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The Effects of Firm Growth and Model Specification Choices on Tests of Earnings Management in Quarterly Settings

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ABSTRACT: Commonly used Jones-type discretionary accrual models applied in quarterly settings do not adequately control for nondiscretionary accruals that naturally occur due to firm growth. We show that the relation between quarterly accruals and backward-looking sales growth (measured over a rolling four-quarter window) and forward-looking firm growth (market-to-book ratio) is non-linear. Failure to control for the effects of firm growth and performance on innate accruals leads to excessive Type I error rates in tests of earnings management. We propose simple refinements to Jones-type models that deal with non-linear growth and performance effects and show that the expanded models are well-specified and exhibit high power in quarterly settings where one is testing for earnings management. The expanded models are able to identify the presence of earnings management in a sample of restatement firms. Our findings have important implications for the use of discretionary accrual models in earnings management research.

Keywords: earnings management; discretionary accruals; firm growth.

JEL Classifications: C15; M40; M41.

I. INTRODUCTION

An extensive body of literature in accounting and finance uses Jones-type model discretionary accrual estimates to test for earnings management. This literature includes studies that test for evidence of earnings management around specific corporate events (e.g., initial public offerings and seasoned equity offerings [IPOs and SEOs], stock acquisitions, stock repurchases, proxy contests, stock splits, and dividend payments), as well as studies that test for cross-sectional differences in earnings management as a function of the firms' contracting characteristics (e.g., stock-based management compensation arrangements and debt contracting environment).[1] We maintain and show that existing Jones-type

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Supplemental material can be accessed by clicking the link in Appendix A.

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[1] The CPV Supplement provides a partial list of these studies (see Appendix A for the link to the downloadable document).

models used in numerous studies fail to control for the non-linear effects of firm growth on innate (nondiscretionary) accruals, particularly in quarterly settings, resulting in high Type I error rates when testing for earnings management.[2]

Growth and accruals are fundamentally related. Dechow, Kothari, and Watts (1998) develop an analytical model that highlights the fact that high sales growth firms require legitimate higher investments in working capital to deal with higher customer demand. Their model implies that growth-related changes in accruals should be treated as nondiscretionary because this component of accruals is predictable and common across growth firms. Thus, in the absence of controls for firm growth, standard Jones-type discretionary accrual estimates will be confounded with innate growth accrual effects. McNichols (2000) is among the first to recognize the confounding effects of growth on discretionary accrual estimates. She finds that firms with greater expected future earnings growth are likely to have greater income-increasing accruals than firms with less expected earnings growth.

There are three primary factors that contribute to the misspecification in Jones-type accrual models used in quarterly settings that lead to high Type I error rates. First, standard Jones-type models use the period-to-period change in sales as one of the main explanatory variables for innate (nondiscretionary) accruals. When applying Jones-type models in quarterly settings, researchers typically use the *adjacent-quarter* change in sales. We maintain that adjacent-quarter change in sales is dominated by seasonality effects and is too short of a horizon to proxy for sustainable growth that impacts managers' operating decisions that affect innate accruals. We propose a longer, four-quarter lagged rolling window sales growth as a more relevant backward-looking growth measure and show that this measure is significantly positively related to quarterly accruals even after controlling for the effects of adjacent-quarter changes in sales. We show that using four-quarter lagged sales growth to control for the effects of firm growth on innate accruals substantially reduces the misspecification (Type I errors) in extant discretionary accrual models used in quarterly settings.

A second major source of misspecification in Jones-type discretionary accrual models is that these models ignore the fact that innate accruals are affected by *future expected growth,* as well as sales growth that has occurred in the current period (i.e., backward-looking growth). There are sound economic reasons why several working capital accruals are innately related to future expected growth (Dechow et al. 1998; Banker, Fang, and Jin 2015); for instance, inventory build-ups or declines often lead expected future changes in sales. Therefore, these effects should be controlled for when estimating discretionary accruals. We show that market-to-book (MB), a commonly used proxy for future expected growth, is strongly positively related to quarterly accruals even after controlling for the effects of adjacent-quarter changes in sales. We show that failure to control for forward-looking growth effects on innate accruals contributes to excessive Type I error rates in discretionary accrual models used in the extant literature.

The third source of misspecification is that Jones-type models typically assume the relation between sales changes and accruals is linear over the entire range of sales growth. Relying on findings in the literature on sticky costs and recent theory and evidence on trade credit, we document that the relation between accruals and both backward-looking and forward-looking growth proxies is non-linear. Failure to consider the non-linear nature of the relation between growth and accruals leads to excessive Type I error rates in quarterly settings where researchers test for earnings management and samples are over-represented by high-growth firms.

Our analysis shows that quarterly discretionary accrual models with return on assets (ROA) matching that have been used in much of the prior earnings management literature are considerably misspecified in a non-linear manner with seasonally adjusted measures of sales growth and with forward-looking growth (MB). Moreover, we show that seasonally adjusted sales growth and MB are correlated with partitioning variables in past research that are deemed to give rise to earnings management. We propose a simple piecewise linear way of controlling for the non-linear effects of performance and growth (both backward-looking and forward-looking) on innate (nondiscretionary) accruals that ameliorates the misspecification problems without sacrificing power.

The remainder of the paper is organized as follows. Section II provides the economic intuition for why backward-looking sales growth and expected future growth are related to accruals in a non-linear fashion. Section III shows that firm growth is a pervasive omitted correlated variable in many settings where researchers have tested for earnings management. Section IV summarizes the specification and estimation of standard Jones-type models that have been implemented in the literature, and demonstrates graphically the bias in discretionary (abnormal) accruals that is likely to result when researchers fail to consider the non-linear relation between firm growth and quarterly accruals. In this section, we also introduce several alternative ways of controlling for the effects of firm growth and performance on accruals. In Section V, we conduct simulations to show the Type I

[2] In a recent commentary about two questionable beliefs from the accounting literature, Ball (2013, 850) states: "There also appears to be a widely held belief among accounting researchers that 'earnings management' is rife. A powerful cocktail of authors' strong priors, strong ethical and moral views, *limited knowledge of the determinants of accruals in the absence of manipulation, and willingness to ignore correlated omitted variables* in order to report a result, seems to have fostered a research culture that tolerates grossly inadequate research designs and publishes blatantly false positives" (emphasis added).

error rates that result when these measures are used to test earnings management in stratified random samples. Section VI uses simulation analysis to compare the power (1 – Type II error rates) of alternative discretionary accrual models. Section VII addresses the concern of whether controlling for sales growth throws the baby out with the bathwater by examining the estimated magnitude and significance of abnormal accruals for a sample of restatement firms. Section VIII presents sensitivity analyses for various variable measurement/design choices, and Section IX concludes and summarizes the implications of our findings for future earnings management research.

II. THEORY RELATING FIRM GROWTH TO ACCRUALS AND WHY ACCRUALS EXHIBIT NON-LINEAR BEHAVIOR WITH RESPECT TO GROWTH

There is an obvious positive relation between firm growth and current accruals. Both past realized growth and future anticipated growth require an investment in working capital just as they require an investment in capital assets. Ohlson (2014, 72) says this more emphatically as: "growth and accruals constitutes two sides of the same coin." McNichols (2000, 313) empirically analyzes the relation between accruals and expected firm growth and concludes: "Empirical findings suggest that aggregate accruals models that do not consider long-term [future] earnings growth are potentially misspecified and can result in misleading inferences about earnings management behavior."

Economic Explanation for Why Firm Growth is Related to Innate Accruals in a Non-Linear Fashion

Dechow et al. (1998) develop an analytical model that highlights the fact that high sales growth firms require higher investments in working capital to deal with higher customer demand. The economic intuition for why change in sales is related to innate (nondiscretionary) accruals is straightforward. Changes in sales are inherently linked to changes in inventory (ΔINV), changes in accounts receivable (ΔAR), changes in accounts payable (ΔAP), changes in other current assets (e.g., ΔDeferred Charges), and current liability (e.g., ΔAccrued Wages) accounts, which are, by definition, accruals. For example, in their model, Dechow et al. (1998) show that the target inventory level for a period is a constant fraction of the *forecasted sales* for the next period.

Research evidence on sticky costs suggests that firms are slower to adjust inventory for sales declines than for sales increases (Banker and Chen 2006; Banker et al. 2015).[3] So inventory accruals vary asymmetrically with respect to negative versus positive sales changes. Anderson, Lee, and Mashruwala (2015) report that labor costs and selling, general, and administrative expenses (SG&A) also exhibit asymmetric behavior with respect to positive and negative changes in sales. This implies that current working capital accruals like wages payable and accrued pension costs will behave asymmetrically with respect to sales declines versus sales increases.

A key insight from the Banker et al. (2015) study is that working capital accruals are triggered both by sales changes that occur in the current period (backward-looking growth) and by expected sales changes in the future (forward-looking growth). In a typical operating cycle, managers make production plans according to sales projections. That is, firms acquire inputs (e.g., hire labor, purchase materials) *before* making sales. This implies that accruals related to accounts payable and wages payable and part of the change in inventory (raw materials and work-in-process for manufacturing firms) will take place before expected future sales increases (or decreases) occur. This, in turn, implies the need for a forward-looking growth measure when modeling nondiscretionary (innate) accruals. This determinant of innate accruals is often missing in standard Jones-type models of nondiscretionary accruals. Other working capital accruals, like changes in accounts receivable and changes in finished goods inventory, are more likely to vary with concurrent changes in sales. This provides the logic behind a backward-looking sales growth term ($\Delta SALES_t$) in standard Jones-type models of nondiscretionary accruals. Regardless of whether the growth proxies are backward-looking or forward-looking, the evidence on sticky costs implies that net accruals (income-increasing minus income-decreasing) are likely to decrease more steeply with sales declines than they increase with sales increases. Thus, net accruals are expected to be non-linear across the sales growth continuum for both backward-looking and forward-looking growth measures.

Recent theory and evidence on trade credit highlights additional reasons for non-linearity in accruals, particularly at the upper end of the sales growth continuum. Petersen and Rajan (1997) argue that firms that are growing more quickly presumably have more investment opportunities. They argue that a proxy for this is the change in sales scaled by total assets, which, again, is the standard driver of nondiscretionary accruals in Jones-type models. One way that firms can achieve excessively high sales growth is by providing more lenient credit terms to customers to stimulate greater sales. Petersen and Rajan (1997) find evidence consistent with this. They find that the AR/Sales ratio increases significantly with sales growth for

[3] Cost stickiness occurs when managers deliberately retain slack resources resulting from a decline in sales activity. Thus, costs do not decline as quickly for negative changes in sales as they increase for positive changes in sales when costs are sticky.

positive growth firms. In this case, accounts receivable will grow at a faster rate than sales. Petersen and Rajan (1997) also find that suppliers have some advantage in financing growing firms. One reason why suppliers are more willing to provide more lenient credit to rapidly growing firms is because they want to capture the rents from future increased business from these customers. This implies that high sales growth firms are able to grow inventory (a current accrual) at a faster rate than the current-period growth in sales. The fact that both growth in receivables and growth in inventory are greater than the growth in sales for high sales growth firms implies that the slope of the Accruals/ΔSales relation will be greater for extreme positive sales growth firms relative to that for intermediate growth firms. Again, this implies that the relation between ΔSales and current accruals is likely to be non-linear.

The above arguments imply that accruals will exhibit an inverted S-shape pattern across the sales growth continuum. At the bottom end of the continuum, realized accruals will be more steeply sloping with respect to changes in sales (largely negative) because of sticky costs than will be the case for intermediate-range sales growth firms. At the upper end of the sales growth continuum, net realized accruals are predicted to rise more steeply relative to sales growth because these firms are granting more lenient credit terms to their customers to stimulate greater sales growth, and also because these firms are able to expand inventories more rapidly due to receiving more lenient trade credit from their suppliers.

The previous discussion yields three important takeaways: (1) growth-related changes in current (working capital) accruals should be treated as nondiscretionary because this component of accruals is predictable and common across growth firms; (2) growth-related innate (nondiscretionary) accruals are likely to be related to both backward-looking and forward-looking growth proxies; and (3) the relation between these growth proxies and accruals is non-linear in a predictable fashion.

Accrual Measures

Following Hribar and Collins (2002), we calculate accruals from the cash flow statement as: ($CHGAR + CHGINV + CHGAP + CHGTAX + CHGOTH$). The bracketed quantities in this expression are the changes in accounts receivable, inventories, accounts payable, taxes payable, and other accounts that affect accruals.[4] Accruals reported in the "other" category on the cash flow statement include some working capital accruals and a variety of non-working capital accruals, like special item gain and loss accruals and write-downs, write-offs, and impairments of fixed assets and value assets. It is important to note that the accrual measure we use in this study omits depreciation and amortization. There are several reasons for this exclusion. First, non-depreciation accruals are easier to manipulate than depreciation accruals as the latter tend to be more visible, rigid, and predictable. Thus, many authors have favored examination of non-depreciation accruals when testing for earnings management (DeFond and Jiambalvo 1994; Beneish 1998; Rangan 1998; Teoh, Welch, and Wong 1998a, 1998b; Young 1999; Louis 2004; Botsari and Meeks 2008; Gong, Louis, and Sun 2008; Baber, Kang, and Li 2011; Burnett, Cripe, Martin, and McAllister 2012; among others). Second, innate accruals such as *CHGAR, CHGINV, CHGAP, CHGTAX,* and parts of *CHGOTH* are more directly related to backward-looking growth (e.g., change in sales) and forward-looking growth (e.g., MB) than may be the case for depreciation and amortization accruals. In this paper, we focus on understanding these relations and their impact on studies of earnings management. Third, Sloan (1996) argues that a large part of the variation in total accruals is explained by current (or working capital) accruals, which are closer to our definition of non-depreciation accruals. Fourth, Louis (2004) argues that in valuing acquisition partners, investment bankers rely more on earnings before interest, taxes, depreciation, and amortization (EBITDA), which also highlights the importance of non-depreciation accruals. For these reasons, throughout the remainder of this paper, unless otherwise indicated, the accrual measure we use reflects accruals from the cash flow statement as noted above.

Proxies for Backward-Looking and Forward-Looking Growth

The analysis in this paper is focused primarily on Type I error rates and power of alternative discretionary accrual models in quarterly settings. As noted above, researchers typically use scaled adjacent-quarter changes in sales ($\Delta SALES_{i,t} = [SALES_{i,t} - SALES_{i,t-1}]/ASSETS_{i,t-1}$, where i denotes firm, t denotes quarter) as the primary explanatory variable in Jones-type models of nondiscretionary accruals when testing for earnings management in quarterly settings. We maintain that a better way to capture the effect of firm growth on accruals is to use a backward-looking growth proxy over a longer, rolling four-quarter window $\left(SG_{i,t} = \frac{SALES_{i,t}}{SALES_{i,t-4}} - 1 = \frac{SALES_{i,t} - SALES_{i,t-4}}{SALES_{i,t-4}}\right)$, i.e., seasonally differenced sales growth. We claim that this measure of growth is less impacted by seasonality effects and, therefore, should be a better proxy for capturing backward-looking sustainable growth that is likely to affect managerial operating decisions that impact innate quarterly accruals. We

[4] Because the indicated changes are the adjustments needed to convert accrual income to cash flows from operations under the indirect approach for arriving at cash flows from operations, it is necessary to multiply these changes by -1 to show the impact of the change in these asset (liability) accounts on accrual earnings.

provide evidence to support this claim below. For our forward-looking growth proxy, we use the market-to-book ratio for equity, MB, at the beginning of the quarter, which is a commonly used proxy for expected growth in the finance and accounting literature. Later, in Section VIII, we consider alternative proxies for forward-looking growth.

Evidence on the Non-Linear Relation between Accruals, Growth Proxies, and Performance

Figure 1, Panel A shows the relation between raw quarterly average accruals for deciles of firm performance (*ROA*) and the two growth proxies (*SG* and *MB*) using the full set of firm-quarters in our sample. We calculate *ROA* as the net income divided by lagged total assets for firm i during the current quarter t (i.e., $NI_{i,t}/ASSETS_{i,t-1}$); *SG* as defined above (i.e., $(SALES_{i,t} - SALES_{i,t-4})/SALES_{i,t-4}$); and *MB* as the ratio of market value and book value of equity as of quarter t–1.[5] We start with a comprehensive sample of 203,090 Compustat firm-quarters that span 1991-Q1 to 2007-Q4. We require that the relevant data to calculate the accrual measures used in this study and the three partitioning variables of *ROA, SG,* and *MB* are available. We additionally require that: (1) total assets exceed $10 million in 2007 dollars; (2) the firm is not in the financial industry (which excludes two-digit SIC [standard industrial classification] codes between 60 and 69); (3) the CRSP share code is 10 or 11 (which excludes American Depository Receipts, Real Estate Investment Trusts, Master Limited Partnerships, certificates, and trusts); (4) there are at least 20 firms in the included two-digit SIC code during a given calendar quarter; and (5) none of the accrual measures (normalized by total assets) exceeds 1.

There are two aspects of Figure 1, Panel A that are noteworthy. First, *ROA, SG,* and *MB* are all associated with considerable variation in raw accruals in quarterly settings. Between the bottom and top deciles, accruals across *ROA* deciles change from −1.44 percent to 0.94 percent of lagged assets (range 2.38 percent), accruals across *SG* deciles change from −0.83 percent to 1.34 percent of lagged assets (range 2.17 percent), and accruals across *MB* deciles change from −0.19 percent to 0.87 percent of lagged assets (range 1.06 percent). Thus, raw accruals are related to both performance and backward-looking and forward-looking firm growth. Note further that while half of the variation in raw accruals with *ROA* occurs between deciles 1 and 2, the variation is more spread out over the full range of *SG* and *MB*. Thus, it is just as important to control for realized and expected sales growth as it is to control for performance when testing for earnings management.

The second important feature of this plot is that the relation between growth and performance and raw quarterly accruals is non-linear, and this is particularly true for *ROA* and *SG*. The fact that the first three deciles of *SG,* which are dominated by firms with negative sales changes, exhibit sharply more negative accruals than is the case for intermediate deciles of *SG* is consistent with the sticky cost explanations outlined above. The fact that the average quarterly accruals are more income-increasing for the upper three deciles compared to the intermediate deciles is also consistent with the trade credit explanations for non-linearity of cost structures offered by Petersen and Rajan (1997). Overall, the main takeaway from this plot is that adding a linear term to control for firm growth in quarterly discretionary accrual models is unlikely to provide an effective control for the effects of firm growth on innate (nondiscretionary) accruals, as we will demonstrate more fully below.

Why Adjacent-Quarter Change in Sales does not Control for the Effects of Firm Growth on Accruals

We summarize 32 published studies that conduct tests of earnings management in quarterly settings in the CPV Supplement. Most of these studies use Jones-type models to measure discretionary (abnormal) accruals. Furthermore, all studies that use Jones-type models to measure discretionary accruals use adjacent-quarter changes in sales to capture the effects of firm growth on accruals. Previously, we claimed that adjacent-quarter changes in sales are confounded by seasonality effects, so that this measure will do a poor job of controlling for the fundamental effects of more sustainable growth on accruals. To demonstrate this empirically, we run the following regression across all firm-quarters within two-digit SIC codes.

$$ACC_{i,t} = \beta_0 + \beta_1 \Delta SALES_{i,t} + \varepsilon_{i,t} \tag{1}$$

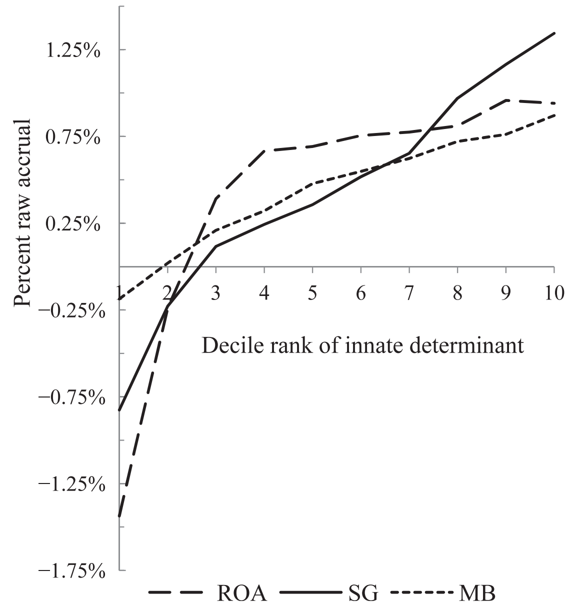
where $ACC_{i,t}$ denotes the accruals as defined above, and $\Delta SALES_{i,t}$ denotes adjacent-quarter change in sales, calculated as $(SALES_{i,t} - SALES_{i,t-1})/ASSETS_{i,t-1}$. We plot the average residuals from this model by *ROA, SG,* and *MB* deciles in Figure 1, Panel B. Note that *SG* is measured over a rolling four-quarter window, as explained above.

There are two aspects of this plot that are noteworthy. First, estimating this relation within two-digit SIC industries mean-adjusts the data, such that by ordinary least squares (OLS) construction, the residual accruals are centered at zero compared to the raw accruals plot in Panel A of Figure 1. Second, this plot demonstrates that controlling for adjacent-quarter change in sales ($\Delta SALES_{i,t}$) when estimating quarterly discretionary accrual models does not adequately control for the effects of firm growth on quarterly accruals. The pattern of the residual accruals (after removing the effects of adjacent-quarter change in sales) across

[5] Our results are similar if we use seasonally lagged *ROA* (i.e., $NI_{i,t-4}/ASSETS_{i,t-5}$) as a measure of firm performance. These results are discussed later in Section VIII and are available in the CPV Supplement.

FIGURE 1
Innate Determinants of Accruals

Panel A: Quarterly Raw Accrual



(continued on next page)

SG and *MB,* as well as *ROA,* deciles is similar to the pattern observed in Panel A of Figure 1 where we plot raw quarterly accruals across deciles of these three firm characteristics, although the magnitudes are reduced. Thus, the non-linear relation between quarterly accruals and our two growth proxies (*SG* and *MB*) remains after controlling for adjacent-quarter change in sales.

