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Does incorporating non-linearity into discretionary accrual models improve their performance?

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ABSTRACT

Using a large sample of firms that restated earnings, this study investigates whether incorporating non-linearity (conditional conservatism) into discretionary accrual models improves their performance in detecting earnings management. The findings of this study are important because discretionary accrual models play a prominent role in several streams of accounting research and the models' ability to isolate the discretionary (managed) component from the non-discretionary (unmanaged) component of total accruals is critical. If the conventional linear discretionary accrual models are mis-specified, it is likely to result in misleading inferences about earnings management behavior. The findings indicate that the non-linear specification improves the performance of most linear models. The findings also indicate that a more sophisticated linear model that incorporates a performance measure and a future growth measure outperforms other simple models.

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1. Introduction

Discretionary (abnormal) accrual models play a prominent role in several streams of accounting research including earnings management, earnings quality, market inefficiency, and accrual manipulation. These streams of research are of interest not only to academics, but also to practitioners and regulators. It is generally assumed that discretionary accruals are the portion of accruals over which management exercises discretion, and this estimated portion of accruals is often used as a proxy for the portion of earnings that is managed. Therefore, the ability of discretionary accrual models to isolate the discretionary component from the non-discretionary component of total accruals is critical to a wide and growing body of accounting research.

The most widely used discretionary accrual models (for example, the Jones Model and the Modified Jones Model) are linear specifications. Ball and Shivakumar (2005) observe that because the accounting recognition of gains and losses is asymmetric, in that losses generally are recognized in a more timely fashion than gains (Basu, 1997), the relation between accruals and cash flows cannot be linear. This observation challenges the linear specification of discretionary accrual models. If linear discretionary accrual models are mis-specified, then the inferences about earnings management conditional on using a linear specification are questionable.

This paper investigates whether incorporating non-linearity into discretionary accrual models improves their performance using a sample of firms that issued financial statement restatements from 1997 to 2005. Here the non-linearity refers to the asymmetric timeliness of loss versus gain recognition. I examine the performance of discretionary accrual models in terms of their ability to detect earnings management as evidenced by firms that restate earnings. This research is important because there is considerable concern in the literature regarding the validity of inferences using discretionary accrual estimates generated from extant linear discretionary accrual models (McNichols, 2000; Ball & Shivakumar, 2005).

Ball and Shivakumar (2006) (hereafter BS) are the first to examine the non-linear specification of discretionary accrual models using a piecewise linear regression framework.[1] They find that the non-linear accrual specification provides a substantial improvement, explaining up to three times the amount of variation in accruals as conventional linear specifications.

This paper extends Ball and Shivakumar (2006) in several ways. First, Ball and Shivakumar (2006) evaluate the improvement of incorporating non-linearity into discretionary accrual models by focusing primarily on the improvement of explanatory power (i.e., adj. R^2) during the estimation stage. While this exercise is informative, it does not provide evidence on whether incorporating non-linearity into discretionary accrual models improves their performance in detecting the *existence* of earnings management. Furthermore, Thomas and Zhang (2000) note that even though a discretionary accrual model has relatively high explanatory power in the estimation stage, it does not necessarily perform well in detecting earnings management that is present in a testing sample. Therefore, whether incorporating non-linearity into discretionary accrual models improves their performance

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[1] In this paper, the "non-linear" and "piecewise linear" are used exchangeably.

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in detecting earnings management is still an open question. This paper attempts to address this important question.

Second, the accrual models examined by Ball and Shivakumar (2006) are the Cash Flow Model (Dechow, Kothari, & Watts, 1998), the Dechow–Dichev Model (Dechow & Dichev, 2002), and the Jones Model (Jones, 1991). Among these three models, the Cash Flow Model is not widely used, the Dechow–Dichev Model is used to derive a measure of earnings quality, and only the Jones Model is widely used in the literature to detect the presence of earnings management. Prior literature finds that refined Jones-type models, e.g., the Modified Jones Model (Dechow, Sloan, & Sweeney, 1995), the Modified Jones Model — Larcker and Richardson (2004), the Forward-Looking Model (Dechow, Richardson, & Tuna, 2003), and the Modified Forward-Looking Model (Collins & Wan, 2005), tend to out-perform the traditional Jones Model in detecting the presence of earnings management (Collins & Wan, 2005). Even though the non-linear specification improves the Jones Model's explanatory power, whether incorporating non-linearity into the *refined* Jones-type models improves their performance is still an unresolved issue. Thus, this paper extends Ball and Shivakumar (2006) by examining whether non-linear specifications of more refined discretionary accrual models enhance detection of earnings management. The discretionary accrual models evaluated in this paper are the Jones Model, the Modified Jones Model, the Modified Jones Model — Larcker and Richardson (2004), the Performance Matched Modified Jones Model, and the Modified Forward-Looking Model.[2] (Each of these models will be described more fully below.)

Firms that have restated earnings provide a useful sample for this evaluation because: (1) it is known that earnings management has occurred; (2) the restatement year(s) can be identified; and (3) the magnitude of earnings that has been managed is measurable. Therefore, with the restatement sample, I can identify the firms that engage in income increasing (income decreasing) earnings management. Another unique feature of this sample is that earnings restatements are real instances of earnings management. Thus, it has comparative advantage over the simulation techniques used by many studies (Dechow et al., 1995; Kang & Sivaramakrishnan, 1995; Kothari, Leone, & Wasley, 2005). Although simulation studies are informative, there is no guarantee that accrual behavior of simulated data is reflective of real earnings management. Moreover, these studies use parameter values estimated from observed data that to some degree are likely managed. Thus, the external validity of these studies may be limited. Using real instances of earnings management enhances the external validity of studies designed to detect earnings management.

This study makes several contributions to the extant literature. First, prior studies find that existing discretionary accrual models fail to generate accurate estimates of the magnitude of discretionary accruals (Thomas & Zhang, 2000; Fields, Lys, & Vincent, 2001). Therefore, there is demand for better discretionary accrual models that more accurately estimate the portion of accruals that is managed (i.e., discretionary accruals) (Kothari, 2001; Guay, 2006). However, much of the research to date has been restricted to linear specifications of discretionary accrual models. This paper extends this line of research by providing evidence on the usefulness of non-linear specifications of discretionary accrual models that take account of the asymmetric timeliness of loss and gain recognition following the work of Ball and Shivakumar (2006).

Second, Guay (2006) speculates that BS non-linear approach to estimate discretionary accruals may have the same effect as performance matching approach (Kothari et al., 2005).[3] This paper provides evidence that the BS approach accomplishes something beyond merely performance matching. My results show that the discretionary accrual models using the BS non-linear specification perform better than the discretionary accrual models with performance matching.

Finally, this paper provides additional evidence on the superior performance of the Modified Forward-Looking Model first proposed by Collins and Wan (2005). The Modified Forward-Looking Model incorporates two adjustments to Forward-Looking models: (1) including return on assets (ROA) to control for the effects of firm performance on abnormal accruals (Dechow et al., 1995; Kothari et al., 2005); and (2) substituting analysts' earnings forecast for look-ahead sales growth, which solves the implementation problem of the forward-looking model proposed by Dechow et al. (2003) (a more complete explanation of these refinements will be provided in Section 2). Collins and Wan (2005) find that the Modified Forward-Looking Model is well specified and out-performs the other models in detecting earnings management.

While I find that the non-linear specification provides significant improvement over the linear specification for all models in detecting the existence of earnings management, I also find that the linear Modified Forward-Looking Model proposed by Collins and Wan (2005) is effective in detecting earnings management. This finding suggests that the Modified Forward-Looking Model captures at least some of the non-linearity due to asymmetric timeliness of loss versus gain recognition. There are two features of the Modified Forward-Looking Model that may account for this finding. First, the Modified Forward-Looking Model includes ROA to control for performance which, according to Guay (2006), may accomplish similar things as the BS's non-linear specification.[4] Second, BS incorporate conditional conservatism into the discretionary accrual models. Conditional conservatism refers to the asymmetric timeliness of earnings reflecting bad versus good news. The bad/good news is about losses/gains that will be realized in the *future*. The Modified Forward-Looking Model includes analysts' earnings forecasts to control for future growth. When analysts generate earnings forecasts, they implicitly take into consideration future gains and losses. Therefore, including analysts' earnings forecasts is likely to capture the conditional conservatism that is incorporated by BS's non-linear specification.

