	33.26%	15.50%
	(0.00%)	(0.00%)	(34.10%)	(15.81%)
$EDAC_t^C$	0.14%	0.00%	30.59%	16.00%
	(0.00%)	(0.00%)	(30.40%)	(16.13%)
DeAngelo:				
$EDAC_t$	0.46%	0.14%	14.84%	6.58%
	(0.46%)	(0.00%)	(14.48%)	(5.95%)
$EDAC_t^C$	0.59%	0.32%	15.86%	8.29%
	(0.46%)	(0.22%)	(15.37%)	(7.55%)
Jones:				
$EDAC_t$	0.32%	0.09%	37.77%	20.05%
	(0.45%)	(0.00%)	(37.36%)	(19.19%)
$EDAC_t^C$	0.23%	0.09%	35.33%	20.49%
	(0.22%)	(0.00%)	(34.47%)	(20.64%)
Modified Jones:				
$EDAC_t$	0.37%	0.14%	35.74%	17.14%
	(0.45%)	(0.00%)	(35.80%)	(16.75%)
$EDAC_t^C$	0.24%	0.09%	32.86%	18.70%
	(0.00%)	(0.00%)	(32.95%)	(18.47%)

PART = Dummy variable that takes on the value of 1 in the test observations (random sample from highest decile of CFO) and 0 otherwise.
$EDAC_t$ = Discretionary accruals
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

The rejection rates represent percentage of regressions in which the variable *PART* is significant at the above levels. These regressions are over four-digit SIC codes:

$EDAC_t = a + b * PART_t + e_t$

$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

Table 14: Results of Tests of Earnings Management in Random Sample vs. Noise Sample Chosen from Extreme Income Deciles: Mean (Median) of 10 Iterations

Alternative Hypothesis	*Earnings management >0*		*Earnings management <0*	
	5%	*1%*	*5%*	*1%*
Random Sample from Lowest Decile of Income:				
$EDAC_t$	2.48%	1.13%	41.20%	26.20%
	(3.09%)	(1.28%)	(40.82%)	(26.10%)
$EDAC_t^C$	2.36%	0.88%	39.63%	25.39%
	(1.94%)	(0.65%)	(39.87%)	(24.84%)
Noise Sample from Lowest Decile of Income:				
$EDAC_t$	5.68%	3.42%	40.87%	27.17%
	(5.66%)	(3.58%)	(40.16%)	(27.53%)
$EDAC_t^C$	4.89%	3.11%	35.46%	25.06%
	(5.20%)	(3.26%)	(35.20%)	(24.37%)
Random Sample from Highest Decile of Income:				
$EDAC_t$	18.80%	9.05%	1.85%	0.69%
	(18.46%)	(8.95%)	(1.84%)	(0.48%)
$EDAC_t^C$	16.70%	8.68%	2.08%	0.92%
	(16.21%)	(8.74%)	(1.86%)	(0.69%)
Noise Sample from Highest Decile of Income:				
$EDAC_t$	27.30%	16.40%	6.17%	3.25%
	(27.18%)	(16.16%)	(5.88%)	(3.27%)
$EDAC_t^C$	25.70%	16.19%	5.42%	3.39%
	(25.48%)	(15.94%)	(5.20%)	(3.25%)

Random sample of 1000 observations are chosen from full sample without replacement.
Noise sample of 1000 observations are the observations in the random sample in which I replace the discretionary accruals components artificially changed with same mean and variance as random sample.
PART = Dummy variable that takes on the value of 1 in the test observations and 0 otherwise
$EDAC_t$ = Discretionary accruals using modified Jones method
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$
The results are from the regressions over two-digit SIC codes:
$EDAC_t = a + b * PART_t + e_t$
$EDAC_t^C = a_1 + b_1 * PART_t + e_{1t}$

Table 15: Results of Regressions on Proxies of Measurement Error:
Mean Coefficients (t-Values)