III. FIRM GROWTH AND EARNINGS MANAGEMENT PARTITIONING VARIABLES

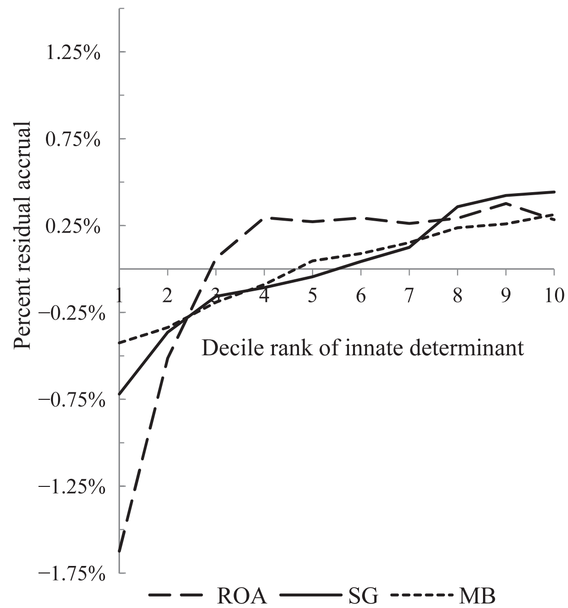
An unbiased test of earnings management requires that measurement error in the discretionary accruals proxy be uncorrelated with the partitioning variable in the research design. McNichols and Wilson (1988) outline a framework that is relevant to assessing the potential bias in earnings management studies that use discretionary accruals estimates. They demonstrate that tests of earnings management are biased in favor of rejecting the null hypothesis of no earnings management when measurement error in the discretionary accrual proxy is positively correlated with the partitioning variable deemed to give rise to earnings management. Below, we demonstrate that the bias in favor of falsely rejecting the true null is large and pervasive in the literature due to failure to properly control for the effects of firm growth on innate (nondiscretionary) accruals. We show this by first documenting a strong positive association between our two growth proxies, sales growth (*SG*) and market-to-book (*MB*), and five different partitioning variables (settings) that prior research has shown to be associated with earnings management.

The five partitioning variables we consider are stock splits, SEOs, stock-for-stock acquisitions, percentage of stock-based (executive) compensation, and abnormal insider selling. We select these five settings for two reasons. First, there are multiple studies that have tested for, and found, evidence of upward earnings management in these settings (see the CPV Supplement). Second, in each of these settings, we conjecture that test samples are likely to be over-represented by high-growth firms. That is, firms are more likely to split their stock, issue new seasoned equity, and use stock to acquire other firms when they are growing rapidly. Moreover, insiders are more likely to sell their shares when the firm is experiencing rapid growth and stock-based compensation is likely a bigger portion of CEO pay for high-growth firms. The data reported below support these conjectures.

For the first three event partitioning variables, we start with our comprehensive sample of 203,090 firm-quarters during 1991 to 2007 from the Compustat and CRSP databases and merge it with samples of firms that announced stock splits, SEOs,

FIGURE 1 (continued)

Panel B: Residuals from Regression of Quarterly Raw Accruals on Change in Sales



In Section II, we argue that *ROA, SG,* and *MB* are innate determinants of accruals. Panel A of this figure shows supporting evidence by plotting how quarterly raw accruals scaled by lagged total assets vary across deciles of each of these three determinants. The quarterly raw accruals $ACC_{i,t}$ are calculated using the cash flow statement, as described in Section III and Table 1. The dataset consists of 203,090 firm-quarters during 1991-Q1 to 2007-Q4, as described there. We calculate *ROA* as the net income divided by total assets during quarter t (i.e., $NI_{i,t}/ASSETS_{i,t-1}$); *SG* as the change in sales from quarter t–4 to t divided by sales during quarter t–4 (i.e., $(SALES_{i,t-1} - SALES_{i,t-4})/SALES_{i,t-4}$); and *MB* as the ratio of market value and book value of equity as of quarter t–1. Panel B next plots the corresponding variation in residuals $\varepsilon_{i,t}$ from the following regression of quarterly raw accruals on change in sales:

$$ACC_{i,t} = \beta_0 + \beta_1 \Delta SALES_{i,t} + \varepsilon_{i,t}. \tag{F1.1}$$

Here, $\Delta SALES_{i,t}$ is the quarterly change in sales measured over adjacent quarters. The regressions are carried out over all firm-quarters belonging to a two-digit SIC code.

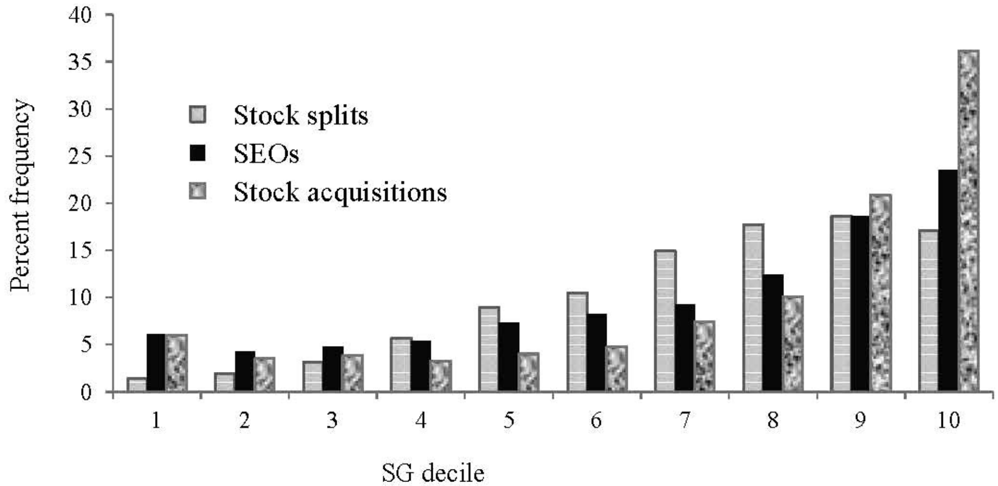
and stock acquisitions. Panel A of Figure 2 shows the frequency distribution of 2,646 stock splits, 2,951 SEOs, and 1,193 stock acquisitions across *SG* deciles, while Panel B shows the distribution across *MB* deciles. (The sampling procedure is described in the figure legend.) There is nearly a monotonic increase in the frequency of the three events as one goes from the lowest to the highest *SG* and *MB* deciles. We find that 57 percent of stock acquisitions, 42 percent of SEOs, and 36 percent of stock splits are done by firms in the top two *SG* deciles (i.e., top quintile). The corresponding numbers in the top two *MB* deciles are 53 percent, 33 percent, and 38 percent.

The left bars of Panel A of Figure 3 show the median stock-based compensation as a percentage of total compensation for firm-years ranked by *SG* deciles, and the right bars in this plot show the percent of all firm-years for which there is abnormal insider selling. (The calculation details are provided in the figure legend.) Panel B shows the same results for *MB* deciles. Once again, we see that both stock-based compensation and abnormal insider selling tend to be concentrated in higher-growth deciles. When one combines the patterns of raw and residual accruals after controlling for adjacent-quarter changes in sales across *SG* and *MB* deciles, reflected in Figure 1 with the frequency distribution of partitioning variables depicted in Figures 2 and 3, the clear inference is that failure to control for firm growth in these settings is likely to result in upward-biased estimates of conventional Jones-type model discretionary accruals and a bias in favor of finding upward (income-increasing) earnings management.

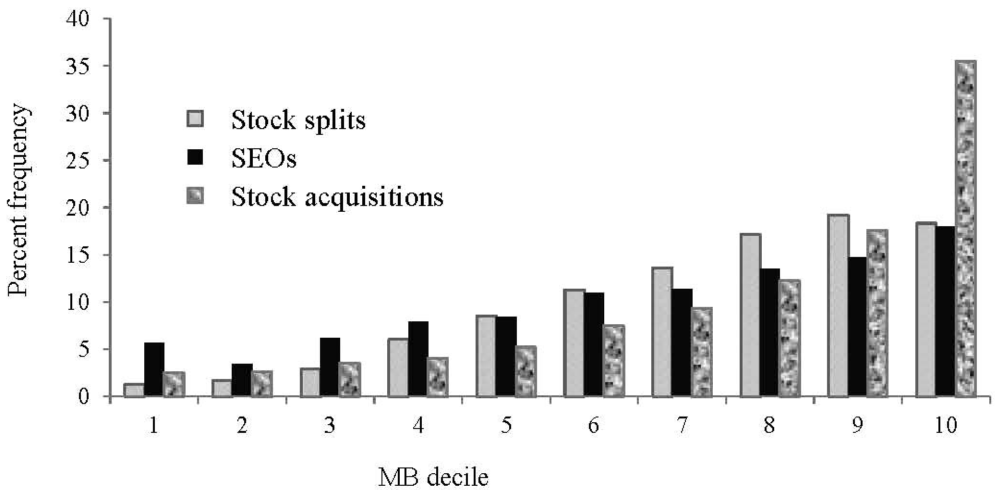
In addition to the five partitioning variables explicitly analyzed in Figures 2 and 3, we find that firm growth is likely correlated with many other partitioning variables examined in the accounting and finance literature. Of the 32 published

FIGURE 2
Sample Distributions across *SG* and *MB* Deciles Underlying Studies of Earnings Management before Select Corporate Events

Panel A: Event Distribution across *SG* (Sales Growth) Deciles



Panel B: Event Distribution across *MB* (Market-to-Book) Deciles



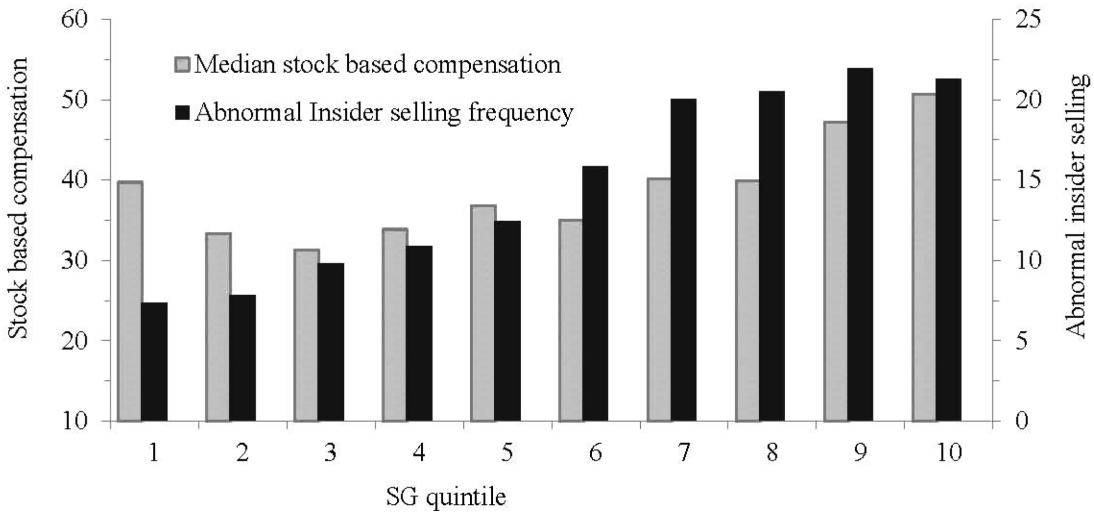
Panel C: Proportions of Firms across *SG* and *MB* Deciles Averaged across the Three Events

Decile Rank→	1	2	3	4	5	6	7	8	9	10
Sales growth SG	4.5	3.3	3.9	4.8	6.7	7.8	10.6	13.4	19.4	25.6
Market-to-book MB	3.1	2.6	4.2	6.0	7.4	9.9	11.4	14.3	17.2	23.9

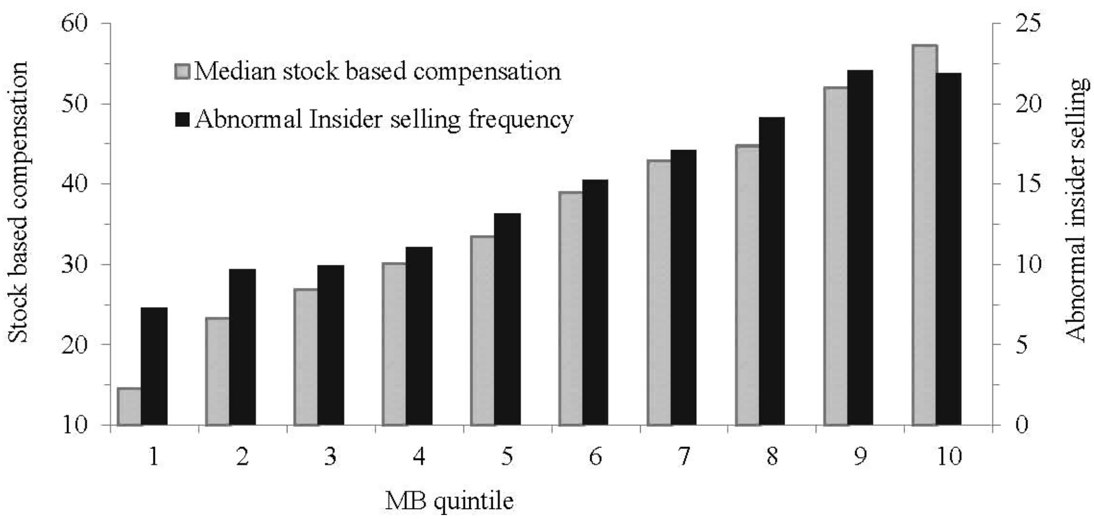
We start with a comprehensive sample of 203,090 firm-quarters during 1991-Q1 to 2007-Q4 from the Compustat and CRSP databases, as described in Section III and Table 1. We merge this sample with samples of firms that announced stock splits, SEOs, and stock acquisitions. Stock splits are identified from the CRSP database using the distribution code of 5523 and a positive split factor, and SEOs and stock acquisitions are identified from the SDC database. We require that the event announcement date and the quarterly earnings announcement date are available. The final samples include 2,646 stock splits, 2,951 SEOs, and 1,193 stock acquisitions.
ROA, SG, and *MB* are defined in Figure 1.

FIGURE 3
Sample Distributions across *SG* and *MB* Deciles Underlying Studies of Executive Compensation and Insider Trading

Panel A: Stock-Based Compensation and Insider Selling across *SG* Deciles



Panel B: Stock-Based Compensation and Insider Selling across *MB* Deciles



We start with a comprehensive sample of 47,650 firm-years during 1991 to 2007 from the Compustat and CRSP databases. From this, we select a subset of firm-years for which stock-based compensation data are available from Execucomp (1992 to 2007) or insider buying and selling data are available from Thomson Financial (1991 to 2007). Stock-based compensation is expressed as a percent of total compensation that equals the sum of salary, bonus, and stock-based compensation. The insider trading data pass through several filters commonly employed in previous literature (form type 4, cleanse code R and H, transaction code P and S, and acquisition and disposal of at least 100 shares). Following Beneish and Vargus (2002), firm-years characterized by abnormal insider selling are identified as follows. First, we sum the total sales and the total purchases of shares by the top five executives, calculate the difference, and divide by the total shares outstanding. Second, we check whether this scaled difference is greater than the corresponding median value for all firm-years with the same market value decile rank. Abnormal insider selling shown here is the percent of firm-year observations that can be attributed to abnormal selling in the relevant decile.

ROA, *SG*, and *MB* are defined in Figure 1.

earnings management studies that analyze quarterly accruals data and are summarized in the CPV Supplement, we estimate that nearly three-fourths of them may be subject to significant Type I specification bias due to the failure of extant Jones-type quarterly discretionary accrual models to properly control for the effect of firm growth on innate accruals when testing for earnings management.

IV. ALTERNATIVE JONES-TYPE MODEL DISCRETIONARY ACCRUAL SPECIFICATIONS

Baseline Model Specifications

The two most popular models for estimating discretionary accruals are the cross-sectional Jones model (Jones 1991) and modified Jones model (Dechow, Sloan, and Sweeney 1995). The quarterly equivalents of these two models as they have been implemented by several studies in the prior literature on earnings management are specified below:[6]

Jones Model

$$ACC_{i,t} = \beta_0 + \beta_1 Q_{1,i,t} + \beta_2 Q_{2,i,t} + \beta_3 Q_{3,i,t} + \beta_4 Q_{4,i,t} + \beta_5 \Delta SALES_{i,t} + \beta_6 ACC_{i,t-4} + \varepsilon_{i,t} \quad (2)$$

In this expression, subscript i indexes firms and t indexes calendar quarters. $ACC_{i,t}$ is accruals as defined previously, and $Q_{1,i,t}$ to $Q_{4,i,t}$ are fiscal quarter dummies that allow for possible fiscal quarter effects in accruals. The $\Delta SALES_{i,t}$ term in this model equals $\frac{SALES_{i,t} - SALES_{i,t-1}}{ASSETS_{i,t-1}}$, which is the quarterly change in sales measured relative to the previous quarter's sales scaled by lagged total assets. However, as pointed out before, these adjacent-quarter changes in sales are confounded by seasonality effects and are measured over too short a period to meaningfully capture true differences in how firm growth is likely to affect innate accruals, which is better captured over longer horizons. Consequently, we suggest controlling for firm growth using seasonally differenced sales growth calculated as $SG = \frac{SALES_{i,t} - SALES_{i,t-4}}{SALES_{i,t-4}}$, which is introduced in various ways in the models below. We include accruals from the same fiscal quarter in the preceding year ($ACC_{i,t-4}$) to control for other possible but unobserved determinants of accruals for the current fiscal quarter. All independent variables except the intercept term are scaled by lagged total assets.

We estimate Equation (2) using all firm-quarters within a given two-digit SIC code and calendar year (i.e., by SIC2year). This is a compromise between two approaches followed in the previous literature. Studies either estimate Jones or Mod-Jones models by pooling all firm-quarters within a given two-digit SIC code, or estimate these models cross-sectionally by including only firm-quarters within a two-digit SIC code and calendar quarter. Our approach allows us to reasonably control for possible time trends in accruals by industry, as well as provide enough observations (degrees of freedom) to accommodate several dummy variables for quintiles of *ROA, SG,* and *MB,* as described below. We verify that our conclusions are not sensitive to the alternative pooling methods described above.

Mod-Jones Model

The Jones model assumes that all sales are nondiscretionary. Dechow et al. (1995) introduce a modification to the Jones model that treats credit sales as discretionary. Modified Jones model discretionary accruals are calculated as the residuals $\xi_{i,t}$ from the following model estimated for all firm-quarters belonging to a two-digit SIC code and calendar year:

$$ACC_{i,t} = \lambda_0 + \lambda_1 Q_{1,i,t} + \lambda_2 Q_{2,i,t} + \lambda_3 Q_{3,i,t} + \lambda_4 Q_{4,i,t} + \lambda_5 (\Delta SALES_{i,t} - \Delta AR_{i,t}) + \lambda_6 ACC_{i,t-4} + \xi_{i,t} \quad (3)$$

where the notations have the same meaning as described above. In addition, $\Delta AR_{i,t}$ denotes the change in accounts receivable. Similar to $\Delta SALES_{i,t}$, $\Delta AR_{i,t}$ is measured over adjacent quarters. We examine the most common way of estimating the modified Jones model that treats all accounts receivable in the event period and the estimation period as discretionary for both the treatment sample and the control sample included in the regression. For brevity, we refer to the common specification given by Equation (3) as the Mod-Jones model in subsequent discussion.

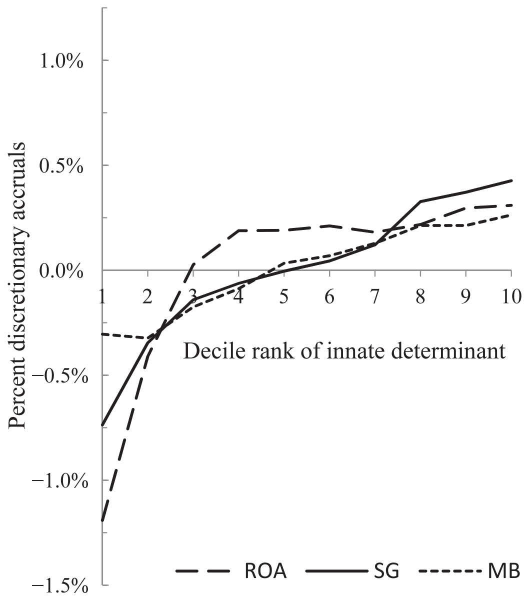
The problem that arises in implementing these models is that the full sample of firm-quarters that are available within a given SIC2year is used to estimate the model parameters for innate (nondiscretionary) accruals. But then these model parameters are often applied to a subset of "treatment" firm-quarters that come from an extreme portion of the *ROA, SG,* or *MB* continuum, and this can result in bias in the discretionary accrual estimates and excessive Type I error rates.

To illustrate the potential bias that can result from using the residuals from these baseline models as proxies for discretionary (abnormal) accruals, we plot the average residuals from these models across deciles of *ROA, SG,* and *MB* in

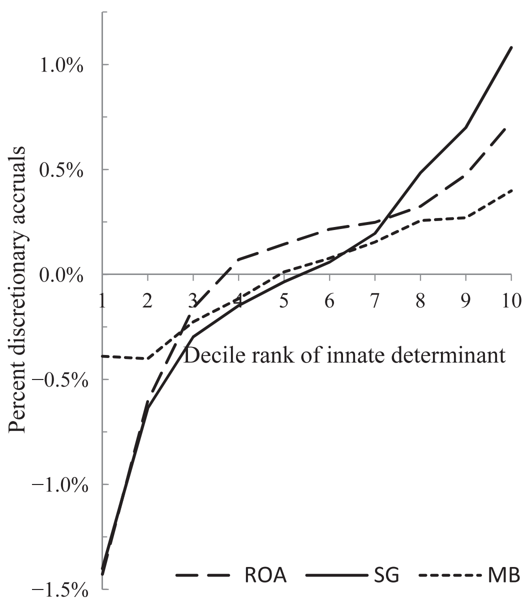
[6] Our specifications of baseline Jones and Mod-Jones models follow similar specifications in many recent papers, including Louis and White (2007), Gong et al. (2008), and Louis, Robinson, and Sbaraglia (2008).