The remainder of the paper is organized as follows. Section 2 describes the alternative discretionary accrual models and the non-linear specification that takes account of the asymmetric timeliness of loss versus gain recognition. Section 3 describes the sample selection. Section 4 discusses the empirical tests and reports the results. The paper concludes in Section 5 with a short summary and suggestions for future research.

2. Discretionary accrual models and non-linearity

2.1. Conventional linear discretionary accrual models

In this sub-section, I discuss the conventional linear discretionary accrual models used in prior literature. The purpose of a discretionary accrual model is to decompose total accruals into two components: non-discretionary accruals and discretionary accruals. Discretionary accruals are the component of earnings that is deemed to reflect the portion of earnings that is managed. The implementation of the models starts with total accruals (TACC). I follow Collins and Hribar (2002) and compute total accruals from the Statement of Cash Flows as follows:

$$TACC_{it} = EBXI_{it} - CFO_{it} \tag{1}$$

[2] The other refined models include the Lagged Model (Dechow et al., 2003), the Forward-Looking Model (Dechow et al., 2003). These models are not examined because Collins and Wan (2005) find that the Modified Forward-Looking Model dominates these models.

[3] The reason for performance matching is because many studies (e.g., Dechow et al., 1995, 1998; Guay et al., 1996; McNichols, 2000) find that estimated discretionary accruals are correlated with a firm's performance.

[4] Guay (2006, p. 252) states that “Ball and Shivakumar's approach recognizes that accruals in the presence of poor performance are expected to be asymmetric relative to accruals in the presence of good performance. As a result, their adjustment to the accruals models may aid researchers in mitigating *performance-induced measurement error*.” Guay further states that “it is possible that Ball and Shivakumar approach and the KLW approach accomplish similar things (this is, both approaches accomplish the correction of the bias caused by performance).”

where TACC = total accruals; EBXI = earnings before extraordinary items and discontinued operations (Compustat #123); and CFO = Cash Flows from Operation (Compustat #308 − Compustat #124).[5]

In order to estimate the parameters for the various discretionary accrual models, an estimation sample and a test sample need to be specified. In this study, I treat all the non-restatement firm-years as the estimation sample and all the restatement firm-years as the test sample. To implement the models, I first estimate the parameters on the estimation sample using the following regression:

$$TACC = \boldsymbol{\beta}\mathbf{X} + \varepsilon \tag{2}$$

where $\mathbf{X}$ = a vector of independent variables (explained in more detail below) scaled by beginning total assets included in the model; and ε = the error term.

With the estimated parameters, the non-discretionary accruals (NDA) in the test sample are calculated as follows:

$$NDA = \hat{\beta}X$$

Then the discretionary accruals (DA) are calculated as follows:

$$DA = TACC\text{–}NDA.$$

In this study, I examine the Jones Model (Jones, 1991), the Modified Jones Model (Dechow et al., 1995), the Modified Jones Model — Larcker and Richardson (2004), the Performance Matched Modified Jones Model (Kothari et al., 2005), and the Modified Forward-Looking Model (Collins & Wan, 2005).[6]

2.1.1. The Jones Model

The Jones, 1991 Model attempts to control for the effects of changes in a firm's economic circumstances on nondiscretionary accruals. To do this, it expresses accruals as a function of the change in sales revenues and the level of gross property, plant, and equipment (PPE). More specifically, it is estimated for each two-digit SIC-year grouping as follows:

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it}) + \beta_3 PPE_{it} + \varepsilon_{it} \tag{3}$$

where TACC = total accruals scaled by beginning total assets, TA_{it-1}; TA_{it-1} = firm i's year t − 1 total assets (Compustat #6); $\Delta SALES_{it}$ = the change in firm i's sales (Compustat #12) from year t − 1 to t scaled by beginning total assets, TA_{t-1}; PPE_{it} = firm i's year t gross property, plant, and equipment (Compustat #7) scaled by TA_{t-1}; and ε_{it} = the error term. Following Kothari et al. (2005), I include a constant in the model because their results indicate that failure to include a constant magnifies misspecification of the Jones models (Kothari et al., 2005, p192).[7]

The idea of the Jones Model is that sales revenue proxies for the economic events that generate current non-discretionary accruals, while gross PPE controls for non-discretionary accruals related to depreciation expense. Thus, the Jones Model makes two key assumptions. First, sales revenues are assumed to be unmanaged so that they can be used as an explanatory variable. If earnings are managed through sales revenues, then the Jones Model will remove part of the managed earnings from the discretionary accruals. The second assumption is that *changes* in current assets and current liabilities (i.e. working capital accruals) are driven by changes in sales revenue. To the extent that current liability accruals (e.g., an increase in accounts payable) is unrelated to current sales revenues, this model potentially suffers from an omitted variables problem (Kang & Sivaramakrishnan, 1995; Kang, 1999).

2.1.2. The Modified Jones Model

The Modified Jones (MJ) Model proposed by Dechow et al. (1995) is designed to eliminate the tendency of the Jones Model to measure discretionary accruals with error when discretion is exercised over revenues. The modification relative to the Jones Model is that the change in sales revenues is adjusted for the change in accounts receivable. The Modified Jones Model assumes that all credit sales are discretionary. This is based on the reasoning that it is easier to manage credit sales than cash sales.

Following Kothari et al. (2005), I estimate the Modified Jones Model for each two-digit SIC-year grouping as follows:

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \varepsilon_{it} \tag{4}$$

where ΔAR_{it} = the change in firm i's accounts receivable (Compustat #302) from year t − 1 to t scaled by TA_{t-1}.

2.1.3. The Modified Jones Model — Larcker and Richardson (2004)

Larcker and Richardson (2004) add the book-to-market ratio (BM) and cash flows from operations (CFO) to the Modified Jones Model. The purpose of including BM is to control for the expected growth in the firm's operations. CFO controls for current operation performance. Larcker and Richardson (2004) find that their model is superior to the Modified Jones Model. The model is estimated for each two-digit SIC-year grouping as follows:

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 BM_{it} + \beta_5 CFO_{it} + \varepsilon_{it} \tag{5}$$

where BM_{it} = ratio of the book value of common equity (Compustat #60) to the market value of common equity (Compustat # 25 × # 199), CFO = Cash flows from operations (Compustat #308) scaled by TA_{t-1}.

2.1.4. The Performance-Matched Modified Jones Model

Empirical evidence suggests that estimated discretionary accruals are correlated with firm performance (e.g., Dechow et al., 1995, 1998; Guay, Kothari, & Watts, 1996; McNichols, 2000; Barth, Cram, & Nelson, 2001; Kothari et al., 2005). Thus, it is important to control for financial performance when estimating discretionary accruals. Kothari et al. (2005) find that the Performance-Matched Modified Jones (PM) Model is better specified and more powerful at detecting earnings management than the traditional Modified Jones Model. Kothari et al. (2005) propose two ways to control for the impact of performance on estimated discretionary accruals: (1) using the discretionary accruals of a firm matched on current performance (ROA) and (2) including a measure of firm performance (ROA) in the discretionary accruals model. In this study, I use the latter approach.

The Performance-Matched Modified Jones Model is estimated for each two-digit SIC-year grouping as follows:

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 ROA_{it} + \varepsilon_{it} \tag{6}$$

where ROA_{it} = firm i's return on assets of year t.

2.1.5. The Modified Forward-Looking Model

The Modified Forward-Looking Model is an extension of the Forward-Looking Model proposed by Dechow et al. (2003). The Dechow et al. (2003) Forward-Looking Model makes three adjustments to the Modified Jones Model. First, the Modified Jones Model assumes all credit sales are discretionary which induces a positive

[5] I subtract the cash portion of discontinued operations and extraordinary items (Compustat #124) from total cash from operations to provide a cash flow from continuing operations. This cash flow definition is consistent with the definition of net income.

[6] The other models are not included because Collins and Wan (2005) find they do not out-perform the Modified Forward-Looking Model. The Jones Model, the Modified Jones Model, the Modified Jones Model — Larcker and Richardson (2004), and the Performance Matched Modified Jones Model are included because they are the most widely used models in the literature.