Dep. Variable	*Intercept*	*CFO*	*Growth*	*Intensity*	*Life*	R^2
Healy:						
$EDAC_t$	-0.004	-0.232	0.028	-0.166	-0.004	31.84%
	(0.169)	(-3.867)	(1.944)	(-2.492)	(-2.388)	
$EDAC_t^C$	-0.002	-0.161	0.018	-0.125	-0.003	29.22%
	(0.226)	(-3.448)	(1.617)	(-2.440)	(-2.284)	
DeAngelo						
:	-0.009	-0.397	0.031	-0.068	-0.005	13.99%
$EDAC_t$	(-0.299)	(-2.181)	(0.733)	(-0.042)	(-0.436)	
$EDAC_t^C$	-0.003	-0.262	0.021	-0.042	-0.003	13.45%
	(-0.245)	(-2.151)	(0.717)	(-0.101)	(-0.450)	
Jones:						
$EDAC_t$	-0.039	-0.219	0.017	-0.059	-0.005	27.76%
	(-1.855)	(-3.905)	(1.266)	(-0.757)	(-3.302)	
$EDAC_t^C$	-0.030	-0.155	0.012	-0.044	-0.004	26.27%
	(-1.859)	(-3.609)	(1.165)	(-0.732)	(-3.225)	
Modified						
Jones:	-0.038	-0.225	0.023	-0.067	-0.005	27.95%
$EDAC_t$	(-1.752)	(-3.919)	(1.748)	(-0.855)	(-3.179)	
$EDAC_t^C$	-0.030	-0.158	0.016	-0.049	-0.004	26.26%
	(-1.765)	(-3.598)	(1.580)	(-0.819)	(-3.112)	

The results are from regressions over four-digit SIC codes:

$EDAC_t = a + b*CFO_t + c*Growth_t + d*Intensity_t + e*Life_t + e_t$

$EDAC_t^C = a_1 + b_1*CFO_t + c_1*Growth_t + d_1*Intensity_t + e_1*Life_t + e_{1t}$

CFO_t = Cash from operations in year t,
$Growth_t = \Delta Revenue_t / Revenue_{t-1}$,
$Intensity_t$ = Gross PPE_t / A_t,
$Life_t = PPE_t / DEP_t$.
$EDAC_t$ = Discretionary accruals
$EDAC_t^C$ = Alternative discretionary accruals = $EDAC_t * RATIO_t$

Table 16: Panel A: Discretionary Accruals (*EDAC*) and Alternative Discretionary Accruals (*EDAC*^{C}) Partitioned by Current Relative Performance and Expected Relative Performance:

Panel A: Discretionary Accruals (*EDAC*):

		Current Relative Performance	
	Poor	***Good***	***All***
Expected Future Relative Performance			
Poor	(i)	**(ii)**	
Mean	0.007	**-0.032**	-0.005
Median	0.006	**-0.022**	-0.003
N	2512	**1221**	3733
Good	**(iii)**	(iv)	
Mean	**0.055**	-0.010	0.009
Median	**0.035**	-0.007	0.005
N	**1221**	2842	4063
All			
Mean	0.023	-0.017	0.002
Median	0.016	-0.012	0.0009
N	3733	4063	7796

Panel B: Alternative Discretionary Accruals (*EDAC*^{C}):

		Current Relative Performance	
	Poor	***Good***	***All***
Expected Future Relative Performance			
Poor	(i)	**(ii)**	
Mean	0.002	**-0.019**	-0.004
Median	0.0001	**-0.005**	-0.0002
N	2619	**1114**	3733
Good	**(iii)**	(iv)	
Mean	**0.036**	-0.005	0.006
Median	**0.013**	-0.0001	0.0005
N	**1112**	2951	4063
All			
Mean	0.012	-0.008	0.0012
Median	0.002	-0.0007	0.000
N	3731	4065	7796

In Panel A, $EDAC_t$ are calculated using modified Jones method.

"Good" current relative performance is where unmanaged earnings (Inc_t – $EDAC_t$) are greater than or equal to two-digit SIC code median unmanaged earnings in year t.

"Poor" current relative earnings performance is where unmanaged earnings (Inc_t – $EDAC_t$) is less than two-digit SIC code median unmanaged earnings in year t.

"Good" expected future relative performance is where earnings forecasts (I/B/E/S consensus of earnings in year t+1 measured as of March in year t+1 lagged by total assets) are greater than or equal to two-digit SIC code median earnings forecasts.

"Poor" expected future relative performance is where earnings forecasts (I/B/E/S consensus of earnings in year t+1 measured as of March in year t+1 lagged by total assets) are less than two-digit SIC code median earnings forecasts.

In Panel B, $EDAC_t^C$ are calculated using modified Jones method.

"Good" current relative performance is where unmanaged earnings (Inc_t – $EDAC_t^C$) are greater than or equal to two-digit SIC code median unmanaged earnings in year t.

"Poor" current relative performance is where unmanaged earnings (Inc_t – $EDAC_t^C$) are less than two-digit SIC code median unmanaged earnings in year t.

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