FIGURE 4
Variation in Quarterly Jones and Mod-Jones Discretionary Accruals across Deciles of Innate Determinants of Accruals

Panel A: Jones Discretionary Accruals



Panel B: Mod-Jones Discretionary Accruals

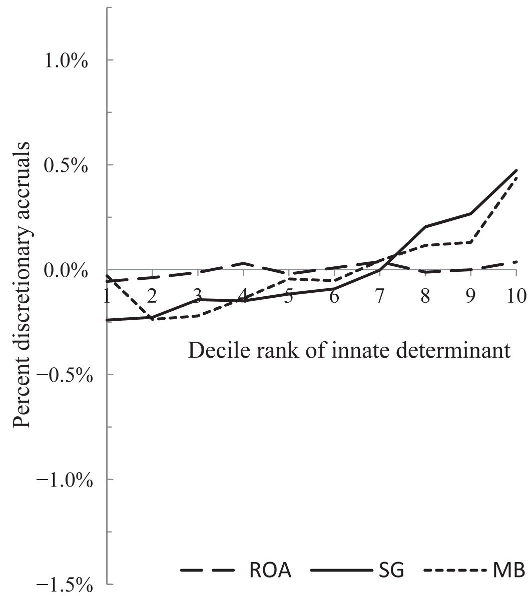


(continued on next page)

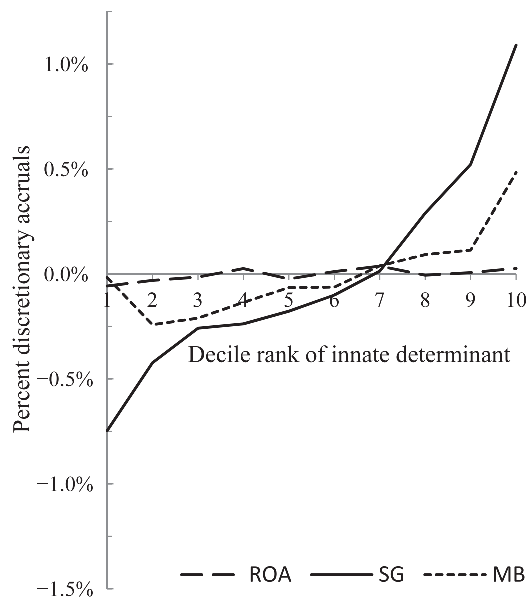
Figure 4. Panel A shows the residuals from the Jones model, while Panel B shows the residuals from the Mod-Jones model. These graphs show that abnormal accruals (scaled by lagged total assets), which are the measures researchers have often relied on to make inferences about earnings management, continue to exhibit a strong positive non-linear association with both backward-looking (*SG*) and forward-looking (*MB*) firm growth, in addition to performance (*ROA*). Clearly, the adjacent-quarter $\Delta SALES_{i,t}$ term used as a regressor in Equations (2) and (3) does not adequately control for the effects of firm growth and performance on innate accruals. It is important to note that the positive non-linear relation between discretionary accruals and *SG* is significantly stronger for the Mod-Jones model compared to the Jones model. This is because $\Delta AR_{i,t}$, which is subtracted

FIGURE 4 (continued)

Panel C: Jones with *ROA* Matching Discretionary Accruals



Panel D: Mod-Jones with *ROA* Matching Discretionary Accruals



The aggregate sample of 203,090 firm-quarters during 1991-Q1 to 2007-Q4 is described in Section III and Table 1. That table also defines *ROA*, *SG*, and *MB*. Jones and Mod-Jones models shown in Panels A and B are specified by Equations (2) and (3) in Section IV. Further, Jones and Mod-Jones models with *ROA* matching shown in Panels C and D are also described in Section IV.

from $\Delta SALES_{i,t}$ in Equation (4), is also affected by backward-looking firm growth. So by subtracting this term from $\Delta SALES_{i,t}$, one effectively filters out some of the effect of firm growth on innate (nondiscretionary) accruals. This means that the effect of firm growth on accruals becomes a greater part of the residuals from this model (i.e., discretionary accruals) than is the case for the standard Jones model.

The plots of Jones and Mod-Jones model residuals depicted in Panels A and B of Figure 4 also show the importance of controlling for firm performance (*ROA*). Both plots show large negative abnormal accruals for the lower two deciles (lowest quintile) of ranked *ROA* values and significant positive abnormal accruals across deciles 4 through 10. Thus, as pointed out by Kothari, Leone, and Wasley (2005), it is important to control for performance when testing for earnings management (see discussion of the corresponding model below). Panels C and D of Figure 4 further show how matching on performance affects the average abnormal accruals of Jones and Mod-Jones models across decile ranks of *ROA, SG,* and *MB*. The average difference in abnormal accruals when matching on *ROA* hovers around zero across all *ROA* deciles. However, the average differences in abnormal accruals are systematically negative (positive) across the lower (upper) deciles of *SG* and *MB*. A main takeaway from the Panel C and D plots is that it is important to control for the effects of both backward-looking growth (*SG*) and forward-looking growth (*MB*), in addition to firm performance, when testing for earnings management. The next section considers alternative ways of simultaneously controlling for the effects of firm performance and growth on innate accruals.

Adjustments to Control for the Effects of Firm Performance and Growth on Innate (Nondiscretionary) Accruals

There are a number of alternative approaches to control for the effects of firm performance and growth on accruals when testing for earnings management. This section outlines these alternative approaches and the trade-offs across these approaches.

Controlling for the Effects of Firm Performance

Kothari et al. (2005) highlight the importance of controlling for the effects of firm performance on innate (nondiscretionary) accruals when testing for earnings management. Two alternative approaches have been applied in the prior literature to control for the effects of performance on innate accruals. One approach is to add a linear *ROA* term to the specifications provided in Equations (2) and (3) above. This approach assumes that the relation between performance and innate accruals is linear throughout the full spectrum of *ROA*. An alternative approach to control for performance is to match sample (treatment) firms and control firms from the same two-digit SIC industry on *ROA* and then take the difference between Jones-type model discretionary accrual estimates for the treatment and matched control firms.

The plot provided in Panel A of Figure 1 suggests that the linearity assumption is likely to be violated. The matching approach has the advantage that it does not assume a linear relation between accruals and *ROA*. But it has one significant disadvantage: the standard deviation of the resulting matched *accrual difference* measure is increased to about $\sqrt{2} = 1.4$ times the standard deviation of measures from non-matching approaches.[7] As we will demonstrate below, *ceteris paribus,* the higher standard deviation of the matched discretionary accrual proxy will artificially lower Type I error rates relative to Jones-type residuals obtained from standard one-step regression models. The matching approach will also lower the power of detecting true earnings management ($1 -$ Type II error). Another important limitation of this approach is that it is difficult to match on more than two firm dimensions that affect innate accruals (in particular, *ROA, SG,* and *MB*).

Inserting quintile dummy variables for *ROA* is an alternate non-linear way of controlling for the effects of performance on innate accruals that does not entail differencing. This approach is described in more detail below. Jones-type models with quintile dummies for *ROA* are only introduced here so that we can provide a more direct contrast between matching (differencing) and non-matching (no differencing) approaches of controlling for performance.

Adding Linear ROA, SG, *and* MB *Terms*

In order to isolate the benefits of controlling for additional growth terms (both backward-looking *SG* and forward-looking *MB*) from controlling for these effects in a non-linear fashion, we first introduce a model that includes additive *linear ROA,* rolling four-quarter *SG,* and *MB* terms in the models outlined above. The Jones model given in Equation (2), augmented in this manner, is specified as follows:

Jones with Linear ROA, SG, *and* MB *Terms*

$$\begin{aligned} ACC_{i,t} = {} & \beta_0 + \beta_1 Q_{1,i,t} + \beta_2 Q_{2,i,t} + \beta_3 Q_{3,i,t} + \beta_4 Q_{4,i,t} + \beta_5 \Delta SALES_{i,t} + \beta_6 ACC_{i,t-4} + \beta_7 ROA_{i,t} + \beta_8 SG_{i,t-4\ to\ t} \\ & + \beta_9 MB_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

We next augment the Mod-Jones model in a similar manner:

[7] This is explained as follows. Suppose the Jones model (or modified Jones model) residuals for the sample firm and matching firm are denoted by $\varepsilon_{i,t}$ and $\varepsilon_{i,t,m}$. The matching procedure calculates discretionary accruals as $\varepsilon_{i,t} - \varepsilon_{i,t,m}$. In a random sample, on average, the standard deviations of the two residuals are approximately equal, so the standard deviation of the difference can be written as the standard deviation of either term multiplied by $\sqrt{2(1-\rho)}$, where ρ is the correlation between the two residuals. The typical value of ρ is quite small.

Mod-Jones with Linear* ROA, SG, *and* MB *Terms

$$ACC_{i,t} = \lambda_0 + \lambda_1 Q_{1,i,t} + \lambda_2 Q_{2,i,t} + \lambda_3 Q_{3,i,t} + \lambda_4 Q_{4,i,t} + \lambda_5(\Delta SALES_{i,t} - \Delta AR_{i,t}) + \lambda_6 ACC_{i,t-4} + \lambda_7 ROA_{i,t} + \lambda_8 SG_{i,t-4\ to\ t} + \lambda_9 MB_{i,t-1} + \xi_{i,t} \quad (5)$$

This approach assumes the relation between accruals and *ROA, SG,* and *MB* is linear over the entire range of these three firm characteristics. The arguments outlined in Section II, along with the results shown in Panel A of Figure 1, suggest that this approach is unlikely to adequately control for the underlying growth effects on innate accruals because these relations are non-linear. Consequently, adding linear *ROA, SG,* and *MB* terms is likely to result in excessive Type I error rates when testing for earnings management using these models in samples that are over-represented by high-growth firms. We include these linear models because a handful of studies introduce linear terms to control for *ROA* and *MB*. More importantly, linear models help in separating the effects of introducing the additional factors of *SG* and *MB* from the effects of doing so in a non-linear fashion. The Jones and Mod-Jones models with only the linear *ROA* term that are mentioned before are simply the truncated versions of Equations (4) and (5) that do not include *SG* and *MB* terms.

Introducing Dummy Variables to Control for the Non-Linear Effects of Performance and Growth on Accruals

Another approach to simultaneously control for the non-linear relation between accruals and firm performance and growth is to introduce dummy variables for different levels of these determinants of innate accruals. The choice of how many discrete dummy variables (categories) to use to capture the non-linearity between performance, growth, and accruals reflects a trade-off between using finer partitions (more categories) versus bumping up against degrees of freedom problems when estimating these models within SIC2year categories. In the interest of parsimony, we use *quintile* dummy classifications in the models below.

Jones with* ROA, SG, *and* MB *Quintile Dummies

$$ACC_{i,t} = \beta_0 + \beta_1 Q_{1,i,t} + \beta_2 Q_{2,i,t} + \beta_3 Q_{3,i,t} + \beta_4 Q_{4,i,t} + \beta_5 \Delta SALES_{i,t} + \beta_6 ACC_{i,t-4} + \sum_k \beta_{7,k} ROA\_Dum_{k,i,t} + \sum_k \beta_{8,k} SG\_Dum_{k,i,t-4\ to\ t} + \sum_k \beta_{9,k} MB\_Dum_{k,i,t-1} + \varepsilon_{i,t} \quad (6)$$

In this equation, the dummy variable $SG\_Dum_{k,i,t-4\text{ to }t}$ takes the value 1 if *SG* from quarter *t*–4 to *t* for firm *i* belongs to the *k*th quintile of *SG* in the aggregate data, and 0 otherwise. Because we include an intercept term, we include dummy variables only for quintile $k = 1$, 2, 4, and 5. Thus, the regression coefficients, $\beta_{8,k}$, of dummy variable $SG\_Dum_{k,i,t-4\text{ to }t}$ can be thought of as the difference between average accruals for *SG* quintile *k* and quintile 3 after controlling for the effect of other variables. Quintile dummy variables for other firm characteristics such as *ROA* and *MB* have a similar interpretation.

Mod-Jones with* ROA, SG, *and* MB *Quintile Dummies

$$ACC_{i,t} = \lambda_0 + \lambda_1 Q_{1,i,t} + \lambda_2 Q_{2,i,t} + \lambda_3 Q_{3,i,t} + \lambda_4 Q_{4,i,t} + \lambda_5(\Delta SALES_{i,t} - \Delta AR_{i,t}) + \lambda_6 ACC_{i,t-4} + \sum_k \lambda_{7,k} ROA\_Dum_{k,i,t} + \sum_k \lambda_{8,k} SG\_Dum_{k,i,t-4\ to\ t} + \sum_k \lambda_{9,k} MB\_Dum_{k,i,t-1} + \xi_{i,t} \quad (7)$$

The quintile dummy approach has several advantages relative to the previous two approaches of including linear controls or subtracting the accruals of a matching firm. First, it accommodates non-linearity in the relation between accruals and firm characteristics. Second, unlike the matching approach, it does not increase the cross-sectional standard deviation of discretionary accrual measures by $\sqrt{2}$. Thus, the power of detecting a given amount of earnings management will be greater for this approach versus the matching approaches. We view Models (6) and (7) as important refinements of basic Jones-type models that provide a general approach of simultaneously controlling for performance and growth effects on innate (nondiscretionary) accruals in a non-linear fashion while retaining the power of the tests. The Jones and Mod-Jones models with only *ROA* quintile dummies that are mentioned earlier are simply the truncated versions of Equations (6) and (7) that do not include *SG* and *MB* terms.

For expositional convenience, we assign a number from 1 to 13 to all of the above discretionary accruals models in Tables 1 and 2. Thus, Model 1 is raw accruals, Model 2 is Jones, Model 3 is Jones with linear *ROA* term, Model 4 is Jones with *ROA* matching, Model 5 is Jones with *ROA* quintile dummies, Model 6 is Jones with linear *ROA, SG,* and *MB* terms, and Model 7 is Jones with *ROA, SG,* and *MB* quintile dummies. Models 8 to 13 are the corresponding variants of Mod-Jones.

V. SPECIFICATION TESTS (TYPE I ERRORS) OF DISCRETIONARY ACCRUAL MODELS USING QUARTERLY DATA

A well-specified model with a low Type I error rate is important to ensure that innocent firms are not classified as guilty of earnings management. In this section, we demonstrate that widely used models of discretionary accruals are not well-specified in samples that are concentrated in high (low) firm growth dimensions (*SG* and *MB*) that affect innate accruals.

Determinants of Type I Error Rates

A well-specified discretionary accrual (*DA*) measure should have a mean of zero in random samples with no earnings management. However, suppose a given discretionary accrual measure (*DA*) is misspecified within a given sample partition so that its average value equals μ instead of zero when there is no earnings management. We call μ the percent misspecification (i.e., as a percent of total assets). Suppose further that the standard deviation of *DA* values estimated within a given partition equals σ, and that a sample of size n is drawn from this partition. Then, following the usual methodology of testing for earnings management, we compute the average value of *DA* in this sample and test whether it is significantly different from zero. Using the central limit theorem, it follows that the test statistic for the sampling distribution of average *DA* values will have a normal distribution with a mean value of μ and a standard deviation of $\sigma/\sqrt{n}$. It can be shown that the Type I error rate, defined as the probability of rejecting a true null hypothesis, H0: $DA = 0$, in favor of the alternate hypothesis, H1: $DA < 0$, will equal $N\left(-(1.645 + \mu\sqrt{n}/\sigma)\right)$, using a one-tailed significance level of 5 percent.[8] Alternately, the probability of rejecting the same null hypothesis in favor of the alternate hypothesis H1: $DA > 0$ will equal $\{1 - N(1.645 - \mu\sqrt{n}/\sigma)\}$. In both expressions, $N(z)$ denotes the probability that a number drawn at random from a standard normal distribution lies between $-\infty$ and z. Note that Type I error rates are positively related to μ and n and negatively related to σ for the more common situation of upward earnings management (i.e., H1: $DA > 0$). This analysis highlights the importance of μ, σ, and n as the key determinants of Type I (and later Type II) error rates that arise from alternative Jones-type models.

Distributional Statistics of Alternative Discretionary Accrual Measures

Table 1 shows the mean value, μ, and the standard deviation, σ, of various discretionary accrual measures from the alternative Jones-type models discussed in Section IV. As noted above, both parameters are important in determining Type I error rates that are reported in subsequent tables. Analogous to Kothari et al. (2005), we show summary statistics for extreme quintiles of *ROA, SG,* and *MB,* which we have shown previously to be related to innate quarterly accruals (see Section II). We also show summary statistics for extreme quintiles of two other firm characteristics—firm size, which is measured by the market value of equity (*MV*), and financial distress (*FD*), which is estimated from a model given by Shumway (2001).[9] We report summary statistics from samples selected from extreme quintiles of *MV* and *FD* because these firm dimensions are often over-weighted in samples where researchers test for earnings management, and we are interested in assessing the degree of misspecification that exists when controls are introduced for innate accruals related to performance and firm growth in such samples.[10]

The first row of Table 1 shows raw accruals for completeness. However, we focus on the next 12 rows that reflect results for the various discretionary accrual models outlined in Section IV—six variations each of the basic Jones and Mod-Jones models. When estimating the Jones or Mod-Jones models cross-sectionally by SIC2year, discretionary accruals that are residuals from Equations (2) and (3) above have, by construction, a mean value of zero in the aggregate sample. This is also true of all matching models and enhancements that include controls for *ROA* only, or *ROA, SG,* and *MB* (see mean values in the "All" column). As discussed in Section IV, we see that matching models increase the standard deviation by a factor of $\sqrt{2}$. So *ROA* matching models

[8] See Downing and Clark (2010, 198) for discussion of the central limit theorem. An analytical derivation of the determinants of Type I error rates is available from the authors upon request.

[9] Shumway's (2001) measure uses a hazard model and both accounting and market-based factors to predict bankruptcy risk. The factors include net income/total assets (ROA), total liabilities/total assets (book leverage), relative size, market-adjusted equity return, and idiosyncratic volatility (Shumway 2001, Table 6, Panel B). Beaver, McNichols, and Rhie (2004) and Bauer and Agarwal (2014) show that Shumway's (2001) model has better predictive power for bankruptcy than Altman's z-ratio.

[10] For example, numerous studies in the auditing literature test for differences in earnings quality and earnings management of clients of Big N versus non-Big N audit firms (Becker, DeFond, Jiambalvo, and Subramanyam 1998; Francis, Maydew, and Sparks 1999). These samples differ systematically on size, or MV of equity. Other studies examine whether firms facing financial distress are more inclined to engage in earnings management (H. DeAngelo, L. DeAngelo, and Skinner 1994; DeFond and Jiambalvo 1994; DeFond and Subramanyam 1998).

TABLE 1

Mean and Standard Deviation of Accrual Measures within the Aggregate Sample of Firm-Quarters and Partitions Formed by Firm Characteristics

		Partitioning Variable									
		ROA		*SG*		*MB*		*MV*		*FD*	
Description	**All**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
1. Raw accruals	0.43	−0.84	0.95	−0.53	1.25	−0.08	0.82	0.18	0.32	0.77	−0.06
	(4.54)	(5.44)	(5.13)	(4.95)	(5.14)	(4.98)	(5.12)	(5.69)	(3.07)	(3.91)	(5.56)
2. Jones	0.00	−0.93	0.34	−0.54	0.40	−0.31	0.24	−0.27	0.01	0.27	−0.37
	(4.05)	(5.08)	(4.37)	(4.61)	(4.72)	(4.39)	(4.64)	(5.09)	(2.57)	(3.40)	(5.10)
3. Jones with linear *ROA* term	0.00	−0.34	−0.03	−0.35	0.40	−0.19	0.21	−0.24	−0.08	0.11	−0.13
	(3.99)	(4.96)	(4.35)	(4.49)	(4.67)	(4.30)	(4.58)	(4.97)	(2.58)	(3.39)	(4.97)
4. Jones with *ROA* matching	0.00	−0.05	0.02	−0.23	0.37	−0.13	0.28	−0.11	−0.17	0.05	−0.01
	(5.63)	(6.99)	(6.12)	(6.25)	(6.33)	(5.95)	(6.34)	(6.59)	(4.35)	(5.11)	(6.71)
5. Jones with *ROA* quintile dummies	0.00	0.00	0.00	−0.30	0.41	−0.18	0.24	−0.23	−0.10	0.11	−0.11
	(3.98)	(5.01)	(4.33)	(4.50)	(4.65)	(4.30)	(4.58)	(4.97)	(2.57)	(3.37)	(4.98)
6. Jones with linear *ROA, SG,* and *MB* terms	0.00	−0.35	−0.09	−0.18	0.12	−0.07	0.05	−0.15	−0.12	0.02	−0.08
	(3.98)	(4.94)	(4.33)	(4.49)	(4.62)	(4.26)	(4.52)	(4.93)	(2.57)	(3.39)	(4.95)
7. Jones with *ROA, SG,* and *MB* quintile dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.10	−0.15	−0.03	−0.03
	(3.92)	(4.94)	(4.25)	(4.45)	(4.59)	(4.24)	(4.52)	(4.89)	(2.55)	(3.32)	(4.91)
8. Mod-Jones	0.00	−1.18	0.68	−1.02	0.89	−0.40	0.33	−0.35	0.04	0.36	−0.43
	(4.06)	(5.11)	(4.34)	(4.63)	(4.72)	(4.44)	(4.64)	(5.16)	(2.52)	(3.39)	(5.15)
9. Mod-Jones with linear *ROA* term	0.00	−0.43	0.19	−0.75	0.85	−0.24	0.29	−0.29	−0.08	0.15	−0.13
	(3.98)	(4.99)	(4.32)	(4.49)	(4.64)	(4.33)	(4.55)	(5.01)	(2.52)	(3.37)	(4.99)
10. Mod-Jones with *ROA* matching	0.00	−0.04	0.02	−0.58	0.81	−0.13	0.30	−0.11	−0.21	−0.01	0.05
	(5.60)	(7.02)	(6.06)	(6.25)	(6.29)	(5.95)	(6.30)	(6.62)	(4.30)	(5.07)	(6.72)
11. Mod-Jones with *ROA* quintile dummies	0.00	0.00	0.00	−0.63	0.83	−0.17	0.26	−0.25	−0.14	0.06	−0.06
	(3.97)	(5.03)	(4.29)	(4.49)	(4.62)	(4.31)	(4.54)	(4.99)	(2.53)	(3.35)	(4.99)
12. Mod-Jones with linear *ROA, SG,* and *MB* terms	0.00	−0.44	0.10	−0.34	0.22	−0.06	0.05	−0.15	−0.12	0.00	−0.04
	(3.94)	(4.93)	(4.25)	(4.47)	(4.59)	(4.26)	(4.45)	(4.92)	(2.51)	(3.33)	(4.92)
13. Mod-Jones with *ROA, SG,* and *MB* quintile dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.10	−0.17	−0.11	0.05
	(3.88)	(4.91)	(4.19)	(4.43)	(4.56)	(4.22)	(4.45)	(4.87)	(2.51)	(3.27)	(4.89)

The aggregate sample consists of all Compustat firm-quarters during 1991-Q1 to 2007-Q4 for which the relevant data to calculate the accrual measures and the partitioning variables reported in this table are available. Five additional sampling criteria are listed in Section II. The final sample consists of 203,090 firm-quarters. The calculation of the various accrual measures is described as follows:

(1) We compute quarterly accruals as: (*CHGAR* + *CHGINV* + *CHGAP* + *CHGTAX* + *CHGOTH*), where the bracketed quantities represent the change in accounts receivable (item *RECCHY*), inventories (item *INVCHY*), accounts payable (item *APALCHY*), taxes (item *TXACHY*), and other items (item *AOLOCHY*), all taken from the quarterly cash flow statement and appropriately differenced to calculate the individual quarterly amounts. We recode missing values of *RECCHY, INVCHY, APALCHY,* and *TXACHY* as 0 if there is a nonmissing value of *AOLOCHY*. Conversely, if *AOLOCHY* is missing, but the other items are not missing, then we recode *AOLOCHY* as 0.