[7] Therefore, I include a constant in all the models investigated in this paper.

correlation between discretionary accruals and current sales growth. The Forward-Looking Model treats the expected change in accounts receivable for a given change in sales as non-discretionary. Second, the Forward-Looking Model includes lagged total accruals as an explaining variable because a portion of total accruals is predictable based on last year's total accruals (Chambers, 1999). Thus, this portion of accruals is non-discretionary. Third, because accruals by their nature are designed to smooth the cash flow effect of financial transactions, a firm that is growing and anticipates future sales will rationally increase inventory balances. The Modified Jones Model classifies such increases as discretionary accruals reflecting earnings management. Including future sales growth in the model corrects this kind of misclassification.

The Forward-Looking Model is estimated as follows:

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2((1+k)DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 TACC_{it-1} + \beta_5 GR\_SALES_{it+}1 + \varepsilon_{it}$$

where k = the regression coefficient from a regression $\Delta AR_{it} = \alpha + k\Delta SALES_{it} + \varepsilon_{it}$ for each two-digit SIC-year grouping; $TACC_{it-1}$ = firm i's total accruals at year t − 1 scaled by TA_{t-1}; and GR_SALES_{it+1} = the change in firm i's sales (Compustat #12) from year t to t + 1 scaled by year t sales.

As noted by Dechow et al. (2003), the information on GR_SALES_{it+1} is not available to financial statement readers until the following year. Therefore, this model suffers from a look-ahead bias.

Collins and Wan (2005) propose a modified version of the Forward-Looking Model that mitigates this look-ahead bias. They make two adjustments to the Forward-Looking Model. First, analysts' long-term earnings growth *forecasts* are used as a proxy for GR_SALES.[8] This proxy is referred as EST_GROWTH. Second, the contemporaneous ROA is included to control for performance (Dechow et al., 1995; Kothari et al., 2005; McNichols, 2000).[9]

I estimate the Modified Forward-Looking Model for each two-digit SIC-year group as follows:

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2((1+k)DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 TACC_{it-1} + \beta_5 EST\_GROWTH_{it} + \beta_6 ROA_{it} + \varepsilon_{it} \quad (7)$$

where EST_GROWTH_{it} = the median of analysts' long-term earnings growth forecasts for firm i for the last month of year t.

2.2. Non-linear discretionary accrual models

The discretionary accrual models outlined in the previous section use a linear specification. Ball and Shivakumar (2005) observe that because the accounting recognition of gains and losses is asymmetric, in that losses generally are recognized in a more timely fashion than gains (Basu, 1997), the relation between accruals and cash flows cannot be linear. Ball and Shivakumar (2006) further argue that the conventional linear discretionary accrual models are mis-specified given the well documented conditional conservatism. Rather, they propose that the correct specification is more likely a piecewise linear function. They estimate piecewise linear discretionary accrual models in the following generic form:

$$TACC = \beta\mathbf{X} + \gamma_1 VAR + \gamma_2 DVAR + \gamma_3 DVAR * VAR + \varepsilon \quad (8)$$

where **X** = a vector of independent variables derived to be determinants of non-discretionary accruals (see discussion in previous section); VAR = a proxy for economic gain or loss; DVAR = a (0,1) dummy variable that takes the value of 1 if VAR implies a loss; and ε = the error term.

The γ_3 parameter is predicted to be positive because of the more timely recognition of losses than gains. Comparing Eq. (8) with Eq. (2), three additional variables are included to capture the piecewise linear relation for non-discretionary accruals caused by asymmetric recognition of losses versus gains — VAR, DVAR, and DVAR ∗ VAR (the interaction between these two variables). I follow Ball and Shivakumar (2006) and employ the piecewise linear framework to incorporate the non-linearity into the four discretionary accrual models examined in this paper (refer to Appendix A for details).

Ball and Shivakumar (2006) employ four proxies for economic gains and losses. The four proxies are cash flows from operations, change in cash flows from operations, industry-adjusted cash flows from operations, and abnormal returns. Each proxy has potential strengths and weaknesses. I use abnormal returns as the proxy for economic gains and losses since abnormal returns reflect investor expectations for future gains and losses.[10] To the extent markets are efficient, abnormal returns should also more accurately reflect the asymmetrically timely recognition of losses versus gains, relative to various measures of cash flows employed in Ball and Shivakumar (2006).

To evaluate the benefit of incorporating non-linearity into discretionary accrual models, Ball and Shivakumar (2006) focus primarily on the improvement of explanatory power during the estimation period. Their findings show that the non-linear specification increases the explanatory power during the estimation stage. But as noted previously, their approach assumes that there is no earnings management for firms in the estimation stage. Thus, it is not clear how the piecewise linear discretionary accrual models perform in detecting the presence of earnings management outside of the estimation stage. In addition, Thomas and Zhang (2000) find that many discretionary accrual models have high explanatory power in the estimation period, but do not perform well in detecting earnings management on a test sample (i.e., out of sample test). Therefore, whether incorporating non-linearity into discretionary accrual models improves their performance in out of sample tests is still an open question. This paper attempts to fill this void in the literature by comparing the performance of the traditional linear and piecewise linear discretionary accrual models in detecting earnings management for a restatement sample where it is known, ex post, the amount of earnings that has been managed.

3. Sample description

My restatement sample is obtained from the studies by the General Accounting Office (GAO, 2002, 2006) that identifies firms involved in accounting irregularities resulting in *material misstatements* of financial results.[11] These reports identify 1966 firms that made 2309 restatement announcements during January 1997 to September 2005.[12] For each

[8] Ideally, I would like to use analysts' long-term sales forecasts. However, sales forecasts are only available for a limited number of firms followed by IBES and Value Line. Thus, I use analysts' long-term earnings forecasts instead. I performed correlation test of sales and earnings long-term forecasts. The Pearson (Spearman) correlation coefficient is 0.5583 (0.8046). The Hoeffding Dependence Coefficient is 0.3255. All three coefficients are highly significant (p-values < 0.0001).

[9] Dechow et al. (1995, p. 193) conclude that "all models reject the null hypothesis of no earnings management at rates exceeding the specified test levels when applied to samples of firms with extreme financial performance." These results illustrate the importance for performance control.

[10] The proxies related to cash flows from operations are not appropriate for this setting. For Performance-Matched Model, ROA is included in the right hand of the regression. Total Accrual is defined as Net Income − CFO. When CFO is used as proxy for economic gains and losses and included as an independent variable, it causes an identity problem and the R^2 is more than 99%.

[11] The GAO defines an accounting irregularity as "an instance in which a company restates its financial statements because they were not fairly presented in accordance with generally accepted accounting principles (GAAP)" (GAO, 2002, p.2).

[12] The GAO database excludes "restatements resulting from mergers and acquisition, discontinued operations, stock splits, issuance of stock dividends, currency-related issues, changes in business segment definitions, changes due to transfers of management, changes made for presentation purposes, general accounting changes under generally accepted accounting principles (GAAP), litigation settlements, and arithmetic and general bookkeeping errors" (GAO, 2002). Also note that a given restatement announcement can refer to a restatement that affects only a single year or to one that affects multiple years.

restatement announcement, I search Lexis Nexis to identify the restated fiscal year.[13] The restated fiscal year is the period which the discretionary accruals are measured. Each restatement firm is matched with another company that does not restate its financial statement at any time during 1997 through 2005. For each restating company, I select a non-restating company that is in the same (two-digit) SIC code and year and is closest in total assets to the restating company. I refer to the control sample as the non-restatement sample.

Panel A of Table 1 details firms excluded due to various sample selection criteria to arrive at my final sample of 112 unique firms. The 1966 firms that made restatement announcements consist of restatements of annual and/or quarterly financial statements. For this study, I exclude quarterly restatements to avoid estimation problems associated with seasonality of revenues and expenses for certain industries, which eliminates 926 firms. Following Hennes, Leone, and Miller's (2008) procedure, I delete 218 firms whose restatements are not caused by accounting irregularity. Another 265 firms are excluded because they do not have analysts' forecasts. I exclude additional 205 firms that do not have CRSP return data. Further, I exclude 50 firms in financial services and utility industry. Finally, I delete observations without sufficient Compustat data to estimate discretionary accrual models, which eliminates another 190 firms. My final restatement sample consists of 112 firms with 246 restatement firm-years.

Panels B and C of Table 1 provide information on the year and industry distribution of the restatement firms. Panel B shows that the sample does not concentrate in any particular year with largest percentage of restatements (20.33%) occurring in 2001. Panel C describes the industry distribution of the restatement sample by two-digit SIC code. The 246 firm-years are in 29 different two-digit Standard Industrial Classifications. Thus, the restatement sample contains a broad cross section of firms. There is no evidence of industry clustering in the sample. The most common restatements occur in the Business Services (2-digit SIC code 73 19.92%) followed by the Computer (2-digit SIC code 35 11.79%).

Table 1
Sample composition.

Panel A: Description of restatement sample

Restatement firms		1966
Less:		
Quarterly restatements	(926)	
Restatements not caused by irregularity	(218)	
Analysts forecasts data are not available	(265)	
CRSP return data are not available	(205)	
Financial and utility firms	(50)	
Insufficient financial data to estimate the models	(190)	
		(1854)
Restatement sample − firm		112
Restatement sample − firm-years		*246*

Panel B: Distribution of restatement fiscal years

Year	Frequency	%
1995	1	0.41%
1996	7	2.85%
1997	14	5.69%
1998	27	10.98%
1999	31	12.60%
2000	46	18.70%
2001	50	20.33%
2002	35	14.23%
2003	28	11.38%
2004	7	2.85%
Total	246	100.00%

Panel C: Industry distribution of restated firm years by 2-digit SIC codes

2-digit SIC	Industry name	# of obs.	%
20	Food	8	3.25%
23	Apparel	8	3.25%
26	Paper and allied products	4	1.63%
28	Chemicals & allied products	21	8.54%
33	Primary metal industries	7	2.85%
34	Fabr metal	4	1.63%
35	Computer	29	11.79%
36	Electric	5	2.03%
37	Transportation equipment	9	3.66%
38	Measure instrument	7	2.85%
42	Motor freight transportation	1	0.41%
47	Transportation services	7	2.85%
48	Communications	9	3.66%
50	Durable goods	11	4.47%
51	Nondurable goods	8	3.25%
53	General merchandise	6	2.44%
54	Food stores	10	4.07%
58	Eating and drinking places	2	0.81%
59	Misc. retail	3	1.22%
61	Nondepositoray credit inst.	3	1.22%
62	Security & commodity brokers	3	1.22%
63	Insurance carries	10	4.07%
64	Ins agents, brokers & service	3	1.22%
73	Business services	49	19.92%
78	Motion pictures	1	0.41%
79	Amusements, recreation	6	2.44%
80	Health services	2	0.81%
87	Professional services	8	3.25%
99	Others	2	0.81%
	Total	246	100.00%

4. Results

4.1. Implementation of discretionary accrual models

To begin my analysis, I first implement the discretionary accrual models examined in this paper. Recall, I use all non-restatement firm-years as the estimation sample to implement the discretionary accrual models. Table 2 provides correlations of the variables for the discretionary accrual models. Three points emerge from observing the correlations. First, the variables, ΔSALES, ΔSALES − ΔAR, and $(1 + k)\Delta$SALES − ΔAR, are highly correlated as expected. Second, another set of variables, VAR, DVAR, and D_VAR, are also highly correlated. Third, the Pearson correlations of other independent variables range from −0.243 to 0.266, suggesting that there is no multicollinearity concern.

Table 3 provides the parameter estimates from various discretionary accrual models. The parameter estimates for Jones Model and Modified Jones Model are consistent with prior studies with a positive coefficient on sales revenues and a negative coefficient on PPE. For Modified Jones Model — Larcker and Richardson (2004) model, the coefficients on BM and CFO are significant. For the Performance Matched Model, the ROA variable, which is included to control for the effect of performance on discretionary accruals, is highly significant. For the Modified Forward-Looking Model, the coefficients on analysts' long-term earnings forecasts and ROA are all significant. For the non-linear Modified Forward-Looking Model, the coefficient on analysts' long-term earnings forecasts becomes insignificant after including the three additional variables that control for conditional conservatism, which indicates the analysts' long-term earnings forecasts and the three variables controlling for conservatism are correlated to a certain extent.

Table 3 also presents the replication of Ball and Shivakumar's (2006) results on my sample. Ball and Shivakumar (2006) predict that (1) γ_3 in Eq. (8) is positive and (2) the adjusted R^2 of the piecewise linear specification will exceed its equivalent in the conventional linear specification. Thus, I focus on these two results when I replicate Ball and Shivakumar (2006) on my sample. First, the coefficients on

[13] For example, Sunbeam Corporation made restatement announcement on June 30, 1998 to restate 1996's financial statements. The restated fiscal year is 1996 while the restatement announcement year is 1998.

Table 2
Correlations.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	TACC		0.164	0.111	0.119	−0.143	0.088	−0.019	0.525	0.275	−0.046	0.100	−0.089	0.183
2	ΔSALES	0.182		0.962	0.969	0.057	−0.124	−0.016	0.174	0.081	0.266	0.207	−0.169	0.169
3	ΔSALES2	0.112	0.940		0.991	0.057	−0.116	−0.014	0.167	0.078	0.240	0.186	−0.154	0.150
4	ΔSALES3	0.124	0.953	0.995		0.055	−0.118	−0.015	0.167	0.078	0.250	0.192	−0.157	0.153
5	PPE	−0.190	0.072	0.077	0.073		0.000	0.071	0.096	−0.133	−0.176	0.051	−0.053	0.098
6	BTM	0.077	−0.197	−0.183	−0.189	0.019		−0.031	0.105	0.074	−0.198	−0.168	0.149	−0.143
7	CFO	−0.158	0.078	0.090	0.087	0.271	−0.020		0.059	−0.009	−0.121	0.000	−0.012	0.047
8	ROA	0.363	0.398	0.363	0.369	0.133	−0.081	0.483		0.241	−0.243	0.171	−0.179	0.321
9	LTACC	0.313	0.094	0.087	0.088	−0.205	0.108	−0.040	0.143		−0.069	0.007	−0.013	0.065
10	Est_Growth	0.020	0.332	0.305	0.314	−0.230	−0.313	−0.414	0.028	0.011		0.168	−0.080	−0.042
11	VAR	0.120	0.243	0.214	0.220	0.086	−0.214	0.201	0.348	0.000	0.094		−0.695	0.697
12	DVAR	−0.075	−0.205	−0.182	−0.187	−0.054	0.193	−0.134	−0.262	0.012	−0.097	−0.851		−0.685
13	D_VAR	0.128	0.229	0.199	0.204	0.095	−0.185	0.237	0.361	0.009	0.033	0.966	−0.881	

This table reports the correlations among several interested variables based on 33,119 firm-year observations in 685 2-digit-SIC and year groups. The Pearson correlations are above the diagonal while the Spearman correlations are below the diagonal. ΔSALES2 is ΔSALES − ΔAR. ΔSALES3 is (1 + k)ΔSALES − ΔAR. All continuous variables are winsorized at 1% and 99% level. Please refer to Appendix A for other variables definitions.

VAR ∗ DVAR are significantly positive for the non-linear Jones Model, Modified Jones Models, Larcker and Richardson (2004) Model, and Performance Matched Model (γ_3 is 0.079, 0.087, 0.084, and 0.016, respectively), while it is *negative* and *insignificant* for the non-linear Modified Forward-Looking Model (γ_3 is −0.057). Second, for the Jones Model, Modified Jones Model, and the Larcker and Richardson (2004) Model, the adjusted R^2s for the non-linear specifications are significantly higher (p-values < 0.01) than those for their linear counterparts. For example, for the Jones Model, the adjusted R^2 increases from 14% under the conventional linear model to 18% under the non-linear specification. However, for the Performance Matched Model and Modified Forward-Looking Model, the adjusted R^2s for the non-liner specification are not significantly different from those for their linear counterparts. Focusing on the γ_3 parameter estimates and the adjusted R^2s, these results show that the non-linear specification provides a significant improvement for the Jones Model and the Modified Jones Model, and Larcker and Richardson (2004) Model. For the Performance Matched Model, the non-linear specification provides modest improvement in that it generates a significant positive γ_3 estimate but does not significantly increase the adjusted R^2. For the Modified Forward-Looking Model, the non-linear specification does not offer much improvement: the γ_3 parameter estimate is *insignificant* and the non-linear specification does *not* increase the adjust R^2. These replication results indicate that as the discretionary

Table 3
Implementation of discretionary accrual models.