(2) We calculate several variants of the Jones model. Equation (2) in the text specifies the baseline Jones model [Row 2 in table]; Equation (4) specifies Jones with linear *ROA, SG,* and *MB* terms [Row 6], while an appropriately shortened version of it specifies Jones with linear *ROA* term [Row 3]; and Equation (6) specifies Jones with *ROA, SG,* and *MB* quintile dummies [Row 7], while an appropriately shortened version of it specifies Jones with *ROA* quintile dummies [Row 5]. Jones with *ROA* matching [Row 4] is described in Section IV.

(3) We calculate several variants of the Mod-Jones (i.e., Modified Jones) model. Equation (3) in the text specifies the baseline Mod-Jones model [Row 8]; Equation (5) specifies Mod-Jones with linear *ROA, SG,* and *MB* terms [Row 12], while an appropriately shortened version of it specifies Mod-Jones with linear *ROA* term [Row 9]; and Equation (7) specifies Mod-Jones with *ROA, SG,* and *MB* quintile dummies [Row 13], while an appropriately shortened version of it specifies Mod-Jones with *ROA* quintile dummies [Row 11]. Mod-Jones with *ROA* matching [Row 10] is described in Section IV.

All variables in all mentioned equations are scaled by lagged total assets and winsorized at the 1 percent and 99 percent levels. The table shows the mean values outside parentheses and standard deviations inside parentheses for various accrual measures. The column under "All" includes the aggregate sample of 203,090 firm-quarters described above. The "Low" and "High" columns under "*ROA*," "*SG*," "*MB*," "*MV*," and "*FD*" include the lowest and the highest quintiles of data arranged by the corresponding firm characteristic. *MV* is the market value of equity as of last quarter $t-1$, but inflation-adjusted and stated in 2007 dollars; and *FD* measures financial distress value of firm as of last quarter $t-1$, calculated using the Shumway (2001) procedure. Higher values of the Shumway measure indicate high *FD*. All accrual measures are in units of percent of assets value. Thus, the first value of 0.43 in the column under "All" implies that accruals in the aggregate sample have a mean value of 0.0043 times assets value.

TABLE 2

Specification Tests: Rejection Rates of the Null Hypothesis of Zero Discretionary Accruals within the Aggregate Sample of Firm-Quarters and Partitions Formed by Various Firm Characteristics

Panel A: H1: Discretionary Accruals < 0

		Partitioning Variable									
	All Firms	***ROA*** Low	***ROA*** High	***SG*** Low	***SG*** High	***MB*** Low	***MB*** High	***MV*** Low	***MV*** High	***FD*** Low	***FD*** High
2. Jones	4.4	**80.4**	*0.8*	**52.8**	*0.8*	**26.0**	*0.4*	**15.6**	4.4	*0.4*	**25.2**
3. Jones with linear *ROA* term	4.4	**30.8**	5.2	**28.8**	*0.8*	**15.6**	*0.8*	**13.6**	8.0	*2.0*	**10.4**
4. Jones with *ROA* matching	4.8	7.6	6.4	**12.4**	*0.8*	**10.8**	*0.4*	6.4	**14.0**	8.0	6.0
5. Jones with *ROA* quintile dummies	4.8	5.2	4.0	**21.2**	*0.8*	**16.0**	*0.4*	**12.4**	**10.8**	*1.6*	8.0
6. Jones with linear *ROA, SG,* and *MB* terms	5.6	**29.2**	5.6	**12.4**	*1.6*	**8.8**	3.6	**9.6**	**15.2**	4.0	6.8
7. Jones with *ROA, SG,* and *MB* quintile dummies	4.0	6.0	3.2	2.4	4.4	6.4	4.4	5.6	**19.2**	7.2	3.6
8. Mod-Jones	4.8	**92.8**	*0.0*	**94.4**	*0.0*	**36.0**	*0.4*	**22.0**	3.2	*0.0*	**30.8**
9. Mod-Jones with linear *ROA* term	4.0	**40.0**	*0.0*	**78.4**	*0.0*	**19.6**	*1.2*	**20.4**	**8.8**	*0.8*	**9.6**
10. Mod-Jones with *ROA* matching	5.6	7.6	6.0	**38.4**	*0.0*	**10.4**	*0.8*	6.0	**15.6**	**8.8**	3.6
11. Mod-Jones with *ROA* quintile dummies	4.4	5.6	4.4	**67.2**	*0.0*	**13.6**	*1.6*	**15.2**	**16.0**	4.0	5.2
12. Mod-Jones with linear *ROA, SG,* and *MB* terms	4.4	**34.0**	*1.2*	**29.6**	*0.8*	**8.4**	3.6	7.6	**15.6**	5.2	5.6
13. Mod-Jones with *ROA, SG,* and *MB* quintile dummies	3.6	6.4	3.2	2.8	4.4	6.8	5.6	6.0	**23.2**	**15.6**	*2.0*

Panel B: H1: Discretionary Accruals > 0

		Partitioning Variable									
	All Firms	***ROA*** Low	***ROA*** High	***SG*** Low	***SG*** High	***MB*** Low	***MB*** High	***MV*** Low	***MV*** High	***FD*** Low	***FD*** High
2. Jones	4.4	*0.0*	**33.6**	*0.0*	**32.0**	*0.0*	**22.8**	*0.8*	5.6	**30.4**	*0.8*
3. Jones with linear *ROA* term	3.6	*0.4*	3.6	*0.0*	**31.6**	*1.6*	**22.8**	*0.8*	*1.2*	**11.2**	2.4
4. Jones with *ROA* matching	5.2	3.6	4.0	*0.4*	**19.6**	*1.6*	**16.0**	3.6	*1.6*	6.4	4.8
5. Jones with *ROA* quintile dummies	3.6	6.4	4.8	*0.0*	**32.8**	*1.6*	**24.4**	*0.8*	*2.0*	**11.6**	2.4
6. Jones with linear *ROA, SG,* and *MB* terms	4.4	*1.2*	4.4	*0.4*	5.6	3.6	**9.2**	*0.8*	*0.8*	4.4	3.6
7. Jones with *ROA, SG,* and *MB* quintile dummies	3.6	5.2	6.0	4.4	2.4	5.2	6.0	*1.6*	*0.4*	3.2	4.8
8. Mod-Jones	4.0	*0.0*	**75.6**	*0.0*	**86.0**	*0.0*	**30.0**	*0.4*	**8.8**	**44.4**	*0.8*
9. Mod-Jones with linear *ROA* term	3.6	*0.4*	**18.0**	*0.0*	**85.2**	*0.4*	**28.8**	*0.8*	*1.6*	**13.2**	*2.0*
10. Mod-Jones with *ROA* matching	4.8	4.4	3.6	*0.0*	**61.6**	2.4	**17.6**	2.4	*0.8*	4.0	5.6
11. Mod-Jones with *ROA* quintile dummies	4.4	6.0	5.6	*0.0*	**84.0**	2.4	**26.4**	*0.8*	*0.4*	6.0	4.4
12. Mod-Jones with linear *ROA, SG,* and *MB* terms	4.8	*0.8*	**11.6**	*0.0*	**13.6**	3.6	**9.2**	*1.2*	*0.0*	3.2	5.6
13. Mod-Jones with *ROA, SG,* and *MB* quintile dummies	4.4	6.4	4.0	2.8	2.8	6.4	8.0	*0.8*	*0.0*	*1.2*	6.8

Models 2–4 and 8–10 in each panel have been used in prior literature.

This table reports the percentage of 250 samples of 200 firms each for which the null hypothesis of zero discretionary accrual is rejected at the 5 percent level using a one-tailed t-test for mean. These samples are drawn at random from the universe of 203,090 Compustat firm-quarters during 1991-Q1 to 2007-Q4, as described in Table 1. That table also describes the calculation of discretionary accrual Models 2 to 13 and the partitioning variables examined in this table. The low and high partitions of any partitioning variable represent the lowest and highest quintiles of the aggregate sample of firm-quarters. We calculate that if the rejection frequency within any one run of 250 samples is below 2.4 percent or above 8.0 percent, then it is statistically significantly different from the model rejection frequency of 5 percent at the 5 percent confidence level in a two-tailed frequency test.

have σ of 5.63 percent and 5.60 percent in the aggregate sample, which is roughly 1.4 times larger than the σ of 4.05 percent and 4.06 percent for the baseline Jones and Mod-Jones models. As we will report in specification results in the next section, higher σ has the effect of lowering Type I error rates for the same percent misspecification μ. It is also true that the higher σ for the matching models means that these models will exhibit lower power, as later shown in Section VI and Figure 5.

Further evidence on potential Type I error rates comes from examining the mean value of discretionary accruals, which we characterize as percent misspecification, or μ, within samples drawn from extreme quintiles of firm characteristics that are noted at the top of Table 1. The following are the important takeaways from this table:

1. The maximum misspecification in the baseline Jones and Mod-Jones models (based on average absolute value of μ calculated over Low and High partitions for each firm characteristic) arises from samples drawn from extreme *ROA* partitions followed by *SG* partitions. In addition, *MB, MV,* and *FD* partitions also show considerable misspecification. The Jones discretionary accruals range from −0.93 percent to 0.40 percent of lagged assets (Row 2), and Mod-Jones discretionary accruals range from −1.18 percent to 0.89 percent of lagged assets (Row 8). The greater misspecification of the Mod-Jones model is consistent with the graphical evidence shown earlier in Panels A and B of Figure 4. In addition to *ROA,* the fact that both the *SG* and *MB* partitions exhibit considerable misspecification is consistent with our claim that both backward-looking and forward-looking firm growths are important determinants of innate accruals.
2. Jones and Mod-Jones models with linear *ROA* terms continue to show substantial misspecification, particularly for the Low *ROA* quintile partition, as well as for Low and High *SG* and *MB* partitions. In contrast, the *ROA* matching versions of the Jones and Mod-Jones models give minimal percent misspecification in samples selected from Low and High *ROA* quintiles (Rows 4 and 10). However, these models yield considerable misspecification for extreme *SG* or *MB* quintiles that range from −0.23 percent to 0.37 percent of lagged assets for Jones with *ROA* matching, and −0.58 percent to 0.81 percent of lagged assets for Mod-Jones with *ROA* matching. In their investigation of annual accruals models, Kothari et al. (2005, 167) state that: "Performance-matched discretionary accruals exhibit only a modest degree of misspecification when firms are randomly selected from an extreme quartile of stocks ranked on firm characteristics such as the book-to-market ratio, firm size, sales growth, and earnings yield." We find that their empirical insights do not automatically apply to Jones-type models applied in quarterly settings.
3. Jones and Mod-Jones models with quintile dummies for *ROA* exhibit no misspecification for Low and High *ROA* quintile partitions, as would be expected. However, these models do yield considerable misspecification for Low and High *SG, MB,* and *MV* partitions that range from −0.30 percent to 0.41 percent of lagged assets for Jones, and from −0.63 percent to 0.83 percent of lagged assets for Mod-Jones.
4. Of the two approaches that can simultaneously control for *ROA, SG,* and *MB* effects, adding linear terms turns out to be less effective than adding quintile dummy variables. As shown in Table 1, adding simple linear terms for *ROA, SG,* and *MB* leads to mean values of μ that range from −0.18 percent to 0.12 percent of lagged assets for the Jones model for extreme *SG* partitions (Row 6), and −0.34 percent to 0.22 percent of lagged assets for the Mod-Jones model (Row 12). The misspecification is even greater in the Low *ROA* partition, with a mean value of μ that equals −0.35 percent for the Jones model and −0.44 percent for the Mod-Jones model. All this is because the relation between performance (*ROA*) and backward-looking growth (*SG*) and quarterly accruals is non-linear, as shown in Figure 1.
5. The Jones-type models with *ROA, SG,* and *MB* quintile dummies exhibit no misspecification across extreme *ROA, SG,* and *MB* partitions (as expected). For the *MV* and *FD* partitions, the quintile dummies models exhibit some misspecification, ranging from −0.15 percent to −0.03 percent of lagged assets for Jones, and from −0.17 percent to 0.05 percent of lagged assets for Mod-Jones. Thus, the quintile dummy variable approach for dealing with the non-linear effects of performance and growth on innate accruals is likely to work well in a variety of empirical settings.

Specification Tests of Alternative Discretionary Accrual Models Using Quarterly Data

Results for Concentrated Samples of Low (High) Growth Firms and Other Firm Characteristics

In this section, we follow the analysis in Kothari et al. (2005) and examine the degree of misspecification (Type I error rates) when samples of $n = 200$ are drawn randomly either from the aggregate sample of Compustat firm-quarters or from the bottom (Low) or top (High) quintile of firm-quarters ranked by *ROA, SG, MB, MV,* and *FD*. We report results for the 12 discretionary accruals models that were examined in Table 1, starting with the baseline quarterly Jones and Mod-Jones models.

The choice of a sample size of 200 observations is somewhat arbitrary. Having all observations from the top or bottom quintile of firm characteristics makes it comparable to a bigger sample with more modest concentration in extreme quintiles. In Section VIII, we report the specification tests for these accrual measures with larger samples, but with a lower concentration of observations in extreme quintiles. We repeat the above sampling procedure 250 times with replacement. Because firm-quarters are selected at random, there is no reason to believe systematic earnings management is present in these samples. Thus, the null hypothesis of no earnings management is assumed to be true. Using an α-level of 5 percent, we measure the percentage of trials for which the null hypothesis of zero discretionary accruals (i.e., no earnings management) is rejected in favor of the alternate hypothesis of either negative or positive discretionary accruals (i.e., downward or upward earnings management) using a one-tailed t-test of means. With 250 replications, there is a 95 percent probability that the measured rejection rate will lie between 2.4 percent and 8.0 percent if the discretionary accrual measure is not misspecified and the null hypothesis is true.

Table 2 presents the simulation results. Panels A and B show the rejection rates against the alternative hypothesis that discretionary accruals are negative and positive, respectively. The first column provides rejection frequencies for samples drawn from the aggregate sample of firm-quarters, and the next five sets of two columns each present results for samples drawn from the bottom and top quintiles of firm-quarters ranked on *ROA, SG, MB, MV,* and *FD*. Rows 2–4 and 8–10 in each panel show rejection rates for the most common versions of Jones-type models that have been applied in the literature to date. Comparison of these rejection rates to the rejection rates shown in Rows 5–7 and 11–13 provide insights into how controlling for firm performance and growth in a linear versus non-linear manner affects Type I error rates. The key results are summarized as follows:

1. For samples drawn from the aggregate set of Compustat firm-quarters, the rejection rates lie between the bounds of 2.4 percent and 8.0 percent in all 24 cases (12 cases where the alternative hypothesis is that discretionary accruals < 0 and 12 cases where the alternative hypothesis is that discretionary accruals > 0). Thus, all models are well-specified when samples are selected from the aggregate sample of firm-quarters. This is not surprising because Jones and Mod-Jones model residuals are mean-zero by construction in the aggregate data, and samples drawn from the aggregate data are well-dispersed across the full spectrum of values of each firm characteristic. Thus, any performance or growth-related biases in discretionary accruals estimates tend to cancel out when firms are randomly selected from the aggregate sample of firm-quarters. These results serve as an important validation check of our simulation procedures.
2. The baseline Jones and Mod-Jones models (Rows/Models 2 and 8 in each panel) that control only for adjacent-quarter changes in sales are misspecified in almost all Low and High partitions of the five firm characteristics (37 out of 40 cases).[11] Some of the largest rejection rates occur in *ROA* partitions, but this is not surprising in view of the findings in Kothari et al. (2005) that failure to control for performance biases discretionary accrual estimates. Because this study focuses on the effects of firm growth on innate accruals, we examine in particular the rejection rate results for samples drawn from the Low and High partitions of *SG* and *MB*. We find that in Low *SG* samples, the researcher erroneously concludes in favor of downward earnings management, and in High *SG* samples, the researcher erroneously concludes in favor of upward earnings management a very high percentage of time for the baseline Jones and Mod-Jones models. The Type I error rates range from six to ten (17 to 19) times the nominal α-level of 5 percent for the baseline Jones (Mod-Jones) model. Thus, looking across models, the Mod-Jones model is associated with the highest Type I errors, with rejection rates as high as 94.4 percent (86.0 percent) in the Low (High) *SG* partitions when the null hypothesis of no earnings management is true. The rejection rates are somewhat lower for Jones model, 52.8 percent (32.0 percent) in the Low (High) *SG* partition, but remain high in absolute terms. Type I error rates are lower, but still high in absolute terms (ranging from five to seven times the nominal alpha level) when samples are selected from extreme *MB* partitions. The Jones and Mod-Jones baseline models also yield excessively high rejection rates when samples are selected from extreme size (*MV*) and financial distress (*FD*) quintiles, but the degree of misspecification is not as severe as it is for the *SG* and *MB* partitions.
3. Adding a linear *ROA* term to control for performance seems to moderate Type I error rates, but they remain high in absolute terms. For example, when the alternative hypothesis is that discretionary accruals are negative (positive), the Jones model with a linear *ROA* term gives rejection rates of 28.8 percent (31.6 percent) when samples are selected from the Low (High) *SG* partition (Row 3 in each panel). For the Mod-Jones model with a linear *ROA* term, the corresponding rejection rates are 78.4 percent (85.2 percent) when samples are drawn from the Low (High) *SG* partition (Row 9 in each panel). In fact, the rejection rates for the Jones and Mod-Jones models with linear *ROA* terms remain misspecified in some of the extreme *ROA* partitions, suggesting non-linearity. Rejection rates are not as large, but remain excessive, for these models when samples are selected from extreme *MB* partitions.
4. Of the two non-linear approaches of controlling for performance (Jones-type models with *ROA* matching and Jones-type models with *ROA* quintile dummies), the matching approach tends to yield lower Type I error rates for Low and High *SG* and *MB* partitions. However, as we explained earlier, this finding is somewhat deceptive. As shown in Table 1, both approaches yield mean discretionary accruals of similar magnitudes for Low and High partitions of *SG* and *MB*. So the lower Type I error rates for the *ROA* matching models in Table 2 are mainly the result of the higher standard deviation of this differencing approach, which makes it harder to reject a true null hypothesis.
5. We next turn our attention to the benefits of controlling for firm growth, in addition to controlling for *ROA* in a linear setting. This discussion compares Row 3 with Row 6, and Row 9 with Row 12, in both panels of Table 2. We first look

[11] Notice that rejection rates lower than 2.4 percent arise from model misspecification similar to rejection rates higher than 8.0 percent (with 95 percent confidence level). For example, consider that Jones discretionary accruals average −0.54 percent and 0.40 percent in Low and High *SG* partitions in Table 1. Both show clear misspecification, because a well-specified model would give discretionary accruals of around 0.00 percent in absence of earnings management. In samples of 200 observations, there is a low probability of rejecting H0: $DA = 0$ in favor of H1: $DA > 0$ in the Low *SG* partition, or rejecting H0: $DA = 0$ in favor of H1: $DA < 0$ in the High SG partition, with these percent misspecifications. Not surprisingly, the corresponding rejection rates are 0.0 percent in Panel B and 0.8 percent in Panel A of Table 2. This example illustrates the association between low rejection rates and percent misspecification that is in an opposite direction to the alternate hypothesis. Since excessively high rejection rates of the null hypothesis are usually a bigger concern, we tend to focus on those in most situations.

at the entirety of all ten partitions formed by Low and High quintiles of the five firm characteristics, variants of both Jones and Mod-Jones models, and alternate hypotheses of negative and positive discretionary accruals, a total of 40 comparisons. We find that adding linear terms for *ROA, SG,* and *MB* produces better-specified test statistics than adding a linear term for *ROA* alone in 31 cases, worse in four cases, and there is a statistical tie in the remaining five cases.[12] The improvement in test statistics is quite substantial in many cases, in particular, for Low and High partitions of *SG* and *MB*. The rejection rates of 28.8 percent and 78.4 percent for Jones and Mod-Jones models with linear *ROA* terms in the Low *SG* partition in Panel A (where the alternate hypothesis is negative discretionary accruals) are reduced to 12.4 percent and 29.6 percent with linear *ROA, SG,* and *MB* terms. More substantial improvements occur in the High *SG* partition in Panel B (where the alternate hypothesis is positive discretionary accruals), as the rejection rates of 31.6 percent and 85.2 percent for Jones and Mod-Jones models with linear *ROA* terms are reduced to 5.6 percent and 13.6 percent with linear *ROA, SG,* and *MB* terms. Improvement in Type I error rates also occurs in Low and High *MB* partitions when we include linear *SG* and *MB* terms, in addition to the linear *ROA* term. This evidence highlights the role of controlling for backward-looking growth (*SG*) and forward-looking growth (*MB*), even in a setting where one assumes all effects on innate accruals are linear.