CY4T	Jones Model		Modified Jones Model		LR Model		PM Model		Modified FL Model	
	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear
a	−0.042	−0.022	−0.042	−0.017	−0.038	−0.014	−0.034	−0.028	−0.024	−0.022
	−23.28	*−8.75*	*−22.50*	*−6.86*	*−17.27*	*−5.20*	*−21.36*	*−11.73*	*−8.39*	*−4.25*
1/TA	−0.143	−0.170	−0.146	−0.160	−0.211	−0.300	0.104	0.242	0.645	0.682
	−3.95	*−2.30*	*−3.79*	*−2.09*	*−5.18*	*−3.19*	*2.99*	*3.63*	*2.06*	*1.28*
ΔSALES*	0.044	0.037	0.031	0.020	0.030	0.020	−0.006	−0.013	−0.017	−0.059
	13.50	*11.22*	*9.92*	*4.99*	*8.17*	*4.63*	*−1.93*	*−3.27*	*−4.06*	*−1.73*
PPE	−0.044	−0.055	−0.043	−0.058	−0.048	−0.056	−0.058	−0.069	−0.072	−0.061
	−15.03	*−18.15*	*−14.62*	*−16.28*	*−14.07*	*−17.14*	*−20.84*	*−23.11*	*−8.37*	*−8.13*
BM					0.006	0.007				
					6.14	*4.03*				
CFO					−0.000	−0.000				
					−7.01	*−7.35*				
ROA							0.327	0.354	0.264	0.298
							37.33	*32.14*	*18.51*	*6.49*
LTACC									0.170	0.176
									16.00	*7.01*
EST_GROWTH									−0.035	−0.013
									−2.17	*−0.58*
VAR		−0.009		−0.005		−0.002		−0.009		−0.018
		−0.89		*−1.23*		*−0.54*		*−2.28*		*−2.04*
DVAR		0.014		0.013		0.012		0.003		−0.025
		6.52		*6.19*		*4.89*		*1.51*		*−0.98*
VAR ∗ DVAR		0.079		0.087		0.084		0.016		−0.057
		10.70		*13.49*		*11.58*		*2.80*		*−0.80*
Adj. R^2	14.26%	17.67%	12.82%	15.93%	15.98%	19.59%	34.87%	33.09%	34.11%	36.20%
$R^2_L - R^2_{NL}$										
p-Value	0.0005		0.0007		0.0007		0.1214		0.1950	

This table is based on the average results of 685 2-digit SIC and year observations. The sample period is 1995-2004. This table presents the regression results for various discretionary accrual models. Parameter estimates are averages from the respective 685 2-digit SIC-year regressions. T-statistics are reported italic below parameter estimates. Standard errors are based on distributions of 2-digit SIC-year parameter estimates.

This table also presents the replication of Ball and Shivakumar's results on my sample. The parameter of VAR ∗ DVAR is predicted to be significantly positive because of more timely recognition of losses than gains. The detailed specifications of the models are explained in Appendix A.

SALES* refers to ΔSALES for Jones Model, ΔSALES − ΔAR for Modified Jones Model, Modified Jones Model − Larcker and Richardson (2004), and Performance Matched Model, and (1+k)ΔSALES − ΔAR for Modified Forward-Looking Model. Please refer to Appendix A for variables definitions.

accrual models become more sophisticated, the improvement of the non-linear specification diminishes.

4.2. Comparison of discretionary accruals

To evaluate the alternative discretionary accrual models' ability to detect the *existence* of earnings management, I first examine whether the estimated discretionary accruals are significantly different between the test (restatement) and control (non-restatement) samples (both mean and median). If a discretionary accrual model generates a significant difference between the discretionary accruals of restatement and non-restatement samples (mean and median), then it is deemed to be a good model for identifying the existence of earnings management. If incorporating non-linearity improves the models' performance in detecting earnings management, I expect the non-linear discretionary accrual models will generate larger differences between the discretionary accruals of restatement and non-restatement samples relative to linear specifications.

Table 4 reports the results. Two points emerge from this test. First, both the mean and median tests indicate that the non-linear specification improves the performance of the Jones Model, the Modified Jones Model, the Larcker and Richardson (2004) Model, and the Performance Matched Model. For instance, the traditional linear Jones Model generates a mean average difference in absolute discretionary accruals between restatement and non-restatement firms of 0.005 (0.5% of last year's total assets), which is insignificant. In contrast, the non-linear Jones Model generates a mean average difference of 0.018 (1.80% of last year's total assets), which is significant at 0.014 level.

Second, for the Modified Forward-Looking Model, both the non-linear and linear specifications generate significant differences in discretionary accruals between non-restatement and restatement firms. For example, the conventional linear Modified Forward-Looking Model generates a mean (median) average difference of 1.20% (1.20%) of last year's total assets between restatement and non-restatement samples, which means the restatement sample has *higher* discretionary accruals than the non-restatement sample. On the other hand, the non-linear Modified Forward-Looking Model generates a mean (median) average difference of 2.49% (1.50%) of last year's total assets between restatement and non-restatement samples, which means the restatement sample has *higher* discretionary accruals than the non-restatement sample. Both the linear and non-linear forms of the Modified Forward-Looking Model produce differences that are highly significant. Thus, the univariate comparison of discretionary accruals of the two samples indicates that non-linear discretionary accrual models out-perform their conventional linear counterparts for the Jones Model, the Modified Jones Model, the Larcker and Richardson (2004) Model, and the Performance Matched Model. For the Modified Forward-Looking Model, the improvement offered by non-linear specification is limited.

4.3. Contingency table tests

A second way of evaluating the performance of linear versus non-linear specifications of alternative discretionary accrual models is to conduct univariate contingency table tests of the association of high versus low discretionary accruals and whether or not a firm had financial statements restatement. I assign firms to three groups based on the *absolute value* of the discretionary accruals. I then conduct contingency table tests on the first (lowest level of discretionary accruals) and the third (highest level of discretionary accruals) groups. A well specified discretionary accrual model should generate a relatively high number of restatement firms assigned to the third group (high discretionary accruals) and a relatively low number of restatement firms assigned to the first group (low discretionary accruals). The hypothesis (in alternative form) is that the proportion of restatement firms in the high discretionary accruals group is greater than the proportion of restatement firms in the low discretionary accruals group. If the non-linear specification is a better specification, I expect that the non-linear discretionary accrual models will do a better job of assigning restatement (non-restatement) firms to the high (low) discretionary accrual group.

Table 5 summarizes the findings from the contingency table tests. The results show that for the Jones Model, the Modified Jones Model, the Larcker and Richardson (2004) Model, and the Performance Matched Model, the non-linear specification out-performs the linear specification in terms of assigning restatement firms to the high discretionary accrual group. For example, out of 246 restatement firms, the conventional linear Jones Model assigns 89 firms (i.e., 36.18%) to the high discretionary accruals group and 80 firms (i.e., 32.52%) to the low discretionary accruals group. The difference is insignificant ($p\text{-value} = 0.19$). In contrast, the non-linear Jones Model assigns 91 firms (i.e., 36.99%) to the high discretionary accruals group and 70 firms (28.45%) to the low discretionary accruals group. The difference is significant ($p\text{-value} = 0.01$). Compared to the conventional linear model, the non-linear Jones Model assigns more (less) restatement observations to high (low) discretionary accrual group. That is, the non-linear specification improves the Jones Model's ability of assigning more restatement firms to the high discretionary accrual group.

For the Modified Forward-Looking Model, both the linear and non-linear specifications generate highly significant results in the predicted direction ($p\text{-value} < 0.0001$ for both specifications). Out of 246 restatement firms, the conventional linear Modified Forward-Looking Model assigns 95 firms (i.e., 38.62%) to the high discretionary

Table 4
Comparison of discretionary accruals.