6. Finally, we examine the Type I error rate effects of simultaneously controlling for the effects of *ROA, SG,* and *MB* in a linear versus non-linear quintile dummies manner. For this investigation, the relevant comparisons are between Row 6 and Row 7, and between Row 12 and Row 13, in both Panels A and B. Across Low and High *ROA, SG,* and *MB* partitions, the non-linear quintile dummies specifications of both Jones and Mod-Jones models clearly yield much better Type I error rates than do the corresponding models that use linear controls for *ROA, SG,* and *MB*. Rejection rates are always within the 95 percent confidence level bounds of 2.4 percent to 8.0 percent around the true rejection rate of 5 percent for the quintile dummies models for all Low and High partitions of *ROA, SG,* and *MB*, while rejection rates are frequently excessive for the Jones and Mod-Jones models that use linear *ROA, SG,* and *MB* terms. Results for the quintile dummy versions of the Jones and Mod-Jones models are mixed when samples are selected from extreme *MV* and *FD* quintiles, with the worst Type I error rate being 23.2 percent for the High *MV* partition and the alternate hypothesis of negative discretionary accruals. Notice that the High *MV* partition has the lowest standard deviation of all discretionary accrual measures in Table 1, which increases the rejection rates.
7. We conclude that in most circumstances, Jones and Mod-Jones models with *ROA, SG,* and *MB* quintile dummies are reasonably well-specified in quarterly settings across firm partitions examined in Table 2.

Replication of Tests for Earnings Management around Stock Splits, SEOs, and Stock Acquisitions

In this section, we investigate whether findings in three settings where researchers have found evidence of significant upward earnings management would likely be overturned if controls were implemented for the non-linear relation between *ROA, SG,* and *MB* and innate accruals. We examine tests for earnings management in quarterly settings around stock splits (Louis and Robinson 2005), seasoned equity offerings (Rangan 1998), and stock-for-stock acquisitions (Louis 2004; Gong et al. 2008). All four of these studies use the Mod-Jones model (or close derivatives thereof) to compute abnormal or discretionary accruals. So in our replication of the tests used in these studies, we use Mod-Jones models. It is important to note that in the Rangan (1998) study, no control for performance was included in the tests. In the other three papers, performance was controlled for by matching on seasonally lagged *ROA* (i.e., ROA_{t-4}). Therefore, to maintain consistency with the methods used in these prior studies, we initially present our replication results using Mod-Jones and Mod-Jones with lagged *ROA* (*LROA*) matching (i.e., matching on ROA_{t-4}). We also present results for Mod-Jones with a linear *LROA* term and Mod-Jones with *LROA* quintile dummies, which are alternate ways to control for performance. These results are presented in Panels A and B of Table 3.

Consistent with the models and findings used in these prior studies, the Mod-Jones model yields highly significant positive discretionary accruals for all three corporate events, with values in Table 3, Panel A ranging from 0.531 percent to 0.665 percent of total assets. The Mod-Jones model with performance matching generally reduces discretionary accruals, but in all three settings, the mean discretionary accruals are still positive and highly significant. This is also the case when using a linear *LROA* term and *LROA* quintile dummies. So using the same model (Mod-Jones) and the same method of controlling for performance (lagged *ROA*, or ROA_{t-4}) applied in these earlier studies, we are able to replicate the findings in these earlier studies of significantly positive upward earnings management around these events.

[12] A model produces better (worse) specified tests than another if its rejection rates are closer to (farther from) the true rejection rate of 5.0 percent. However, if the rejection rates for both models are equal, or both within the statistical bounds of 2.4 percent to 8.0 percent on the true rejection rate of 5.0 percent, then we call it a statistical tie.

TABLE 3

Biases in Discretionary Accrual Estimates *before Select Corporate Events*

Panel A: No Additional Controls for Performance or Growth

Discretionary Accrual Measure	Stock Splits Louis and Robinson (2005)	SEOs Rangan (1998)	Stock Acquisitions Louis (2004) and Gong et al. (2008)
Mod-Jones	0.531	0.578	0.665
	(6.79)***	(7.88)***	(5.65)***

Panel B: Using *LROA* (Lagged *ROA*), *SG,* and *MB* Controls

Discretionary Accrual Measure	Stock Splits Louis and Robinson (2005)	SEOs Rangan (1998)	Stock Acquisitions Louis (2004) and Gong et al. (2008)
Mod-Jones with linear *LROA* term	0.508	0.585	0.658
	(6.50)***	(8.01)***	(5.61)***
Mod-Jones with *LROA* matching	0.502	0.530	0.472
	(4.51)***	(5.04)***	(2.65)***
Mod-Jones with *LROA* quintile dummies	0.432	0.573	0.625
	(5.57)***	(7.90)***	(5.31)***
Mod-Jones with linear *LROA, SG,* and *MB* terms	0.174	0.305	0.066
	(2.29)**	(4.26)***	(0.56)
Mod-Jones with *LROA, SG,* and *MB* quintile dummies	−0.008	0.215	0.052
	(−0.10)	(3.04)***	(0.45)

Panel C: Using *CROA* (Current *ROA*), *SG,* and *MB* Controls

Discretionary Accrual Measure	Stock Splits Louis and Robinson (2005)	SEOs Rangan (1998)	Stock Acquisitions Louis (2004) and Gong et al. (2008)
Mod-Jones with linear *CROA* term	0.234	0.556	0.547
	(3.01)***	(7.63)***	(4.62)***
Mod-Jones with *CROA* matching	0.103	0.339	0.329
	(0.93)	(3.24)***	(1.84)**
Mod-Jones with *CROA* quintile dummies	0.125	0.493	0.588
	(1.62)*	(6.83)***	(4.96)***
Mod-Jones with linear *CROA, SG,* and *MB* terms	−0.013	0.297	0.018
	(−0.18)	(4.15)***	(0.15)
Mod-Jones with *CROA, SG,* and *MB* quintile dummies	−0.148	0.190	0.051
	(−1.98)**	(2.68)***	(0.44)
n	2,646	2,951	1,193

*, **, *** Denote statistical significance at the 10 percent, 5 percent, and 1 percent levels in one-tailed tests.

We start with a comprehensive sample of 203,090 firm-quarters during 1991 to 2007 from the Compustat and CRSP databases, as described in Table 1, and merge it with samples of firms that announced stock splits, SEOs, and stock acquisitions. Stock splits are identified from the CRSP database using distribution code 5523 and a positive split factor, and SEOs and stock acquisitions are identified from the SDC database. We calculate the discretionary accrual measures using Compustat data for quarter t, which is the fiscal quarter with an earnings announcement date immediately preceding the announcement date of the corporate event. These discretionary accrual measures are defined in Table 1. *LROA* in this table refers to four-quarters lagged *ROA*, or ROA_{t-4}, which is used as the measure of firm performance by Louis and Robinson (2005), who analyze stock splits, and Louis (2004) and Gong et al. (2008), who analyze stock acquisitions. t-statistics are reported in parentheses. *CROA* refers to current *ROA*, or ROA_t, which is used as the measure of firm performance in all other places in this paper.

In contrast to the evidence in support of upward earnings management noted above, when using the quintile dummies approach to control for the non-linear effects of performance and growth on accruals (last line in Panel B of Table 3), the mean discretionary accruals are much lower, ranging from −0.008 percent to 0.215 percent of total assets. For the Mod-Jones model with the three quintile dummies, only the SEO sample continues to yield significantly positive discretionary accruals of 0.215

percent of total assets. Thus, consistent with the prior findings of Rangan (1998), there does appear to be some upward earnings management associated with SEOs, although the degree of upward management appears to be less than previously documented. Notice, also, that using linear terms to control for the effects of performance and growth on accruals only achieves partial reduction in the magnitude of discretionary accruals.

For completeness, and to be consistent with the way we control for performance in Tables 1 and 2, in Panel C of Table 3, we present results for Mod-Jones models with controls for current performance (*CROA*, or ROA_t, elsewhere in this paper simply referred to as *ROA*) and *SG* and *MB* growth measures. Because none of the prior studies used *CROA* to control for performance in their tests, these model results are not directly comparable to the results of these earlier studies. We find that discretionary accrual measures for SEOs and stock acquisitions are similar for Mod-Jones models with *CROA* or *LROA* controls. However, this is not so for stock splits. Mod-Jones models with *CROA* controls alone (whether linear or non-linear) significantly reduce the estimated magnitude of discretionary accruals in the stock split sample. Further, the Mod-Jones with *CROA, SG,* and *MB* quintile dummies model produces significantly negative mean discretionary accruals, which is just the opposite of the prediction in the Louis and Robinson (2005) study. In part, these results for stock splits may be attributed to the higher effectiveness of *CROA* controls relative to *LROA* controls in measuring discretionary accruals, as argued by Kothari et al. (2005). Alternatively, these results may also be attributed to a downward bias in discretionary accrual estimates when matching on contemporaneous performance and treatment firms have above-average cash flows from operations (*CFO*), as alluded to by Kothari et al. (2005, footnote 11) and discussed later in our Section VIII. It turns out that stock split firms have higher than average *CFO,* thus, lower accruals than *CROA*-controlled firms that are likely to have average *CFO* and correspondingly higher accruals.

The important takeaway from the analysis in Table 3 is that controlling for the non-linear effects of growth on innate accruals considerably reduces the estimated magnitude of discretionary accruals in these settings. Thus, consistent with the claim made by Ball (2013) (see footnote 2 in this paper), it appears that some of the earlier studies of earnings management in these settings may have reported false positive results.

VI. POWER OF ALTERNATIVE DISCRETIONARY ACCRUAL MEASURES TO DETECT EARNINGS MANAGEMENT

Simulation Results of Model Power

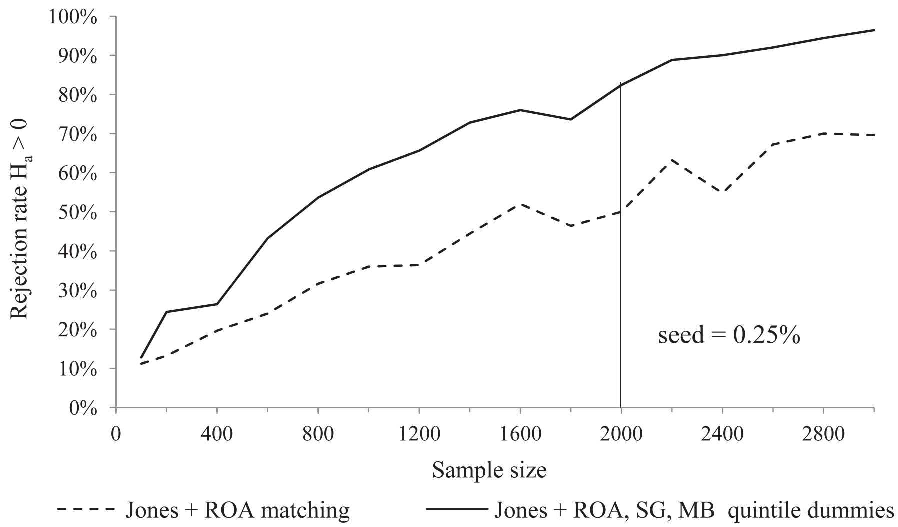
We define model power as the ability of a discretionary accrual (*DA*) model/measure to reject the null hypothesis H0: $DA = 0$ in favor of the alternate hypothesis H1: $DA > 0$ when it is known that the true *DA* equals $\delta > 0$, or, alternately, the ability to reject in favor of the alternate hypothesis H1: $DA < 0$ when it is known that the true *DA* equals $\delta < 0$. Both tests are one-tailed as in most situations, the researcher has prior beliefs about whether the firms under investigation are likely to engage in upward or downward earnings management based on the incentives of managers and shareholders. As upward earnings management seems to be the more common situation examined in prior research, we focus on this alternate hypothesis rather than on downward earnings management. Because the effect of misspecification (μ in Table 1) and the degree of earnings management seeded in the data (δ) can have similar effects on model power, one needs to test the power of alternative discretionary accrual models on a sample partition where the models have the same percent misspecification or the misspecification is zero. The aggregate sample of all firm-quarters is the only partition that has this property.

We now illustrate the effect of the sample size n and the standard deviation σ on model power with simulations. Panel A of Figure 5 shows two variants of Jones models, with *ROA* (i.e., $ROA_{i,t}$) matching (the current practice) and with *ROA, SG,* and *MB* quintile dummies (our recommendation).[13] Panel B shows the corresponding variants of Mod-Jones model. We select 250 random samples with varying sample sizes of 100 to 3,000 observations drawn from the aggregate dataset of all firm-quarters so that all discretionary accrual measures have $\mu = 0$. We next induce a fixed earnings management seed $\delta = 0.25$ percent of lagged assets in all observations by increasing the raw accruals by that amount. We also add half of the seed, or 0.125 percent, to *ROA,* assuming that accruals make up half of *ROA*. The model power results based on the probability of rejecting the null hypothesis of no earnings management in favor of the alternate hypothesis of upward earnings management support our predictions. For a sample size of 2,000 observations, Jones with *ROA* matching detects positive discretionary accruals (i.e., rejects the null hypothesis of zero discretionary accruals) 50 percent of the time, while Jones with *ROA, SG,* and *MB* quintile dummies detects the same seed 82 percent of the time. We find similar results for the variants of Mod-Jones model in Panel B. These results stand in contrast with the general conclusion reached in a recent literature survey paper by Dechow, Ge, and

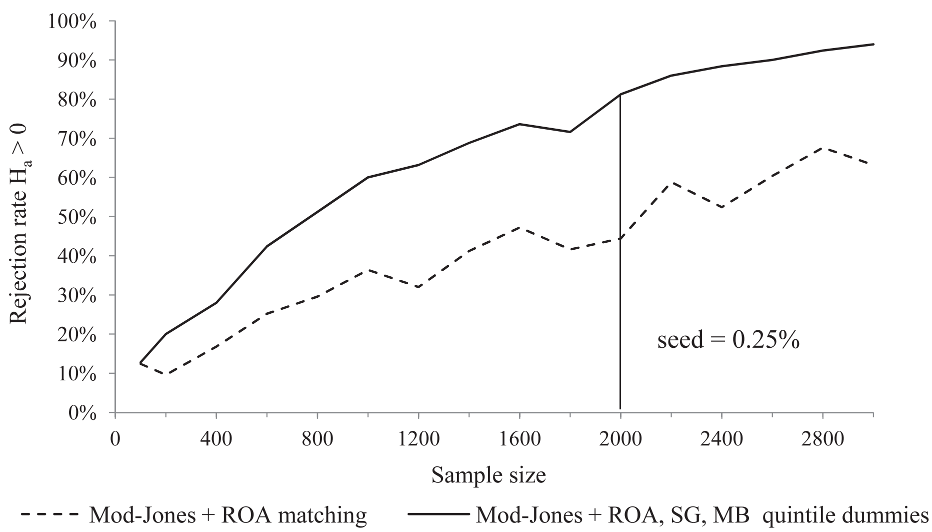
[13] Models that use a linear *ROA* term, linear *ROA, SG,* and *MB* terms, and *ROA* quintile dummies were used in previous tables to parse out the contribution of firm growth and to do so in a linear versus non-linear manner. In the interest of parsimony, these models are no longer considered in subsequent tables.

FIGURE 5
Power Tests as a Function of Sample Size and Standard Deviation of Discretionary Accrual Measures

Panel A: Power Tests in the Aggregate Sample of All Firm-Quarters—Jones Model Variants



Panel B: Power Tests in the Aggregate Sample of All Firm-Quarters—Mod-Jones Model Variants



The aggregate data include all 203,090 Compustat firm-quarters described in Table 1. The figure shows the percentage of 250 random samples of between 100 and 3,000 firm-quarters each for which the null hypothesis of zero discretionary accrual is rejected at the 5 percent significance level using a one-tailed t-test for mean. Since our samples are not stratified along any firm characteristic, the results show raw model power without confounding with any misspecification. For each sample firm-quarter, we increase the raw accrual by 0.25 percent of lagged total assets. In addition, we add half of the seed, or 0.125 percent, to *ROA* (implicitly, *CFO* changes by −0.125 percent). The higher the rejection rate, the more powerful the discretionary accrual measure in detecting earnings management. We only present the *ROA* matching models and the *ROA, SG,* and *MB* quintile dummies models for illustration because they differ considerably in their standard deviation as shown in Table 1.
All discretionary accrual measures are defined in Table 1.

Schrand (2010) that earnings management tests based on Jones-type models suffer from low power even when relatively large amounts of earnings management (1 to 5 percent of total assets in annual data) are seeded into the data. The power results depicted in Figure 5 clearly show that the power of the *ROA* matching versions of Jones and Mod-Jones models is considerably lower than the quintile dummy versions of these models.

The Effects of Model Misspecification on Model Power

In this section, we examine the misattribution of model power created by the mixing up of μ (percent misspecification) and δ (percent seeded earnings management) effects in stratified subsamples. Table 4 has three panels that report detection rates for varying seed levels for random samples of 200 drawn from the aggregate sample (Panel A), the High *SG* quintile (Panel B), and the Low *SG* quintile (Panel C). First, Panel A can be thought of as extending the evidence of Figure 5 with different seed sizes, but a constant sample size of 200 drawn from the aggregate sample. As explained before, in the aggregate sample (i.e., not stratified and, thus, well-dispersed), there is no misspecification with any model, hence no confounding of power and misspecification. It is further interesting to see that our quintile dummies model again stands up as quite powerful in absolute terms and relative to the *ROA* matching model. Both Jones and Mod-Jones versions of the quintile dummies model pick up an earnings management of ± 0.5 percent of lagged assets half the time, and an earnings management of ± 1.0 percent of lagged assets almost all the time, despite a modest sample size.

Second, consider the Mod-Jones and Mod-Jones with *ROA* matching, both of which are misspecified in High and Low *SG* partitions, as shown in Tables 1 and 2. Table 4, Panel B shows that even when a *negative* earnings management of $\delta = -0.25$ percent of lagged assets is seeded into High *SG* samples, one rejects the null hypothesis of no earnings management in favor of the alternate hypothesis of *upward* earnings management with a probability of 64.4 percent using Mod-Jones and 37.2 percent using Mod-Jones with *ROA* matching. This odd result occurs because $\mu + \delta$ remains a significantly positive amount (0.64 percent in the first case and 0.56 percent in the second case) despite a negative seed of $\delta = -0.25$ percent of lagged assets (see Table 1 for μ values). Conversely, Panel C shows that these models reject the null hypothesis of no earnings management in favor of the alternate hypothesis of *downward* earnings management with a probability of 76.4 percent (Mod-Jones) and 17.2 percent (Mod-Jones with *ROA* matching) even when a *positive* earnings management of $\delta = +0.25$ percent is seeded into a Low *SG* sample. Other rows in this table show that only models with *ROA, SG,* and *MB* quintile dummies detect earnings management with a high probability when it is present and, at the same time, raise minimum false alarms when the samples are concentrated in extreme *SG* quintiles.

The results in Table 4 yield an important insight. From our survey of the literature, it appears that Mod-Jones with *ROA* matching is a popular model used in the earnings management literature, following Dechow et al. (1995) and Kothari et al. (2005). Our evidence shows that the seemingly high power using the Mod-Jones and Mod-Jones with *ROA* matching models in high-growth samples does not represent true power, but is a result of misspecification, as seen by rejection rates in the base case when no seed is added ($\delta = 0$ percent).

VII. DOES ADJUSTING FOR FIRM GROWTH THROW THE BABY OUT WITH THE BATHWATER?

Background, Motivation, and Qualitative Arguments

Anecdotal evidence suggests a link between firm growth and earnings manipulation. First, it is argued that higher-growth firms have an incentive to maintain their higher valuations even if it requires manipulating earnings through revenues, as well as expenses. Thus, it is possible that the relation between firm growth (both *SG* and *MB*) and accruals shown in Figure 1 with the aggregate sample of firm-quarters is partly the result of earnings management, in which case, controlling for *SG* and *MB* may partly throw the baby out with the bathwater when testing for earnings management. Second, even if the incentive to manage earnings is not greater for higher-growth firms, the fact that some firms indulge in revenue manipulation may induce a spurious relation between the associated sales growth and raw accruals in the cross-section of all firms. Thus, controlling for sales growth as a part of firm growth may, again, partly throw the baby out with the bathwater. In this section, we present several arguments, as well as empirical evidence with a sample of restatement firms, to show that these concerns are minimal, at least relative to the alternate concern that not controlling for firm growth will falsely classify a part of nondiscretionary accruals as discretionary accruals.