	Mean					Median				
	Restatement sample	Non-restatement sample	Difference	t value	p-Value	Restatement sample	Non-restatement sample	Difference	z value	p-Value
DA_J	0.066	0.061	0.005	0.98	0.326	0.050	0.040	0.010	1.26	0.104
DA_J_NL	0.073	0.055	0.018	2.46	0.014	0.044	0.036	0.008	2.34	0.010
DA_MJ	0.067	0.061	0.006	1.05	0.293	0.051	0.040	0.011	1.62	0.053
DA_MJ_NL	0.075	0.055	0.020	2.36	0.019	0.043	0.033	0.010	1.98	0.024
DA_LR	0.068	0.062	0.006	1.03	0.305	0.048	0.041	0.006	1.44	0.075
DA_LR_NL	0.070	0.057	0.013	2.08	0.038	0.046	0.036	0.010	1.98	0.024
DA_PM	0.056	0.053	0.003	0.52	0.603	0.042	0.034	0.008	1.44	0.075
DA_PM_NL	0.065	0.051	0.014	1.81	0.071	0.039	0.032	0.007	1.62	0.053
DA_MFL	0.060	0.048	0.012	2.18	0.030	0.044	0.033	0.012	2.88	0.002
DA_MFL_NL	0.071	0.046	0.025	3.44	0.001	0.045	0.030	0.015	3.06	0.001
OBS	246	246				246	246			

This table provides result from comparison of discretionary accruals between restatement and non-restatement firms using the absolute value of the estimates from various discretionary accrual models.
For definition of the DA variables, please refer to Appendix A.

accruals level and 63 firms (i.e., 25.61%) to the low discretionary accruals level, while the non-linear Modified Forward-Looking Model assigns 98 firms (i.e., 39.83%) to the high discretionary accruals level and 68 firms (27.64%) to the low discretionary accruals level. Both specifications generate highly significant results. Untabulated binomial tests indicate that there is no significant difference between the proportions for linear and non-linear Modified Forward-Looking Models. Thus, I conclude that the non-linear specification offers little improvement over the linear Modified Forward-Looking Model in assigning more restatement firms to the high discretionary accruals level.

4.4. Logistic regression results

A final way of analyzing the performance of linear versus non-linear discretionary accrual models is to conduct logistic regression analyses to determine how well discretionary accruals from each model detect the presence of earnings management, where earnings restatement is the proxy for earnings management. Using a logit framework, the model is as follows:

$$\mathrm{Ln}[P_{iR}/(1-P_{iR})] = \beta_0 + \beta_1 \mathrm{abs}\left(\mathrm{DA}^i\right) + \text{other control variables} \tag{9}$$

where P_{iR} = the probability of firm i is a restatement firm; DA^i = discretionary accrual estimate according to model i; and abs(x) = absolute value of x.

This specification only answers the question whether an estimate from a specific model is useful in detecting earnings management. It does not provide a direct answer to whether the non-linear specification provides significant improvement over the linear specification in detecting earnings management. Thus, I propose a method to address this question. In the same specification, I include both discretionary accruals estimated from a linear model ($\mathrm{DA_L}$) and the difference (DIFF) between the discretionary accruals estimated from non-linear ($\mathrm{DA_{NL}}$) and linear models ($\mathrm{DA_L}$). The specification is as follows:

$$\mathrm{Ln}[P_{iR}/(1-P_{iR})] = \beta_0 + \beta_1 \mathrm{abs}\left(\mathrm{DA}^i_L\right) + \beta_2 \mathrm{DIFF}^i + \text{other control variables} \tag{10}$$

where $\mathrm{DA}^i{}_L$ = discretionary accrual estimate according to linear model i; $\mathrm{DIFF}^i = \mathrm{abs}(\mathrm{DA}^i{}_{NL}) - \mathrm{abs}(\mathrm{DA}^i{}_L)$; and abs(x) = absolute value of x. If the non-linear specification provides significant improvement over the linear specification, I expect the coefficient on DIFF^i, β_2, to be positive and significant.

The absolute values of DA are used as independent variables in the logistic regressions following prior studies (for example, Bartov, Gul, & Tsui, 2001). Following Phillips, Pincus, and Rego (2003), I include ΔCFO (Cash Flows from Operation) to control for the change in fundamental economic performance. I also include $\Delta\mathrm{CFO}^2$ to allow for a possible nonlinear relation. To control for industry and year effects, I run the regression with fixed industry and year effect. I only report the coefficients on DA^i_L and DIFF^i for simplicity.

Table 6 provides results for the logistic regression analyses. I note three important things in Table 6. First, for Jones, Modified Jones, LR, and Performance Matched models, the coefficient on $\mathrm{DA_L}$ are insignificant, which suggests that these linear models are not effective in detecting earnings management. Second, for the Modified Forward-Looking Model, unlike the other three models, the coefficient on $\mathrm{DA_L}$ is positive (3.6766) and is significant (p-value = 0.04), suggesting that discretionary accruals estimated from the linear Modified Forward-Looking Model are useful in detecting the presence of earnings management. Third, the coefficients on DIFF^i are significant for all the models, indicating that non-linear specification provides significant improvement over the linear specification in identifying the existence of earnings management that results in restatement.

In summary, all three earnings management detection tests provide consistent conclusions. First, the non-linear specification provides significant improvement to the Jones Model, the Modified Jones Model, the Larcker and Richardson (2004) Model, and the Performance Matched Model. Second, Ball and Shivakumar's (2006) approach accomplishes something beyond merely performance matching. This conclusion is based on a comparison of *non-linear* Modified Jones Model and *linear* Performance Matched Modified Jones Model. Both models make some adjustment to the Modified Jones Model. They are different in that the non-linear Modified Jones Model employs Ball and Shivakumar's piecewise linear specification incorporating conservatism while the linear Performance Matched Model adds ROA to control for performance. The results indicate that the non-linear Modified Jones Model outperforms the linear Performance Matched Model in all three tests (please refer to Table 4, 5, and 6). Thus, I conclude that Ball and Shivakumar's approach accomplishes something more than performance matching as suggested by Guay (2006). Third, both linear and non-linear Modified Forward-Looking models perform well in detecting the existence of earnings management.

4.5. Income increasing, income decreasing subsamples

With the restatement sample, both the originally reported and restated earnings can be observed. Therefore, it is possible to identify whether a firm engages in income increasing or income decreasing earnings management. Of the 246 restatement years, I have 192 firm years in the income increasing group and 54 in the income decreasing group. Next, I perform the same analyses on the two subsamples to evaluate the performance of the alternative models.

Table 5
Contingency table tests.

	Jones Model				Modified Jones Model				LR Model				Performance Matched Model				Modified Forward-Looking Model			
	Linear		Non-linear		Linear		Non-linear		Linear		Non-linear		Linear		Non-linear		Linear		Non-linear	
Restated	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
High DA	89	75	91	73	87	77	93	71	87	77	95	69	85	79	92	72	95	69	98	66
Low DA	80	84	70	94	80	84	72	92	84	80	73	91	78	86	75	89	63	101	68	96
p-Value	0.1884		0.0135		0.2538		0.0135		0.4125		0.0101		0.2538		0.0385		0.0003		0.0006	

This table reports the results of contingency tables tests which examines the association of high versus low discretionary accruals and whether or not a firm had financial statement restatement. I assign firms to 3 groups based on the absolute value of the discretionary accruals. I then conduct the contingency table tests on the first (Low DA) and the third (High DA) groups. A well specified discretionary accrual model should generate a relatively high number of restatement firms assigned to the high DA quintile and a relatively low number of restatement firms assigned to the low DA quintile.
The alternative hypothesis is the proportion of restatement firms in the high discretionary accruals quintile is greater than the proportion of restatement firms in the low discretionary accruals quintile.
For definition of the DA variables, please refer to Appendix A.

Table 6
Comparison of linear versus non-linear DA measures.

$$\mathrm{Ln}[P_{iR}/(1-P_{iR})] = \beta_0 + \beta_1 \mathrm{abs}\left(\mathrm{DA}^i\right) + \beta_2 \mathrm{DIFF}^i + \beta_3 \mathrm{DCFO} + \beta_4 \mathrm{DCFO}^2 + \sum \beta_i \mathrm{IND}_i + \sum \beta_t \mathrm{YEAR}_t.$$

	Pred. sign	DA	p-Value	Pred. sign	DIFF	p-Value	Log Likelihood	Pseudo R^2
Jones Model	+	2.133	0.149	+	5.438	0.052	8.725	0.023
Modified Jones Model	+	2.270	0.124	+	5.658	0.047	9.179	0.025
LR Model	+	2.077	0.14	+	5.417	0.05	8.950	0.024
Performance Matched Model	+	0.762	0.64	+	5.946	0.08	7.067	0.019
Modified Forward-Looking Model	+	3.677	0.04	+	12.838	0.00	19.341	0.051

This table presents the results from logistic regression analyses. The predicted signs for both DA and DIFF are positive. The results are based on 246 restatement firms and 246 non-restatement firms. The sample period is 1995–2004. Please refer to Appendix A for variables definitions.

Table 7 reports the results for the income increasing subsample. The three tests generate similar results as for the whole sample. That is, the non-linear specification improves the performance of the linear discretionary accrual models. The linear Modified Forward-Looking Model also performs well in detecting earnings management.

Table 8 presents the results from the income decreasing subsample. The panels offer mixed results. Therefore, it is hard to make a conclusion whether non-linear specification improves the performance of the discretionary accrual models. One reason is that the sample size is small (only 54 restated firm years), especially for the contingency table tests (the sample size needs to be greater than 80 to make reasonable inferences from the contingency table test). Another reason may be that firms managing earnings downward are systematically different from those engaging in income increasing earnings management.

4.6. Discussion

The findings from earnings management detection analyses are interesting in that while all non-linear models are significant in detecting the existence of earnings management, the linear Modified Forward-Looking Model is also significant. One explanation is that the adjustments made to the Modified Forward-Looking Model capture some of the non-linearity due to asymmetric timeliness of loss versus gain recognition.

This conclusion is based on two arguments. First, in commenting on the Ball and Shivakumar (2006) study, Guay (2006) notes, “Ball and Shivakumar's approach recognizes that accruals in the presence of poor performance are expected to be asymmetric relative to accruals in the presence of good performance. As a result, their adjustment to the accruals models may aid researchers in mitigating performance-induced measurement error.” Guay further states that

Table 7
Income increasing subsample.

Panel A: Comparison of discretionary accruals

	Mean					Median				
	Restatement sample	Non-restatement sample	Difference	t value	p-Value	Restatement sample	Non-restatement sample	Difference	z value	p-Value
DA_J	0.028	0.008	0.020	2.13	0.034	0.029	0.011	0.018	2.24	0.012
DA_J_NL	0.002	−0.007	0.009	0.74	0.462	0.018	−0.002	0.020	2.65	0.004
DA_MJ	0.028	0.008	0.020	2.12	0.034	0.029	0.013	0.016	1.63	0.052
DA_MJ_NL	0.002	−0.006	0.008	0.70	0.484	0.021	0.000	0.021	2.44	0.007
DA_LR	0.028	0.009	0.020	1.96	0.051	0.024	0.017	0.007	1.22	0.111
DA_LR_NL	0.016	−0.002	0.018	1.96	0.051	0.023	0.001	0.022	2.65	0.004
DA_PM	0.009	−0.010	0.019	2.35	0.019	0.010	−0.006	0.016	1.83	0.033
DA_PM_NL	−0.002	−0.012	0.010	0.91	0.363	0.004	−0.005	0.009	1.42	0.077
DA_MFL	0.012	−0.007	0.019	2.29	0.023	0.012	−0.004	0.016	2.85	0.002
DA_MFL_NL	0.014	−0.008	0.022	2.52	0.012	0.013	−0.002	0.015	2.03	0.021
OBS	192	192				192	192			

Panel B: Contingency table tests

	Jones Model				Modified Jones Model				LR Model				Performance Matched Model				Modified Forward-Looking Model			
	Linear		Non-linear		Linear		Non-linear		Linear		Non-linear		Linear		Non-linear		Linear		Non-linear	
Restated	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
High DA	71	57	73	55	69	59	72	56	72	56	75	53	69	59	73	55	76	52	79	49
Low DA	61	67	54	74	51	67	55	73	66	62	57	71	57	71	56	72	52	76	57	71
p-Value	0.1302		**0.0121**		0.1908		**0.0226**		0.2654		**0.0166**		0.0845		**0.0226**		**0.0020**		**0.0042**	

Panel C: Logistic regression

	Pred. sign	DA	p-Value	Pred. sign	DIFF	p-Value	Log likelihood	Pseduo R^2
Jones Model	+	2.828	0.051	+	4.489	0.061	9.560	0.033
Modified Jones Model	+	3.085	0.038	+	5.121	0.051	9.582	0.033
LR Model	+	2.739	0.051	+	5.948	0.027	8.247	0.028
Performance Matched Model	+	1.558	0.204	+	4.158	0.090	11.692	0.040
Modified Forward-Looking Model	+	4.574	0.015	+	11.491	0.005	11.851	0.041

Table 8
Income decreasing subsample.

Panel A: Comparison of discretionary accruals

	Mean					Median				
	Restatement sample	Non-restatement sample	Difference	t value	p-Value	Restatement sample	Non-restatement sample	Difference	z value	p-Value
DA_J	−0.016	0.023	−0.044	2.13	0.034	0.029	0.011	0.018	2.24	0.012
DA_J_NL	−0.016	0.006	−0.026	0.74	0.462	0.018	−0.002	0.020	2.65	0.004
DA_MJ	−0.015	0.024	−0.043	2.12	0.034	0.029	0.013	0.016	1.63	0.052
DA_MJ_NL	−0.016	0.008	−0.028	0.70	0.484	0.021	0.000	0.021	2.44	0.007
DA_LR	−0.023	0.020	−0.050	−2.54	0.013	0.024	0.017	0.007	1.22	0.111
DA_LR_NL	−0.018	0.011	−0.033	−1.60	0.112	0.023	0.001	0.022	2.65	0.004
DA_PM	−0.021	−0.002	−0.022	2.35	0.019	0.010	−0.006	0.016	1.83	0.033
DA_PM_NL	−0.023	−0.003	−0.024	0.91	0.363	0.004	−0.005	0.009	1.42	0.077
DA_MFL	−0.021	0.008	−0.032	2.29	0.023	0.012	−0.004	0.016	2.85	0.002
DA_MFL_NL	−0.008	0.010	−0.018	2.52	0.012	0.013	−0.002	0.015	2.03	0.021
OBS	54	54				54	54			

Panel B: Contingency table tests

	Jones Model				Modified Jones Model				LR Model				Performance Matched Model				Modified Forward-Looking Model			
	Linear		Non-linear		Linear		Non-linear		Linear		Non-linear		Linear		Non-linear		Linear		Non-linear	
Restated	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
High DA	16	19	17	18	15	20	18	17	17	18	20	15	16	19	17	18	19	16	21	14
Low DA	19	16	16	19	18	17	15	20	19	16	16	19	22	13	20	15	10	25	11	24
p-Value	0.8305		0.6838		0.8309		0.3162		0.7633		0.2367		0.9538		0.8309		0.0257		0.0150	

Panel C: Logistic regression

	Pred. sign	DA	p-Value	Pred. sign	DIFF	p-Value	Log likelihood	Pseudo R^2
Jones Model	−	−6.075	0.039	−	11.955	0.105	12.056	0.143
Modified Jones Model	−	−6.260	0.032	−	10.738	0.139	11.531	0.137
LR Model	−	−7.096	0.014	−	5.559	0.306	10.035	0.120
Performance Matched Model	−	−6.159	0.066	−	−6.292	0.363	4.682	0.058
Modified Forward-Looking Model	−	−8.719	0.010	−	5.126	0.150	8.641	0.104

"it is possible that Ball and Shivakumar approach and the KLW approach accomplish similar things (that is, both approaches accomplish the correction of the bias caused by performance)." Following this logic, the Modified Forward-Looking Model includes ROA to control for performance which may accomplish similar things as Ball and Shivakumar's non-linear specification, according to Guay (2006)'s argument. Second, Ball and Shivakumar (2006) incorporate conditional conservatism into discretionary accrual models. Conditional conservatism refers to the asymmetric timeliness of earnings reflecting bad versus good news. The bad/good news is about losses/gains that will be realized in the *future*. The Modified Forward-Looking Model includes analysts' earnings forecasts to proxy for future growth. When analysts generate earnings forecasts, they implicitly take into consideration future gains and losses. Therefore, including analysts' earnings forecasts is likely to capture conditional conservatism to a certain extent. Therefore, the improvement of the non-linear specification for the Modified Forward-Looking Model is not as substantial as that for other models.

5. Conclusions

The role of a discretionary accrual model is to decompose total accruals into non-discretionary and discretionary accruals. Measures of discretionary accruals are widely used in the accounting research literature. However, the most widely used discretionary accrual models are linear specifications. Ball and Shivakumar (2005) observe that because the accounting recognition of gains and losses is asymmetric, in that losses generally are recognized in a more timely fashion than gains (Basu, 1997), the relation between accruals and cash flows cannot be linear. This observation challenges the linear specification of discretionary accrual models.