Our first argument on this topic is similar to the main argument given by Kothari et al. (2005) to address the concern that *ROA* matching may wash away some of the discretionary accruals. Kothari et al. (2005) point out that any experiment to measure event-driven earnings management should capture the effect related to the event that is beyond what may be attributed to firm characteristics such as performance (*ROA*) or, in our case, performance and growth (*ROA, SG,* and *MB*). This only requires that the matching firms not have a similar event to the sample (treatment) firms during a reasonable period around the event date. For example, in our event studies of stock splits, SEOs, or stock acquisitions, we exclude any firm with a similar

TABLE 4

Power Tests: Detection Rates of Earnings Management for Different Seed Levels within the Aggregate Sample of Firm-Quarters and High and Low *SG* Quintiles

Panel A: The Aggregate Sample, n = 200, Seed Size as Shown

	Tests of H0: *DA* = 0 versus H1: *DA* < 0					Tests of H0: *DA* = 0 versus H1: *DA* > 0				
Seed as percent of assets (δ)	0.25	0.00	−0.25	−0.50	−1.00	−0.25	0.00	0.25	0.50	1.00
Jones	0.4	4.4	18.0	48.4	98.0	0.0	4.4	26.0	54.0	97.6
Jones with *ROA* matching	1.2	5.6	16.4	33.2	70.8	2.0	6.4	13.2	30.8	77.6
Jones with *ROA, SG,* and *MB* quintile dummies	0.4	4.0	20.0	50.0	98.0	0.0	3.6	24.4	51.2	97.2
Mod-Jones	0.8	4.8	20.0	49.6	97.2	0.0	4.0	23.2	54.4	96.0
Mod-Jones with *ROA* matching	1.6	6.0	15.2	29.6	70.0	1.2	5.2	9.6	26.0	77.6
Mod-Jones with *ROA, SG,* and *MB* quintile dummies	0.4	3.6	18.4	48.4	94.8	0.0	4.4	20.0	48.4	95.2

Panel B: The High *SG* Quintile, n = 200, Seed Size as Shown

	Tests of H0: *DA* = 0 versus H1: *DA* < 0					Tests of H0: *DA* = 0 versus H1: *DA* > 0				
Seed as percent of assets (δ)	0.25	0.00	−0.25	−0.50	−1.00	−0.25	0.00	0.25	0.50	1.00
Jones	0.0	0.8	1.6	7.6	53.2	9.2	32.0	66.4	84.8	98.8
Jones with *ROA* matching	0.4	0.8	2.4	5.6	29.6	6.0	20.8	40.8	68.0	92.8
Jones with *ROA, SG,* and *MB* quintile dummies	0.8	4.4	14.4	39.6	89.6	1.2	2.4	14.8	41.6	89.6
Mod-Jones	0.0	0.0	0.0	0.8	6.8	64.4	86.0	96.8	98.8	100.0
Mod-Jones with *ROA* matching	0.0	0.0	0.0	0.4	4.0	37.2	62.8	79.2	91.6	99.2
Mod-Jones with *ROA, SG,* and *MB* quintile dummies	0.8	4.4	17.6	38.0	90.0	0.8	2.8	13.2	39.2	88.0

Panel C: The Low *SG* quintile, n = 200, Seed Size as Shown

	Tests of H0: *DA* = 0 versus H1: *DA* < 0					Tests of H0: *DA* = 0 versus H1: *DA* > 0				
Seed as percent of assets (δ)	0.25	0.00	−0.25	−0.50	−1.00	−0.25	0.00	0.25	0.50	1.00
Jones	20.4	52.8	78.8	93.2	100.0	0.0	0.0	0.0	3.2	36.0
Jones with *ROA* matching	4.0	12.8	27.6	47.6	82.0	0.4	0.8	3.2	16.4	53.2
Jones with *ROA, SG,* and *MB* quintile dummies	0.8	2.4	18.4	42.8	88.4	0.0	4.4	15.2	36.8	90.8
Mod-Jones	76.4	94.4	100.0	100.0	100.0	0.0	0.0	0.0	0.0	4.0
Mod-Jones with *ROA* matching	17.2	35.2	59.2	81.6	96.8	0.0	0.0	0.0	2.8	18.4
Mod-Jones with *ROA, SG,* and *MB* quintile dummies	1.2	2.8	17.2	41.6	90.0	0.0	2.8	14.8	38.0	88.4

Detection rates of earnings management are the same as rejection rates of the null hypothesis of zero discretionary accruals in favor of either positive or negative discretionary accruals. Thus, Panels A to C of this table report the percent of 250 samples of 200 firms each where the null hypothesis of zero discretionary accrual is rejected at the 5 percent level using a one-tailed t-test for mean as a function of seed size. The seed ranges in size between −1.00 percent and 1.00 percent of assets, and it is added to the raw accruals of each sample firm before carrying out the Jones or Mod-Jones model regressions, as described in Table 1. In addition, half of the seed is added to *ROA* (implicitly, *CFO* changes by minus half of the seed). In Panel A (power tests), the samples are drawn from the universe of 203,090 Compustat firm-quarters during 1991-Q1 to 2007-Q4, and in Panels B and C (mix-up of power and specification tests), the samples are drawn from the high and the low *SG* quintiles.
Table 1 describes the aggregate sample and the calculation of various accrual measures examined in this table.

event from consideration as a matching firm for that quarter. Doing this ensures that the measured differences in discretionary accruals are attributed to the event being studied and not to the firm characteristics of performance and growth.

Second, we refer back to the relation between raw accruals and firm growth in Figure 1, which shows that accruals are sharply income-increasing with positive firm growth and income-decreasing with negative firm growth. We have explained this relation with reference to an extensive literature on sticky costs facing low-growth firms on the downside, and the needs and opportunities of high-growth firms to increase accounts receivable and inventories on the upside because of lenient credit terms. Thus, our explanations offered in Section II suggest that this relation is driven by nondiscretionary accruals. The alternate viewpoint that this relation is driven by discretionary accruals, or earnings management, may have some validity for high-growth firms, but it fails to provide a viable explanation for low (negative) growth firms. In other words, it cannot explain why low-growth or negative-growth firms choose negative discretionary accruals. In many cases, negative-growth firms are already in financial distress, so it seems unlikely that their managers would further suppress firm earnings by taking large negative (income-decreasing) accruals, which may jeopardize their compensation and even threaten their own and their firm's survival. We do recognize that firms sometimes take a big bath in earnings, which results in large negative accruals. But that is likely to be a rare phenomenon rather than a persistent effect for a major portion of our sample firm-quarters. Thus, we argue that the relation between firm growth and raw accruals over the full range of firm growth values is more likely to arise from an underlying economic causality proposed in this paper, or a nondiscretionary accrual effect.

Empirical Tests with a Sample of Restatement Firms

In this section, we examine whether controlling for firm growth measured by *SG* and *MB* in tests of earnings management throws the baby out with the bathwater in cases where earnings management is likely to be present. Specifically, we examine a comprehensive sample of restatements retrieved from the Audit Analytics Restatement database. An advantage of this database, as pointed out by Lobo and Zhao (2013), is that it does not include technical restatements that are made due to mergers, discontinued operations, changes in accounting principles, etc. Following their study, we restrict our analysis to material restatements that were disclosed through separate 8-K filings. We intersect this database with our aggregate sample of 203,090 firm-quarters during 1991-Q1 to 2007-Q4, as described in Table 1. This leads to a sample of 8,266 restatement firm-quarters. We further divide this sample into the first subset of 7,200 cases where the firm had originally overstated the income, and the second subset of 1,066 cases where the firm had originally understated the income. In addition, we report statistics for a sub-subset of 1,459 revenue restatement firm-quarters out of the first subset of 7,200 firm-quarters.

Distribution of Restatements across SG *and* MB *Deciles*

We start by examining whether restatements and their direction are significantly related to firm growth (*SG* and *MB*). The top panel of Figure 6 shows that the 7,200 firms that had originally overstated their income are evenly distributed across *SG* deciles. The same can be said about their distribution across *MB* deciles in the bottom panel. Both panels also show the distribution of 1,066 firms that had originally understated their income. The smaller sample of understating firms leads to a less uniform distribution of firms across *SG* or *MB* deciles, but there is no clear monotonic pattern across *SG* or *MB* deciles. Overall, there is no evidence to suggest that extreme values of *SG* or *MB* are associated with firms that restate (or originally misstate) their earnings. The same holds true for revenue restatements (not shown in the figure). These findings support our main proposition that *SG* and *MB* are innate determinants of accruals and are inconsistent with the alternative viewpoint that these firm characteristics mainly capture cases of earnings management.

Model Power to Detect Restatements

We now assess the power of the Jones, Jones + *ROA* matching, and Jones + *ROA, SG,* and *MB* quintile dummies models, and their Mod-Jones equivalents, to detect earnings management in samples of restatement firms using unrestated (i.e., originally reported) Compustat data. Table 5 shows the alternative discretionary (abnormal) accrual measures for non-restatement firms and restatement firms that are further partitioned by whether the firms had originally overstated or understated their earnings.

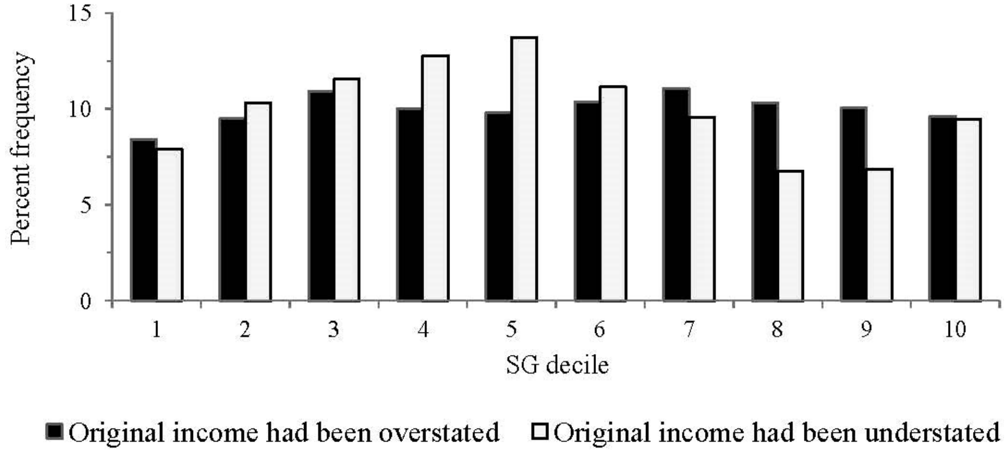
Given that the non-restatement sample includes 96 percent of the observations in the aggregate sample of firm-quarters, the mean values of discretionary accruals in Table 5 are close to zero for all six models for this sample. In contrast, the mean discretionary accruals range from 0.11 percent to 0.20 percent of lagged assets for all restatement firm-quarters when the firms had originally overstated income, and 0.29 percent to 0.35 percent of lagged assets for the subset of firm-quarters that involved revenue restatements. For the revenue restatement sample, Jones and Mod-Jones models with quintile dummies for *ROA, SG,* and *MB* give discretionary accrual estimates (0.30 percent) that are similar to those generated by Jones (0.34 percent) and Mod-Jones (0.35 percent) models, and in all cases, significant at the 1 percent level in one-tailed tests. Thus, controlling for growth via *SG* and *MB* quintile dummies does not significantly impact these models' ability to identify earnings management. The *ROA* matching models also give similar discretionary accruals.

Table 5 also shows the six discretionary accrual measures for all restatement firm-quarters where firms had originally understated their income. However, all of these measures are insignificant, possibly given the smaller sample size, which is one-seventh as large for originally understating firms as for originally overstating firms.

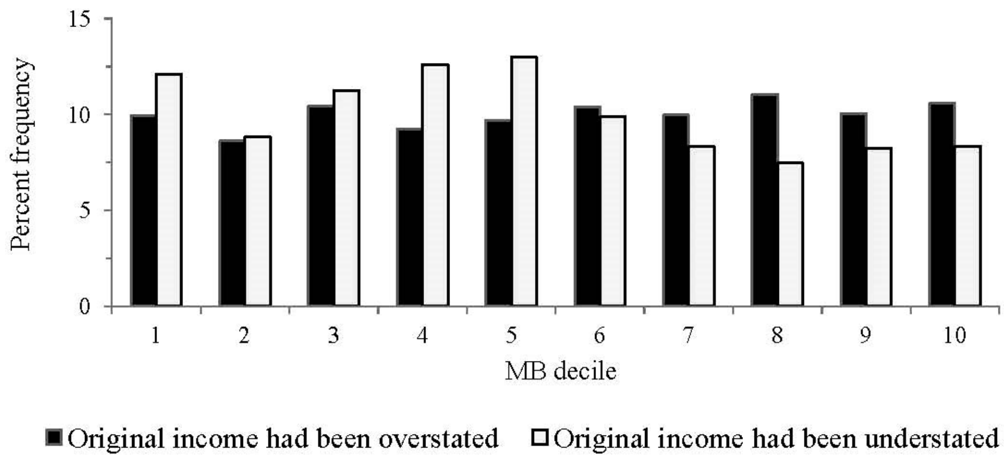
Table 6 presents a multivariate logit model to further test the power of discretionary accrual models to detect restatement firm-quarters. The sample includes all firm-quarters for which the relevant data on independent variables are available. The

FIGURE 6
Distribution of Restatement Firm-Quarters across *SG* and *MB* Deciles

Panel A: Distribution of Restatement Firm-Quarters across *SG* Deciles



Panel B: Distribution of Restatement Firm-Quarters across *MB* Deciles



We identify restatement firm-quarters using the Audit Analytics Advanced Non-Reliance Restatement database. Following Lobo and Zhao (2013), we restrict our analysis to material restatements that were disclosed through separate 8-K filings. We intersect this database with our aggregate sample of 203,090 firm-quarters during 1991-Q1 to 2007-Q4, as described in Table 1. This leads to a sample of 8,266 restatement firm-quarters. We further divide this sample into the first subset of 7,200 cases where the firm had originally overstated the income, and the second subset of 1,066 cases where the firm had originally understated the income. Figure 1 describes the calculation of *SG* and *MB*.

dependent variable is a restatement dummy that takes the value of 1 for restatement firm-quarters, and 0 otherwise. In addition to discretionary accrual measures, we include measures of firm size (*MV*) and firm growth (*SG* and *MB*) as independent variables, since firm growth is often conjectured to directly increase the incentives for earnings management (the very notion underlying the baby-with-the-bathwater effect). However, all six logit regressions show that firm size is the most significant determinant of restatements, while both firm growth proxies, *SG* and *MB*, are insignificant.[14] Similar to

[14] Firm size may be a significant determinant of restatements because regulators like the Securities and Exchange Commission (SEC) and auditing firms place greater emphasis on larger firms when investigating accounting irregularities.

TABLE 5

Discretionary Accrual Measures for Restatement Firm Quarters versus Non-Restatement Firm Quarters

Discretionary Accrual Measure	Non-Restatement Firm-Quarters n = 194,824		Restatement Firm-Quarters: Subset for Which the Firm Had Originally *Overstated* Income: *All* Restatement Firm-Quarters n = 7,200		Restatement Firm-Quarters: Subset for Which the Firm Had Originally *Overstated* Income: *Revenue* Restatement Firm-Quarters n = 1,459		Restatement Firm-Quarters: Subset for Which the Firm Had Originally *Understated* Income: *All* Restatement Firm-Quarters n = 1,066	
	Mean	**t-stat**	**Mean**	**t-stat**	**Mean**	**t-stat**	**Mean**	**t-stat**
Jones	−0.01	−0.63	0.16	3.42***	0.34	3.18***	0.01	0.14
Jones with *ROA* matching	−0.01	−0.73	0.14	2.21***	0.29	1.95**	0.05	0.31
Jones with *ROA, SG,* and *MB* quintile dummies	−0.00	−0.46	0.11	2.43***	0.30	2.93***	0.04	0.35
Mod-Jones	−0.01	−0.75	0.20	4.20***	0.35	3.34***	−0.00	0.03
Mod-Jones with *ROA* matching	−0.01	−0.85	0.17	2.70***	0.33	2.32**	0.03	0.23
Mod-Jones with *ROA, SG,* and *MB* quintile dummies	−0.01	−0.55	0.13	2.90***	0.30	3.08***	0.04	0.45

*, **, *** Denote statistical significance at the 10 percent, 5 percent, and 1 percent levels in one-tailed tests.
We identify restatement firm-quarters using the Audit Analytics Advanced Non-Reliance Restatement database. Following Lobo and Zhao (2013), we restrict our analysis to material restatements that were disclosed through separate 8-K filings. We intersect this database with our aggregate sample of 203,090 firm-quarters during 1991-Q1 to 2007-Q4, as described in Table 1. This leads to a sample of 8,266 restatement firm-quarters. We further divide this sample into the first subset of 7,200 cases where the firm had originally overstated the income (using the res_adverse flag), and the second subset of 1,066 cases where the firm had originally understated the income (using the res_improves flag, both flags included in the database). Finally, we also report statistics for a sub-subset of 1,459 revenue restatement firm-quarters out of the first subset of 7,200 firm-quarters.
Table 1 defines *ROA, SG,* and *MB* and describes the calculation of various discretionary accrual measures reported in this table.

Figure 6, this table shows that high-growth firms are not more likely to restate earnings, after controlling for firm size. Thus, the baby-with-the-bathwater concern related to adjusting for firm growth in the case of restatements is likely to be minimal. Consequently, discretionary accruals using Jones and Mod-Jones models with *ROA, SG,* and *MB* quintile dummies are significant determinants of restatement, similar to the corresponding measures using the basic Jones and Mod-Jones models, as well as their *ROA* matching versions. The multivariate evidence of Table 6 is thus consistent with the univariate evidence of Table 5.

The combined evidence of Figure 6 and Tables 5 and 6 suggests that discretionary accrual models that control for both performance and growth via using quintile dummy variables do not throw the baby out with the bathwater by removing a significant part of earnings that are managed as part of the control for non-linear effects of performance and sales growth on innate accruals. Our findings suggest that the quintile dummy models proposed in this paper do as well as the existing discretionary accrual models in picking up the direction and magnitude of earnings management that is present in restatement samples and that restatements and their direction are not significantly related to *SG* and *MB*.[15]

VIII. SENSITIVITY ANALYSES

In this section, we briefly report the results of several variable measurement/design choices that potentially have an important bearing on the Type I error rate results reported in Section V. Details are tabulated in the CPV Supplement.

Matching on Lagged Rather than Current ROA

Prior research that seeks to control for firm performance when testing for earnings management by matching on *ROA* is divided between using current *ROA* (*CROA*, or $ROA_{i,t}$), as we have done in presenting the results above, and lagged *ROA*

[15] We also conduct analyses of samples of firms that received Accounting and Auditing Enforcement Release (AAER) notices from the SEC. These results are consistent with findings using restatements described in this section and are available in the CPV Supplement. Thus, tests using both samples (AAERs and restatements) show that the quintile dummy models we propose to control for firm growth are powerful in detecting earnings management when it is present. In sum, there is little evidence to suggest that these models throw the baby out with the bathwater.

TABLE 6

Multivariate Logit Model Tests of the Power of Discretionary Accrual Measures to Detect Restatement Firm-Quarters

Dependent Variable	Model (6.1)	Model (6.2)	Model (6.3)	Model (6.4)	Model (6.5)	Model (6.6)
Intercept	−4.084	−4.086	−4.086	−4.082	−4.086	−4.085
	(−107.24)***	(−107.28)***	(−107.27)***	(−107.18)***	(−107.27)***	(−107.26)***
Jones	0.011					
	(3.53)***					
Jones with *ROA* matching		0.005				
		(2.47)***				
Jones with *ROA, SG,* and *MB* quintile dummies			0.009			
			(2.80)***			
Mod-Jones				0.013		
				(4.16)***		
Mod-Jones with *ROA* matching					0.006	
					(2.96)***	
Mod-Jones with *ROA, SG,* and *MB* quintile dummies						0.010
						(3.20)***
Log Assets	0.149	0.150	0.149	0.149	0.150	0.149
	(24.52)***	(24.57)***	(24.55)***	(24.49)***	(24.58)***	(24.54)***
SG	−0.000	0.002	0.002	−0.007	−0.001	0.001
	(−0.02)	(0.09)	(0.11)	(−0.33)	(−0.06)	(0.05)
MB	−0.003	−0.003	−0.002	−0.003	−0.003	−0.002
	(−1.02)	(−0.99)	(−0.96)	(−1.03)	(−0.98)	(−0.95)

*, **, *** Denote statistical significance at the 10 percent, 5 percent, and 1 percent levels in one-tailed tests.
The sample of restatement firm-quarters is described in Table 5. In this table, we test the detection power of alternate discretionary accrual measures using a logit model. The dependent variable is a restatement dummy that takes the value of 1 for the restatement firm-quarters where the firm had originally overstated the income, and 0 for the non-restatement firm-quarters. The relevant data are available for 7,022 restatement firm-quarters and 184,906 non-restatement firm-quarters.
Table 1 describes the calculation of all discretionary accrual measures and the control variables.

(*LROA*, or $ROA_{i,t-4}$). Kothari et al. (2005, footnote 11) note that a downside of matching on *CROA* is that it can induce test misspecification when samples are over-represented by firms on some dimension that is correlated with operating cash flows. Size (*MV*) and financial distress (*FD*) are two firm dimensions we consider in Table 2 (Type I error rate results) that are highly correlated with operating cash flows. Because accruals are strongly negatively correlated with operating cash flows, matching on current *ROA* can induce a bias in favor of falsely rejecting a true null (excessive Type I error rates) when treatment firms come from low or high operating cash flow quintiles, but the matched control firms come from a broader spectrum of cash flows.

In the CPV Supplement, we repeat our simulations with *LROA*. We focus on the *ROA* matching models (Rows 4 and 10) and quintile dummies models (Rows 7 and 13) in Table 2_*LROA* for comparison. Across 64 cells on Type I error rates, we find 21 cases where *CROA* controls result in better specified tests than *LROA* controls, 19 cases where the reverse is true, and 24 cases where both approaches perform equally well. This is a statistical tie. Looking further, we find that *CROA* matching models produce better specified tests than *LROA* matching models. However, the reverse is true for the quintile dummy models. Overall, based only on Type I rejection rates, the choice between *CROA* and *LROA* controls for the effect of firm performance on accruals is a matter of indifference. But when test samples are over-represented by firms with high or low operating cash flows, using *LROA* may be a better choice. The more important finding of our paper is that the quintile dummy variable modifications to the Jones and Mod-Jones models exhibit no excessive Type I error rates when samples are selected from extreme quintiles of our two firm growth proxies, *SG* and *MB*. In contrast, models that only match on performance, whether using *CROA* or *LROA*, exhibit excessive Type I error rates in these sample partitions. Thus, it is important to control for firm growth, both backward-looking and forward-looking, in addition to firm performance when testing for earnings management.

Alternative Proxies for Forward-Looking Growth

The market-to-book (*MB*) ratio that we use as a proxy for forward-looking growth may also capture overvaluation, risk, and asset tangibility that may be correlated with firms' tendencies to engage in earnings management. This could potentially introduce biased Type I error rate tests when samples are drawn from extreme *MB* quintiles. In the CPV Supplement, we consider specification results for quintile dummy variable models that use two alternative forward-looking growth proxies: (1) realized four-quarter ahead sales growth $\left(RSG = \frac{Sales_{i,t+4} - Sales_{i,t}}{Sales_{i,t}}\right)$; and (2) analysts' consensus forecast of long-term earnings growth (*FEG*), following McNichols (2000).[16]

We find that the quintile dummy models with *ROA, SG,* and any one of the three alternate forward-looking growth proxies do reasonably well in 14 high and low partitions formed by *ROA, SG, MB, RSG, FEG, MV,* and *FD*. On the whole, *MB* tends to do slightly better than *RSG* and *FEG*. The final choice between which alternate proxies of future firm growth to use in a quintile dummy model to control for non-linear effects of forward-looking growth on innate accruals should be guided by the type of event analyzed and the firm characteristics of the sample under consideration.

Results Based on Total Accruals

The main results in the tables above are based on accruals from the cash flow statement calculated as: ($CHGAR + CHGINV + CHGAP + CHGTAX + CHGOTH$), which excludes depreciation and amortization. In the CPV Supplement, we repeat our main specification tests of Table 2 with quarterly total accruals that additionally include depreciation and amortization. Our conclusion regarding the misspecification that results from failing to control for the non-linear effects of firm growth on innate accruals remains qualitatively the same.