This paper extends Ball and Shivakumar (2006) by investigating whether incorporating non-linearity into discretionary accrual models improves their relative performance in detecting the presence of earnings management using a sample of firms that issued earnings restatements from 1997 to 2005. Using restatement firms provides a unique setting to examine this question because the sample represents firms that are known to have engaged in earnings management. I employ three tests to access the relative performance of linear and non-linear discretionary accrual models: (1) comparison of (absolute value of) discretionary accruals between restatement and non-restatement firms; (2) contingency table tests to examine the association between discretionary accruals and earnings restatements; and (3) logistic regression analysis to examine how well a discretionary accrual model detects the occurrence of restatement. The results from these three tests indicate that the linear models, except linear Modified Forward-Looking Model, are not effective in detecting earnings management. On the other hand, all the non-linear models do a good job of detecting earnings management, suggesting the non-linear specification improves the linear models' performance. One explanation for the superior performance of the linear Modified Forward-Looking Model is that the adjustments made to the model already capture to a certain extent the non-linearity caused by asymmetric timeliness of loss versus gain recognition.

This study contributes to the extant accounting research literature in several ways. First, this paper is one of the first to examine the non-linear specification of discretionary accrual models in a comprehensive manner. I provide direct evidence on whether the non-linear specification improves the discretionary accrual models' performance, which fills the void in the literature. Second, this paper enhances our understanding of what Ball and Shivakumar's (2006) approach actually accomplishes. The evidence indicates that Ball and Shivakumar's (2006) approach accomplishes something beyond just performance matching.

Third, this paper provides additional supporting evidence for the superior performance of the Modified Forward-Looking Model. Collins and Wan (2005) first propose the Modified Forward-Looking Model and provide evidence that this model is better specified and out-performs the other models both in terms of detecting earnings management and accurately estimating the magnitude of managed earnings. This paper provides further evidence that the Modified Forward-Looking Model out-performs the other models in all three tests. Future research may consider using this model.

The accrual process is central to financial reporting system. Ball and Shivakumar (2006) recognize the role of accruals in asymmetrically timely gain and loss recognition. Thus, they incorporate the asymmetric timeliness of loss versus gain recognition (i.e., conditional conservatism) into discretionary accrual models. Guay (2006) acknowledges that "their innovation advances research on modeling the accruals process and is sure to play an important role in accounting research on both nondiscretionary and discretionary components of accruals." Thus, future research can follow this direction to further explore how to incorporate the conditional conservatism into discretionary accrual models from two perspectives. First, Ball and Shivakumar (2006) employ a piecewise linear regression with a single kink to incorporate the conditional conservatism into discretionary accrual models. One concern is that Ball and Shivakumar's (2006) approach may not be sufficient to incorporate conservatism into discretionary accrual models. Moreover, Moreira and Pope (2006) find that for the bad news firms, the relation between accruals and the proxy for economic gains or losses is non-linear. Thus, further exploration of the incorporation of conservatism into discretionary accrual models is warranted. Future research may explore whether it can be modeled with a piecewise linear regression with multiple kinks or with a quadratic form.

Second, Ball and Shivakumar (2006) identify four proxies for economic gains and losses and find that each one has its own strength and weakness. It is critical to have a good proxy for economic gains and losses in order to better incorporate conservatism into the models and accurately estimate discretionary accruals. Future research can consider better proxies for economic gains and losses. Since Ball and Shivakumar (2006) find each of the four proxies has its own strengths and weaknesses, one avenue would be to derive a factor from the four proxies using factor analysis.

Third, the Dechow and Dichev (2002) model examined in Ball and Shivakumar (2006) is not considered in this paper. Given the influence of that model and the importance to have a good measure for earnings quality, future research can examine whether the non-linear Dechow and Dichev Model generates a better earnings quality measure than the traditional linear model.

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Appendix A. Summary of discretionary accrual models

1. The linear Jones Model (Jones)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it}) + \beta_3 PPE_{it} + \varepsilon_{it}.$$

2. The linear Modified Jones Model (MJ)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \varepsilon_{it}.$$

3. The linear Larcker and Richardson (2004) Model (LR)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 BM_{it} + \beta_5 CFO_{it} + \varepsilon_{it}.$$

4. The linear Performance-Matched Modified Jones Model (PM)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 ROA_{it} + \varepsilon_{it}.$$

5. The linear Modified Forward-Looking Model (MFL)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2((1+k)DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 TACC_{it-1} + \beta_5 EST\_GROWTH_{it} + \beta_6 ROA_{it} + \beta_7(DCOGS_{it} - \Delta INV_{it}) + \varepsilon_{it}.$$

6. The non-linear Jones Model (Jones)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it}) + \beta_3 PPE_{it} + \gamma_1 VAR + \gamma_2 DVAR + \gamma_3 DVAR * VAR + \varepsilon_{it}.$$

7. The non-linear Modified Jones Model (MJ)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \gamma_1 VAR + \gamma_2 DVAR + \gamma_3 DVAR * VAR + \varepsilon_{it}.$$

8. The non-linear Larcker and Richardson (2004) Model (LR)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 BM_{it} + \beta_5 CFO_{it} + \gamma_1 VAR + \gamma_2 DVAR + \gamma_3 DVAR * VAR + \varepsilon_{it}.$$

9. The non-linear Performance-Matched Modified Jones Model (PM)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2(DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 ROA_{it} + \gamma_1 VAR + \gamma_2 DVAR + \gamma_3 DVAR * VAR + \varepsilon_{it}.$$

10. The non-linear Modified Forward-Looking Model (MFL)

$$TACC_{it} = \alpha + \beta_1(1/TA_{it-1}) + \beta_2((1+k)DSALES_{it} - DAR_{it}) + \beta_3 PPE_{it} + \beta_4 TACC_{it-1} + \beta_5 EST\_GROWTH_{it} + \beta_6 ROA_{it} + \gamma_1 VAR + \gamma_2 DVAR + \gamma_3 DVAR * VAR + \varepsilon_{it}.$$

Variable definitions (Please refer to text for more details):

TACC	Total accruals (EBXI − CFO), scaled by beginning total assets (Compustat #6).
EBXI	earnings before extraordinary items and discontinued operations (Compustat #123).
CFO	Cash Flows from Operation (Compustat #308 − Compustat #124).
ΔSALES	The change in firm i's sales (Compustat #12) from year t − 1 to t scaled by beginning total assets.
ΔAR	The change in firm i's accounts receivable from year t − 1 to t (Compustat #302) scaled by beginning total assets.
PPE	Firm i's year t gross property, plant, and equipment (Compustat #7) scaled by beginning total assets.
ROA	Firm i's return on assets of year t.
k	The regression coefficient from a regression
ΔAR_{it}	$\alpha + k\Delta SALES_{it} + \varepsilon_{it}$ for each two-digit SIC-year grouping.
LTACC	Firm i's total accruals at year t − 1.
GR_SALES	The change in firm i's sales (Compustat #12) from year t to t + 1 scaled by year t sales.
EST_GROWTH	The median of analysts' long-term earnings growth forecasts for the last month of year t.
VAR	A proxy for economic gain or loss. It is measured as abnormal returns
DVAR	A (0,1) dummy variable that takes the value of 1 if VAR implies a loss.
DA_J	Discretionary accruals estimated from Jones Model.
DA_J_NL	Discretionary accruals estimated from non-linear Jones Model.
DA_MJ	Discretionary accruals estimated from Modified Jones Model.
DA_MJ_NL	Discretionary accruals estimated from non-linear Modified Jones Model.
DA_LR	Discretionary accruals estimated from Larcker and Richardson (2004) Model.
DA_LR_NL	Discretionary accruals estimated from non-linear Larcker and Richardson (2004) Model
DA_PM	Discretionary accruals estimated from Performance Matched Model.
DA_PM_NL	Discretionary accruals estimated from non-linear Performance Matched Model.
DA_MFL	Discretionary accruals estimated from Modified Forward-Looking Model.
DA_MFL_NL	Discretionary accruals estimated from non-linear Modified Forward-Looking Model.
DIFF	Difference of absolute value of discretionary accrual estimations from non-linear model versus linear model.

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