How Less Concentrated Samples of High-Growth Firms Impact Type I Error Rate Results

The specification tests in Table 2 show the Type I error rates when relatively small samples (200 observations) are drawn *entirely* from firm-quarters in the High (Low) *SG* and *MB* quintiles, as well as samples drawn from quintiles of other firm characteristics related to accruals. However, the partitioning variables in most studies are only partially over-represented by high (low) growth firms. Thus, the degree to which firm growth may confound test results varies depending on the event chosen.

In the CPV Supplement, we report rejection rates when more realistic sample sizes of 1,000 observations are drawn with varying proportions of High *SG* quintile firms in the sample. Those results show that when 50 percent of the samples are comprised of High *SG* quintile firm-quarters (similar to what we observe for SEO and stock acquisitions samples), rejection rates equal 16.8 percent for the Jones model with *ROA* matching and 46.8 percent for the Mod-Jones model with *ROA* matching, significantly higher than the nominal alpha level of 5 percent when the null hypothesis of no earning management is true. So Type I error rates remain too high even when only 50 percent of samples are made up of high-growth firms.

IX. CONCLUSIONS

We show that quarterly discretionary accrual models with *ROA* matching that have been used in much of the prior earnings management literature are considerably misspecified in a non-linear manner with seasonally adjusted measures of sales growth. Moreover, we show that seasonally adjusted sales growth is correlated with partitioning variables in past research that are deemed to give rise to earnings management. We propose a simple piecewise linear way of controlling for the non-linear effects of performance and growth (both backward-looking and forward-looking) on innate (nondiscretionary) accruals that ameliorates the misspecification problems without sacrificing power.

Our findings have important implications not only for studies conducted in quarterly settings, but for the vast number of studies that have been conducted in annual settings, as well. In unreported results, we find that annual accruals are related to both backward-looking and forward-looking measures of growth in a non-linear fashion. We estimate that failure to take account of the non-linear effects of firm growth on innate accruals in annual models results in Type I error rates that are as high as 26 percent in samples of 200 observations drawn from extreme *SG* quintiles using the Mod-Jones model with *ROA* matching. That is more than five times the nominal alpha level of 5 percent. Thus, controlling for performance and growth in discretionary accrual models is also necessary in annual settings. An important contribution of our study lies in recognizing that the quintile dummies approach can correct for multiple factors that impact innate accruals (such as *ROA, SG,* and *MB*), which is unlike the matching firm approach that is generally limited to matching on one or two firm dimensions.

Finally, we show that the Jones-type models that control for the non-linear effects of *ROA, SG,* and *MB* on innate accruals by using quintile dummies do a good job of identifying earnings management in aggregate samples of restatement firms. Estimates of discretionary accruals that are generated from the quintile dummy variable models in these samples are

[16] The alternate proxies also have certain disadvantages. For example, the *RSG* proxy may introduce a look-ahead bias in the discretionary accrual measure, while the *FEG* proxy may not be available for many small firms.

comparable to those given by models that do not control for *SG* or *MB*. Thus, there is a minimal concern of throwing the baby out with the bathwater when controlling for firm growth and sample firms managing earnings through revenue manipulation.

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APPENDIX A

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Internet Supplement to

The Effects of Firm Growth and Model Specification Choices on Tests of Earnings Management in Quarterly Settings

by

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Appendix 1

Previous literature on earnings management that use discretionary accrual models

<u>This is only a partial list</u>

A.1 *Event studies of earnings management around IPOs and SEOs*

Rangan (1998)[bs,qtr], Teoh et al. (1998a, 1998b)[comb,ann], Shivakumar (2000)[cf,qtr], Hribar and Collins (2002)[cf,ann], Kim and Park (2005)[cf,qtr], Fan (2007)[cf,ann], Ball and Shivakumar (2008)[cf,ann]

A.2 *Event studies of earnings management around stock acquisitions*

Erickson and Wang (1999)[comb,qtr], Louis (2004)[bs,qtr], Botsari and Meeks (2008)[comb,ann], Gong et al. (2008a)[bs,qtr], Pungaliya and Vijh (2009)[cf,qtr]

A.3 *Event studies of earnings management around stock repurchases*

Louis and White (2007)[bs,qtr], Gong et al. (2008b)[bs,qtr]

A.4 *Event studies of earnings management around proxy contests*

DeAngelo (1988)[bs,ann], Collins and DeAngelo (1990)[bs,ann]

A.5 *Event studies of earnings management around stock splits*

Louis and Robinson (2005)[bs,qtr]

A.6 *Event studies of earnings management to maintain dividend payment*

Daniel et al. (2008)[cf,ann]

A.7 *Cross-sectional relation between earnings management and performance-based executive compensation*

Gaver et al. (1995)[bs,ann], Holthausen et al. (1995)[bs,ann], Guidry et al. (1999)[bs,ann], Baker et al. (2003)[bs,ann], Cheng and Warfield (2005)[cf,ann], Bergstresser and Philippon (2006)[bs,ann], Burns and Kedia (2006)[bs,ann], Cohen et al. (2008)[cf,ann], Cornett et al. (2008)[cf,ann], McAnally et al. (2008)[cf,ann], Jiang et al. (2010)[cf,ann]

A.8 *Cross-sectional relation between earnings management and option grants, option exercises, option repricings, and stock trading*

Beneish and Vargus (2002)[bs,ann], Bartov and Mohanram (2004)[cf,ann], Coles et al. (2006)[bs,qtr]

A.9 *Cross-sectional studies of earnings management to avoid debt covenant violations*

Dechow et al. (1996)[bs,ann], Beneish (1999)[bs,ann]

A.10 *Cross-sectional studies of audit quality and earnings management*

Becker et al. (1998)[cf,ann], DeFond and Subramanyam (1998)[comb,ann], Francis et al. (1999)[bs,ann], Bartov et al. (2001)[bs,ann], Bradshaw et al. (2001)[cf,ann], Frankel et al. (2002)[cf,ann], Myers et al. (2003)[comb,ann], Larcker and Richardson (2004)[cf,ann], Prawitt et al. (2009)[cf,ann]

Superscripts bs, cf, and comb denote that the study analyzes raw accruals obtained from balance sheet, cash flow statement, and a combination of the two. In some cases the study may analyze primarily cf accruals, but bs accruals when cf are not available. In such cases, we use the code cf. Superscripts ann and qtr denote that the study analyzed annual and quarterly data.

Appendix 2

A survey of research methodologies and empirical findings for published earnings management studies that use quarterly accruals data

We analyze a sample of 32 articles that examine quarterly accrual data. This sample includes 22 articles referenced in Dechow, Ge, and Schrand (2010) and an additional 10 articles referenced in the Web of Knowledge. The articles are published in the *Review of Accounting Studies* (RAS, 7), *Journal of Accounting and Economics* (JAE, 6), *The Accounting Review* (TAR, 5), *Journal of Accounting Research* (JAR, 4), *Journal of Financial Economics* (JFE, 4), *Contemporary Accounting Research* (CAR, 2), *International Journal of Accounting* (IJA, 1), *Journal of Business Finance and Accounting* (JBFA, 1), *Journal of Finance* (JF, 1), and *Journal of Financial and Quantitative Analysis* (JFQA, 1) during 1998 to 2012. We scan each article to obtain the summary information reported in this appendix. Some articles cannot be identified as belonging to any category, while some others may belong to more than one category. Thus, the sum of entries in any row need not equal 32.

Description	**Frequency**
Total articles using quarterly accrual data	32
Raw accrual measure	Balance sheet approach: 15 Cash flow statement: 10 Both: 3
Discretionary accrual model	Jones: 14 Modified Jones: 14 ROA Adjustment: 11 **Growth effect considered: 4**[a]
Cross-sectional or time-series application of Jones-type models	Cross-sectional application: 24 Time-series application: 5 Both: 0
The partitioning variable is likely to be correlated with firm growth	**Yes: 24** **No: 7** **Unclear: 1**
Correlation between discretionary accrual model and conclusion in favor of earnings management	Jones model and evidence of earnings management: 14 Modified-Jones model and evidence of earnings management: 14
Article concludes in favor of earnings management	Yes: 32 No: 0

[a] The noted studies consider the growth effect on accruals and make ad-hoc adjustments, usually by adding a growth proxy (such as market-to-book) to a regression.

Internet Appendix 3: Detailed information on studies summarized in Appendix 2

Article	Topic (partitioning variable)	Partitioning variable likely corr. with firm growth?	Sample	Methodology for computing discretionary accruals: Jones	Modified Jones	ROA adjust-ment	Growth effect considered	BS or CF	Quarterly, Time-series (TS) or cross-sectional (CS)	Evidence of earnings mgmt.
Abarbanell and Lehavy (JAR, 2003)	Analyst recommendations	Yes	22,173 firm quarters between 1985-1998		X			BS	Quarterly, TS	Yes
Baber, Chen, and Kang (RAS, 2006)	Supplementary financial disclosure	No	10,248 firm quarters between 1992-Q4 and 1995-Q3	X				CF	Quarterly, TS	Yes
Baber, Kang, and Li (TAR, 2011)	Reversals of quarterly accruals	Yes	129,323 firm quarters from 1993 to 2007	X				BS	Quarterly, CS	Yes
Baker, Collins, and Reitenga (CAR, 2009)	CEO stock option grants	Yes	21,388 firm quarters between 1992-2003		X	X	X	BS	Quarterly, TS	Yes
Balsam, Bartov, and Marquardt (JAR, 2002)	Supplementary financial disclosure in 10-Q	No	613 firm quarters during 1996-1998	X				Both	Quarterly, CS	Yes
Bartov, Givoly, and Hayn (JAE, 2002)	Meeting or beating earnings expectations	Yes	65,000 firm quarters between 1983-1997	X				BS	Quarterly, CS	Yes
Barua, Legoria, Moffitt (JBFA, 2006)	Analyst benchmarks	Unclear	23,348 firm quarters between 1992-2002		X			BS	Quarterly, CS	Yes
Brown and Pinello (JAR, 2007)	Financial reporting process (interim vs. annual)	No	29,684 firm quarters between 1993-2005		X			CF	Quarterly, CS	Yes
Burnett, Cripe, Martin and McAllister (TAR, 2012)	Accretive Stock Repurchases	No	4,987 firm quarters between 1988-2009		X			CF	Quarterly, CS	Yes

Article	Topic (partitioning variable)	Partitioning variable likely corr. with firm growth?	Sample	Methodology for computing discretionary accruals					Quarterly, Time-series (TS) or cross-sectional (CS)	Evidence of earnings mgmt.
				Jones	Modified Jones	ROA adjust-ment	Growth effect considered	BS or CF		
Cohen, Mashruwala, and Zach (RAS, 2010)	Firms “suspected” of earnings management and life-cycle stage	Yes	919 to 1,110 firms and 28,492 to 34,889 monthly observations						TS model of monthly advertising expenditures.	Yes
Coles, Hertzel, and Kalpathy (JAE, 2006)	Stock option reissues	Yes	159 firms during 2001-2002	X				BS	Quarterly, CS	Yes
Das, Shroff, and Zhang (CAR, 2009)	Fourth quarter earnings reversal	Yes	71,963 observations during 1988-2004	X	X		X	CF	Quarterly, CS	Yes
Erickson and Wang (*JAE* 1999)	Earnings mgmt (EM) by stock acquirers	Yes	55 stock acquirers between 1985-1990	X				Both	Quarterly, CS	Yes
Ertimur, Livnat, and Martikainen (RAS, 2003)	Growth vs. value stocks	Yes	20,487 quarterly forecasts from 1996 to 2001						Revenue vs. expense surprises estimated cross-sectionally	Yes
Gong, Louis, and Sun (JF 2008a)	Stock repurchases	Yes	1,720 repurchases between 1984-2002	X		X		BS	Quarterly, CS	Yes
Gong, Louis, and Sun (JAE 2008b)	Post merger lawsuits	Yes	103 litigated stock acquisitions between 1996-2002		X	X		BS	Quarterly, CS	Yes
Hafzalla (RAS, 2009)	Leveraged buyouts	Yes	127 treatment firms with only mgmt. involvement and 216 control firms with both manager and outside involvement	X				CF	Quarterly, CS	Yes
Han and Wang (TAR, 1998)	Political costs and Oil companies	Yes	76 firms in 1990	X				BS	Quarterly, CS	Yes

Article	Topic (partitioning variable)	Partitioning variable likely corr. with firm growth?	Sample	Methodology for computing discretionary accruals					Quarterly, Time-series (TS) or cross-sectional (CS)	Evidence of earnings mgmt.
				Jones	Modified Jones	ROA adjust-ment	Growth effect considered	BS or CF		
Jo and Kim (JFE, 2007)	Disclosure frequency (SEO sample)	Yes	1,950 SEOs between 1990-1997		X	X		CF	Quarterly, CS	Yes
Jo, Kim, and Park (RAS, 2007)	Underwriter choice (SEO sample)	Yes	1,950 SEOs between 1990-1997		X	X		CF	Quarterly, CS	Yes
Keung, Lin, and Shih (JAR, 2010)	Zero or small positive analyst earnings surprise	Yes	139,885 firm quarters from 1992 to 2006		X	X		CF	Quarterly, CS	Yes
Kim and Park (JFQA, 2005)	Seasoned equity offerings	Yes	1040 SEOs from 1989-2000		X	X		CF	Quarterly, CS	Yes
Louis (JFE, 2004)	Stock acquirers	Yes	236 stock acquirers between 1992-2000		X	X	X	BS	Quarterly, CS	Yes
Louis and White(JFE, 2007)	Repurchase tender offers	Yes	177 repurchase tender offers from 1981-2001			X		BS	Quarterly, CS	Yes
Louis and Robinson (JAE, 2005)	Stock splits	Yes	2,271 stock splits between 1990-2002		X	X		BS	Quarterly, CS	Yes
Louis, Robinson, and Sbaraglia (RAS, 2008)	Disclosure of accrual information in earnings release and accrual anomaly	No	11,708 firm quarters between 1999-2002	X		X		BS	Quarterly, CS	Yes
McAnally, Srivastava, and Weaver (TAR, 2008)	Stock option grants	Yes	54,934 firm quarters from 1992-2005						Use analyst forecasts as earnings benchmark	Yes
McVay, Nagar, and Tang (RAS, 2006)	Insider trading	Yes	21,952 firm-quarters where firms just meet-or –beat analysts forecasts from 1990-1999	X				BS	Quarterly, CS	Yes

Article	Topic (partitioning variable)	Partitioning variable likely corr. with firm growth?	Sample	Methodology for computing discretionary accruals					Quarterly, Time-series (TS) or cross-sectional (CS)	Evidence of earnings mgmt.
				Jones	Modified Jones	ROA adjust-ment	Growth effect considered	BS or CF		
Rangan (JFE, 1998)	Seasoned equity offerings	Yes	712 SEOs between 1987-1990		X		X	BS	Quarterly, TS	Yes
Schrand and Walther (TAR, 2000)	Prior period earnings amount used as benchmark. Nonrecurring nature of gains losses included in benchmark	No	130 obs. With gain or loss on sale of PPE > 5% of annual or quarterly income from 1988 to 1994						Current quarter performance relative to prior quarters benchmark used in earnings announcement	Yes
Shivakumar (JAE, 2000)	Seasoned equity offerings	Yes	2,995 SEOs between 1983-1992	X				Both	Quarterly, CS	Yes
Yang and Krishnan (IJA, 2005)	Audit committee expertise and stock holdings and earnings mgmt.	No	Random sample of 250 firms between 1996-2000	X				CF	Quarterly, CS	Yes

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Table IS-1

Discretionary accrual measures for AAER firm quarters versus non-AAER firm quarters

Our sample of AAERs resulting in restatement of quarterly earnings starts with the comprehensive set of AAERs created by Dechow et al. (2011). We drop cases that are unrelated to earnings misstatement, or where the relevant dates cannot be identified. We intersect this database with our aggregate sample of 203,090 firm-quarters during 1991-Q1 to 2007-Q4 as described in Table 1. This leads to a sample of 2,206 AAER firm-quarters. We further divide this sample into the first subset of 2,119 cases where the firm had originally overstated the income and the second subset of 87 cases where the firm had originally understated the income. Finally, we also report statistics for a sub-subset of 1,093 revenue AAER firm-quarters out of the first subset of 2,119 firm-quarters. Table 1 describes the calculation of various discretionary accrual measures reported in this table. We measure firm performance by current ROA, or $ROA_{i,t}$. The notations *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels in one-tailed tests.

	Non-AAER firm-quarters		AAER firm-quarters					
			Subset for which the firm had originally **overstated** income				Subset for which the firm had originally **understated** income	
	N=200,884		**All** AAER firm-quarters N=2,119		**Revenue** AAER firm-quarters N=1,093		**All** AAER firm-quarters N=87	
	Mean	*t*-stat	Mean	*t*-stat	Mean	*t*-stat	Mean	*t*-stat
Jones	-0.01	-0.52	0.48	5.98***	0.72	5.92***	-0.13	-0.29
Jones with ROA matching	-0.01	-0.59	0.38	3.29***	0.68	4.01***	-0.85	-1.47
Jones with ROA, SG, and MB quintile dummies	-0.00	-0.32	0.29	3.70***	0.49	4.16***	-0.21	-0.49
Mod-Jones	-0.01	-0.59	0.55	6.72***	0.72	5.85***	-0.13	-0.32
Mod-Jones with ROA matching	-0.01	-0.62	0.35	3.04***	0.55	3.20***	-0.76	-1.32
Mod-Jones with ROA, SG, and MB quintile dummies	-0.00	-0.27	0.24	3.17***	0.39	3.34***	-0.25	-0.60

Reference: Dechow, P., W. Ge, C. Larson, and R. Sloan, 2011. Predicting material accounting misstatements. *Contemporary Accounting Review* 28: 17-82.

Table IS-2

Multivariate logit model tests of the power of discretionary accrual measures to detect AAER firm-quarters

The sample of AAER firm-quarters is described in Table IS-1 of this Internet Supplement. This table only includes income-increasing AAER firm-quarters. We test the detection power of alternate discretionary accrual measures using a logit model. The dependent variable is a restatement dummy that takes the value of one for the restatement firm-quarters where the firm had originally overstated the income, and zero for the non-restatement firm-quarters. The relevant data are available for 2,096 AAER firm-quarters and 189,747 non-AAER firm-quarters. Table 1 describes the calculation of all discretionary accrual measures and the control variables. We continue to measure firm performance by current ROA, or $ROA_{i,t}$. The notations *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels in one-tailed tests.

Dependent variable	(IS2.1)	(IS2.2)	(IS2.3)	(IS2.4)	(IS2.5)	(IS2.6)
Intercept	-6.372 (-87.04)***	-6.358 (-87.20)***	-6.365 (-87.13)***	-6.369 (-86.98)***	-6.356 (-87.19)***	-6.360 (-87.16)***
Jones	0.034 (5.81)***					
Jones with ROA matching		0.015 (3.65)***				
Jones with ROA, SG, and MB quintile dummies			0.025 (4.25)***			
Mod-Jones				0.034 (5.94)***		
Mod-Jones with ROA matching					0.013 (3.20)***	
Mod-Jones with ROA, SG, and MB quintile dummies						0.021 (3.51)***
Log assets	0.296 (27.95)***	0.294 (27.87)***	0.295 (27.87)***	0.296 (27.91)***	0.294 (27.84)***	0.294 (27.86)***
SG	0.211 (7.06)***	0.215 (7.26)***	0.215 (7.26)***	0.199 (6.57)***	0.212 (7.09)***	0.214 (7.22)***
MB	0.027 (8.40)***	0.027 (8.50)***	0.027 (8.54)***	0.027 (8.38)***	0.027 (8.52)***	0.027 (8.55)***

Table 1_LROA

Mean and standard deviation of accrual measures within the aggregate sample of firm-quarters and partitions formed by firm characteristics

This table repeats the tests of Table 1 in the main paper by using seasonally lagged ROA (LROA, or $ROA_{i,t-4}$) as the measure of firm performance here instead of current ROA (CROA, or $ROA_{i,t}$) there. Please see that table for all other details.

Partitioning variable →	All	ROA		SG		MB		MV		FD	
Description		Low	High	Low	High	Low	High	Low	High	Low	High
1. Raw accruals	0.43	0.08	0.63	-0.53	1.25	-0.08	0.82	0.18	0.32	0.77	-0.06
	(4.54)	(5.43)	(5.03)	(4.95)	(5.14)	(4.98)	(5.13)	(5.69)	(3.07)	(3.91)	(5.56)
2. Jones	0.00	0.00	0.05	-0.54	0.40	-0.31	0.24	-0.27	0.01	0.27	-0.37
	(4.05)	(5.03)	(4.27)	(4.61)	(4.72)	(4.39)	(4.64)	(5.09)	(2.57)	(3.40)	(5.10)
3. Jones with linear ROA term	0.00	-0.05	0.08	-0.54	0.39	-0.32	0.33	-0.28	0.02	0.29	-0.39
	(4.04)	(5.00)	(4.26)	(4.59)	(4.71)	(4.37)	(4.62)	(5.07)	(2.57)	(3.39)	(5.07)
4. Jones with ROA matching	0.00	0.01	-0.02	-0.51	0.38	-0.29	0.19	-0.27	-0.02	0.21	-0.33
	(5.69)	(7.11)	(5.96)	(6.23)	(6.43)	(6.05)	(6.38)	(6.71)	(4.38)	(5.15)	(6.82)
5. Jones with ROA quintile dummies	0.00	0.00	0.00	-0.52	0.40	-0.29	0.22	-0.25	-0.00	0.25	-0.34
	(4.02)	(5.01)	(4.24)	(4.58)	(4.69)	(4.35)	(4.62)	(5.04)	(2.57)	(3.38)	(5.06)
6. Jones with linear ROA, SG, and MB terms	0.00	-0.07	0.04	-0.34	0.10	-0.17	0.06	-0.18	-0.04	0.17	-0.31
	(4.03)	(4.97)	(4.24)	(4.59)	(4.67)	(4.33)	(4.57)	(5.02)	(2.56)	(3.39)	(5.04)
7. Jones with ROA, SG, and MB quintile dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.10	-0.09	0.06	-0.19
	(3.96)	(4.94)	(4.16)	(4.52)	(4.62)	(4.28)	(4.55)	(4.95)	(2.55)	(3.33)	(4.98)
8. Mod-Jones	0.00	-0.09	0.24	-1.02	0.89	-0.40	0.33	-0.35	0.04	0.36	-0.43
	(4.06)	(5.08)	(4.27)	(4.64)	(4.72)	(4.44)	(4.64)	(5.16)	(2.52)	(3.39)	(5.15)
9. Mod-Jones with linear ROA term	0.00	-0.05	0.21	-1.01	0.89	-0.39	0.34	-0.34	0.04	0.35	-0.42
	(4.05)	(5.04)	(4.26)	(4.61)	(4.70)	(4.42)	(4.62)	(5.14)	(2.52)	(3.38)	(5.12)
10. Mod-Jones with ROA matching	0.00	0.01	-0.02	-0.95	0.87	-0.31	0.24	-0.29	-0.03	0.23	-0.33
	(5.70)	(7.17)	(5.96)	(6.26)	(6.43)	(6.08)	(6.39)	(6.77)	(4.33)	(5.13)	(6.88)
11. Mod-Jones with ROA quintile dummies	0.00	0.00	0.00	-0.98	0.89	-0.31	0.28	-0.29	-0.00	0.27	-0.34
	(4.03)	(5.05)	(4.24)	(4.60)	(4.68)	(4.40)	(4.61)	(5.11)	(2.52)	(3.37)	(5.11)
12. Mod-Jones with linear ROA, SG, and MB terms	0.00	-0.09	0.13	-0.53	0.21	-0.16	0.06	-0.18	-0.04	0.15	-0.25
	(4.00)	(4.97)	(4.20)	(4.59)	(4.67)	(4.35)	(4.52)	(5.04)	(2.51)	(3.34)	(5.05)
13. Mod-Jones with ROA, SG, and MB quintile dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.09	-0.10	0.00	-0.11
	(3.92)	(4.93)	(4.11)	(4.52)	(4.61)	(4.28)	(4.50)	(4.95)	(2.51)	(3.28)	(4.97)

Table 2_LROA

Specification tests: Rejection rates of the null hypothesis of zero discretionary accruals within the aggregate sample of firm-quarters and partitions formed by various firm characteristics

This table repeats the tests of Table 2 in the main paper by using seasonally lagged ROA (LROA, or $ROA_{i,t-4}$) as the measure of firm performance here instead of current ROA (CROA, or $ROA_{i,t}$) there. Please see that table for all other details.

Green colored cells	CROA gives better model specification than LROA	21 cases
Red colored cells	LROA gives better model specification than CROA	19 cases
Blue colored cells	Both CROA and LROA give equally well-specified results	24 cases

If both models give rejection rates in the normal range of 2.4% to 8.0%, then they are equally well-specified. If one model gives rejection rates within the normal range and another gives rejection rates outside that range, the former is better specified. If both models give rejection rates outside the normal range, the one that deviates by less is better specified. All comparisons are based on corresponding cells in this table and Table 2 in the main paper.

Partitioning variable →	All firms	ROA		SG		MB		MV		FD	
		Low	High	Low	High	Low	High	Low	High	Low	High
Figures in **bold** (***bold italic***) signify rejection rates that significantly exceed (fall below) the 5% significance level of the test and indicate that such tests are biased against (in favor of) accepting the null hypothesis)											
Panel A: H_1: Discretionary accruals < 0											
2. Jones	4.4	6.4	4.4	**52.8**	***0.8***	**26.0**	***0.4***	**15.6**	4.4	***0.4***	**25.2**
3. Jones with linear ROA term	4.0	**9.2**	3.6	**54.4**	***0.4***	**27.2**	***0.4***	**17.2**	4.0	***0.0***	**26.4**
4. Jones with ROA matching	4.4	4.4	7.2	**26.4**	***0.0***	**16.8**	***1.2***	**9.2**	4.8	2.4	**17.6**
5. Jones with ROA quintile dummies	4.4	6.8	4.8	**53.2**	***0.8***	**22.0**	***0.8***	**14.8**	4.8	***0.4***	**23.2**
6. Jones with linear ROA, SG, and MB terms	6.4	**9.6**	4.0	**25.6**	***2.0***	**13.6**	3.6	**10.8**	6.0	***0.8***	**20.8**
7. Jones with ROA, SG, and MB quintile dummies	5.6	7.6	5.2	3.2	4.8	5.6	4.0	5.6	**10.4**	2.4	**12.0**
8. Mod-Jones	4.8	**9.2**	***0.4***	**94.4**	***0.0***	**36.0**	***0.4***	**22.0**	3.2	***0.0***	**30.8**
9. Mod-Jones with linear ROA term	4.0	**8.4**	***0.4***	**94.0**	***0.0***	**36.4**	***0.4***	**22.8**	3.2	***0.0***	**29.6**
10. Mod-Jones with ROA matching	4.8	3.6	7.2	**73.2**	***0.0***	**20.0**	***1.6***	**11.2**	5.2	***2.0***	**15.6**
11. Mod-Jones with ROA quintile dummies	4.8	7.6	5.2	**92.8**	***0.0***	**27.6**	***0.8***	**18.8**	4.8	***0.0***	**25.6**
12. Mod-Jones with linear ROA, SG, and MB terms	5.2	**11.6**	***2.0***	**52.8**	***0.8***	**12.4**	4.0	**11.2**	7.2	***0.8***	**16.4**
13. Mod-Jones ROA, SG, and MB quintile dummies	4.0	8.0	6.4	3.2	4.4	6.4	5.2	4.8	**12.4**	6.8	6.4
Panel B: H_1: Discretionary accruals > 0											
2. Jones	2.8	5.6	6.0	***0.0***	**32.0**	***0.0***	**22.8**	***0.8***	5.6	**30.4**	***0.8***
3. Jones with linear ROA term	3.6	4.8	7.6	***0.0***	**31.6**	***0.0***	**24.0**	***0.8***	5.6	**32.4**	***0.8***
4. Jones with ROA matching	2.8	6.0	4.4	***0.0***	**17.2**	***0.8***	**10.8**	***1.6***	4.0	**12.8**	***1.2***
5. Jones with ROA quintile dummies	4.0	5.6	3.6	***0.0***	**32.0**	***0.0***	**22.8**	***0.8***	4.4	**27.2**	***1.2***
6. Jones with linear ROA, SG, and MB terms	3.6	4.0	5.6	***0.0***	6.0	***1.2***	**10.0**	***0.8***	2.8	**16.8**	***1.2***
7. Jones with ROA, SG, and MB quintile dummies	4.0	6.0	4.8	4.4	2.8	6.4	6.8	***2.0***	***1.6***	7.6	***2.0***
8. Mod-Jones	4.4	4.4	**20.4**	***0.0***	**86.0**	***0.0***	**30.0**	***0.4***	**8.8**	**44.4**	***0.8***
9. Mod-Jones with linear ROA term	4.0	5.2	**18.0**	***0.0***	**86.0**	***0.0***	**32.0**	***0.4***	7.6	**41.2**	***0.8***
10. Mod-Jones with ROA matching	3.6	6.4	5.2	***0.0***	**65.2**	***1.2***	**13.6**	***1.6***	3.6	**16.8**	***1.2***
11. Mod-Jones with ROA quintile dummies	4.8	6.0	3.2	***0.0***	**86.4**	***0.4***	**27.6**	***0.8***	3.6	**29.6**	***1.2***
12. Mod-Jones with linear ROA, SG, and MB terms	4.4	4.0	**12.4**	***0.0***	**12.0**	***0.4***	**10.0**	***1.2***	2.4	**15.6**	***1.6***
13. Mod-Jones ROA, SG, and MB quintile dummies	4.8	6.4	4.4	4.4	3.6	6.8	7.2	***1.2***	***1.6***	2.4	2.4

Table 4_LROA

Power tests: Detection rates of earnings management for different seed levels within the aggregate sample of firm-quarters and high and low SG quintiles

This table repeats the tests of Table 4 in the main paper by using seasonally lagged ROA (LROA, or $ROA_{i,t-4}$) as the measure of firm performance here instead of current ROA (CROA, or $ROA_{i,t}$) there. Please see that table for all other details.

	Tests of H_0: DA = 0 vs. H_1: DA < 0					Tests of H_0: DA = 0 vs. H_1: DA > 0				
Seed as percent of assets (δ) →	0.25	0.00	-0.25	-0.50	-1.00	-0.25	0.00	0.25	0.50	1.00
Panel A: The ***aggregate sample****, n = 200, seed size as shown*										
Jones	0.4	4.4	25.2	51.2	97.2	0.8	2.8	17.6	51.6	95.2
Jones with ROA matching	1.6	4.4	14.0	34.8	80.4	0.0	2.8	13.2	28.0	78.8
Jones with ROA, SG, and MB quintile dummies	0.4	5.6	24.0	52.0	97.2	0.4	4.0	19.2	52.4	94.4
Mod-Jones	0.0	4.8	22.0	54.0	97.6	0.8	4.4	20.4	50.8	95.6
Mod-Jones with ROA matching	1.6	4.8	14.0	31.6	82.0	0.0	3.6	10.4	29.6	78.4
Mod-Jones with ROA, SG, and MB quintile dummies	0.4	4.0	22.0	52.8	96.4	0.4	4.8	18.4	49.6	95.2
Panel B: The ***high SG quintile****, n = 200, seed size as shown*										
Jones	0.0	0.8	1.6	7.6	53.2	9.2	32.0	66.4	84.8	98.8
Jones with ROA matching	0.0	0.0	1.2	6.8	34.8	6.0	17.2	36.8	62.8	94.0
Jones with ROA, SG, and MB quintile dummies	0.8	4.8	15.6	40.4	91.2	0.8	2.8	14.0	42.4	91.2
Mod-Jones	0.0	0.0	0.0	0.8	6.8	64.4	86.0	96.8	98.8	100.0
Mod-Jones with ROA matching	0.0	0.0	0.0	0.4	6.0	38.0	65.2	81.6	92.0	100.0
Mod-Jones with ROA, SG, and MB quintile dummies	0.8	4.4	19.2	39.2	93.2	0.4	3.6	13.2	43.2	90.0
Panel C: The ***low SG quintile****, n = 200, seed size as shown*										
Jones	20.4	52.8	78.8	93.2	100.0	0.0	0.0	0.0	3.2	36.0
Jones with ROA matching	12.0	26.4	52.0	74.4	98.0	0.0	0.0	0.4	2.8	26.4
Jones with ROA, SG, and MB quintile dummies	0.8	3.2	16.8	46.0	90.4	0.0	4.4	16.0	40.0	91.2
Mod-Jones	76.4	94.4	100.0	100.0	100.0	0.0	0.0	0.0	0.0	4.0
Mod-Jones with ROA matching	46.8	73.2	89.6	95.6	99.6	0.0	0.0	0.0	0.0	2.8
Mod-Jones with ROA, SG, and MB quintile dummies	0.8	3.2	18.8	44.0	91.6	0.0	4.4	16.4	38.8	91.2

Table 5_LROA

Discretionary accrual measures for restatement firm quarters versus non-restatement firm quarters

This table repeats the tests of Table 5 in the main paper by using seasonally lagged ROA (LROA, or $ROA_{i,t-4}$) as the measure of firm performance here instead of current ROA (CROA, or $ROA_{i,t}$) there. Please see that table for all other details.

	Non-restatement firm-quarters		Restatement firm-quarters					
			Subset for which the firm had originally **overstated** income				Subset for which the firm had originally **understated** income	
	N=194,824		**All** restatement firm-quarters N=7,200		**Revenue** restatement firm-quarters N=1,459		**All** restatement firm-quarters N=1,066	
	Mean	*t*-stat	Mean	*t*-stat	Mean	*t*-stat	Mean	*t*-stat
Jones	-0.01	-0.63	0.16	3.42***	0.34	3.18***	0.01	0.14
Jones with ROA matching	-0.02	-1.15	0.06	0.92	0.27	1.81*	-0.12	-0.78
Jones with ROA, SG, and MB quintile dummies	-0.01	-0.54	0.14	2.95***	0.32	3.05***	0.01	0.08
Mod-Jones	-0.01	-0.75	0.20	4.20***	0.35	3.34***	-0.00	0.03
Mod-Jones with ROA matching	-0.01	-0.82	0.10	1.58	0.35	2.37**	-0.10	-0.69
Mod-Jones with ROA, SG, and MB quintile dummies	-0.01	-0.61	0.15	3.37***	0.32	3.16***	0.01	0.12

Table 6_LROA

Multivariate logit model tests of the power of discretionary accrual measures to detect restatement firm-quarters

This table repeats the tests of Table 6 in the main paper by using seasonally lagged ROA (LROA, or $ROA_{i,t-4}$) as the measure of firm performance here instead of current ROA (CROA, or $ROA_{i,t}$) there. Please see that table for all other details.

Dependent variable	(6.1)	(6.2)	(6.3)	(6.4)	(6.5)	(6.6)
Intercept	-4.084 (-107.24)***	-4.083 (-107.28)***	-4.086 (-107.27)***	-4.082 (-107.18)***	-4.082 (-107.26)***	-4.085 (-107.25)***
Jones	0.011 (3.53)***					
Jones with ROA matching		0.002 (1.11)				
Jones with ROA, SG, and MB quintile dummies			0.010 (3.16)***			
Mod-Jones				0.013 (4.16)***		
Mod-Jones with ROA matching					0.004 (1.65)*	
Mod-Jones with ROA, SG, and MB quintile dummies						0.011 (3.48)***
Log assets	0.149 (24.52)***	0.149 (24.49)***	0.149 (24.54)***	0.149 (24.49)***	0.149 (24.49)***	0.149 (24.53)***
SG	-0.000 (-0.02)	0.002 (0.11)	0.003 (0.12)	-0.007 (-0.33)	0.000 (0.01)	0.001 (0.06)
MB	-0.003 (-1.02)	-0.002 (-0.97)	-0.002 (-0.96)	-0.003 (-1.03)	-0.002 (-0.97)	-0.002 (-0.95)

Table IS-3

Specification tests with alternate measures of future firm growth

This table continues the specification tests of Table 2 in the main paper with two additional measures of future firm growth and two corresponding partitioning variables. These additional measures are RSG, the realized sales growth $\frac{Sales_{i,t+4} - Sales_{i,t}}{Sales_{i,t}}$, and FEG, the IBES forecast of (long-term) earnings growth. Similar to Table 2, this table reports the percentage of 250 samples of 200 firms each for which the null hypothesis of zero discretionary accrual is rejected at the 5% significance level using the one-tailed t-test for mean. The aggregate sample consists of 203,090 Compustat firm-quarters during 1991-Q1 to 2007-Q4 for which MB is available. This sample is used for calculating Type I error rates of Jones, Jones with ROA matching, and Jones with ROA, SG, and MB quintile dummies models as well as the corresponding Mod-Jones model variants. However, the sample for calculating Jones with ROA, SG, and RSG quintile dummies model and its Mod-Jones variant uses the subset of 187,679 observations for which RSG is available, and the sample for calculating Jones with ROA, SG, and FEG quintile dummies model and its Mod-Jones variant uses the subset of 119,841 observations for which FEG is available. Most other model and simulation details are similar to those in Table 2 in the main paper. We continue to measure firm performance by current ROA, or $ROA_{i,t}$. The low and high partitions formed by any firm characteristic are the corresponding lowest and highest quintiles of data using the aggregate sample of firm-quarters. We calculate that if the rejection frequency within any one run of 250 samples is below 2.4% or above 8.0%, then it is statistically significantly different from the model rejection frequency of 5% at the 5% confidence level in a two-tailed frequency test.

Partitioning variable →	ROA		SG		MB		RSG		FEG		MV		FD	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Figures in **bold** (***bold italic***) signify rejection rates that significantly exceed (fall below) the 5% significance level of the test and indicate that such tests are biased against (in favor of) accepting the null hypothesis)														
Panel A: H_1: Discretionary accruals < 0														
Jones	**80.4**	***0.8***	**52.8**	***0.8***	**26.0**	***0.4***	4.0	***2.0***	**10.4**	***1.2***	**15.6**	4.4	***0.4***	**25.2**
Jones with ROA matching	7.6	6.4	**12.4**	***0.8***	**10.8**	***0.4***	3.2	2.4	**10.4**	***1.6***	6.4	**14.0**	8.0	6.0
Jones with ROA, SG, MB quintile dum	6.0	3.2	2.4	4.4	6.4	4.4	2.8	4.4	4.8	2.8	5.6	**19.2**	7.2	3.6
Jones with ROA, SG, RSG quintile dum	3.6	2.4	3.6	4.8	**10.8**	***1.2***	4.0	5.6	4.0	***1.2***	**11.6**	**9.6**	2.8	**9.6**
Jones with ROA, SG, FEG quintile dum	4.8	2.4	7.2	4.8	7.6	***1.6***	3.2	2.8	6.4	4.4	**24.8**	**10.4**	2.4	7.6
Mod-Jones	**92.8**	***0.0***	**94.4**	***0.0***	**36.0**	***0.4***	2.8	2.8	**16.4**	***0.4***	**22.0**	3.2	***0.0***	**30.8**
Mod-Jones with ROA matching	7.6	6.0	**38.4**	***0.0***	**10.4**	***0.8***	2.8	3.2	**16.0**	***0.8***	6.0	**15.6**	**8.8**	3.6
Mod-Jones with ROA, SG, MB quintile dum	6.4	3.2	2.8	4.4	6.8	5.6	***1.6***	7.6	2.8	2.8	6.0	**23.2**	**15.6**	***2.0***
Mod-Jones with ROA, SG, RSG quintile dum	4.4	4.0	4.0	4.4	8.0	***2.0***	5.6	6.4	3.2	2.4	**9.6**	**12.4**	**8.8**	4.0
Mod-Jones with ROA, SG, FEG quintile dum	5.2	***1.6***	6.0	5.2	5.6	2.8	3.6	4.0	6.4	5.6	**22.0**	**12.8**	5.2	4.8

Table IS-3 continued … Specification tests with alternate measures of future firm growth

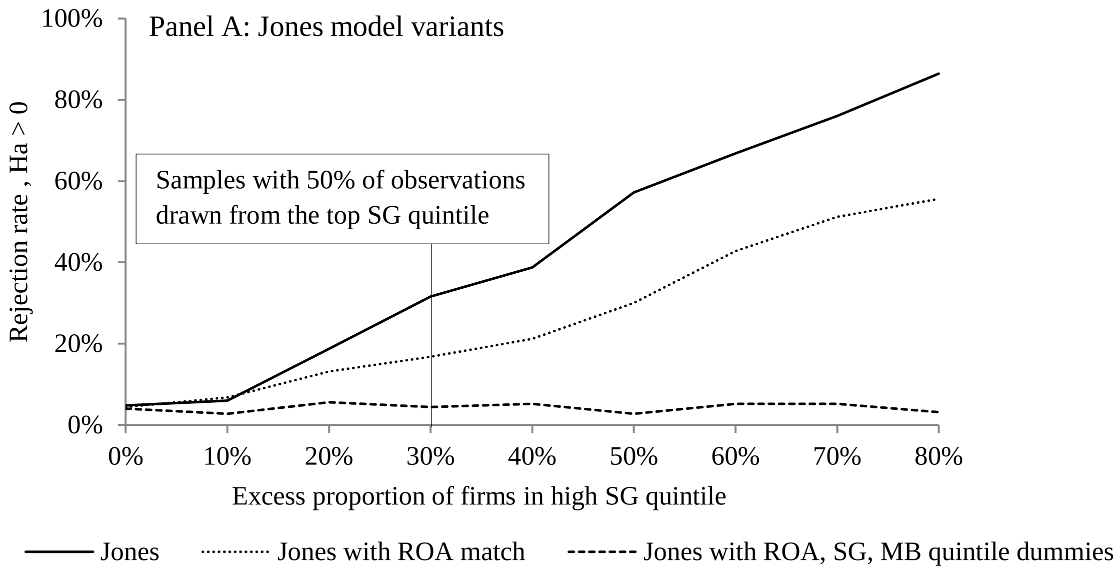
Partitioning variable →	ROA		SG		MB		RSG		FEG		MV		FD	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Figures in **bold** (***bold italic***) signify rejection rates that significantly exceed (fall below) the 5% significance level of the test and indicate that such tests are biased against (in favor of) accepting the null hypothesis)														
Panel B: H_1: Discretionary accruals > 0														
Jones	***0.0***	**33.6**	***0.0***	**32.0**	***0.0***	**22.8**	4.0	**11.2**	2.8	**17.6**	***0.8***	5.6	**30.4**	***0.8***
Jones with ROA matching	3.6	4.0	***0.4***	**19.6**	***1.6***	**16.0**	6.8	7.2	***2.0***	**9.6**	3.6	***1.6***	6.4	4.8
Jones with ROA, SG, MB quintile dum	5.2	6.0	4.4	2.4	5.2	6.0	5.6	6.8	3.6	**10.8**	***1.6***	***0.4***	3.2	4.8
Jones with ROA, SG, RSG quintile dum	5.6	6.8	4.4	7.2	2.4	7.2	3.6	6.4	4.4	**12.4**	***0.4***	***1.6***	7.6	***2.0***
Jones with ROA, SG, FEG quintile dum	4.4	***2.0***	5.2	3.2	2.8	6.4	**10.4**	4.0	4.8	5.2	***0.4***	***1.2***	7.6	4.8
Mod-Jones	***0.0***	**75.6**	***0.0***	**86.0**	***0.0***	**30.0**	4.4	**11.6**	***0.8***	**28.0**	***0.4***	**8.8**	**44.4**	***0.8***
Mod-Jones with ROA matching	4.4	3.6	***0.0***	**61.6**	2.4	**17.6**	8.0	**8.8**	***0.4***	**14.8**	2.4	***0.8***	4.0	5.6
Mod-Jones with ROA, SG, MB quintile dum	6.4	4.0	2.8	2.8	6.4	8.0	**11.2**	5.6	3.6	7.6	***0.8***	***0.0***	***1.2***	6.8
Mod-Jones with ROA, SG, RSG quintile dum	6.0	6.8	3.6	4.8	4.8	7.2	3.6	6.4	4.8	**8.4**	3.6	***0.4***	2.8	3.6
Mod-Jones with ROA, SG, FEG quintile dum	5.2	***2.0***	4.4	4.8	5.6	5.6	**11.2**	3.6	3.2	4.8	***0.0***	***0.8***	4.0	6.0

Table IS-4

Specification tests with total accruals

This table repeats the specification tests of Table 2 in the main paper with total accruals instead of non-depreciation accruals. Total accruals ($TA_{i,t}$) are calculated as the difference between earnings before extraordinary items and discontinued operations ($EBXI_{i,t}$) and cash flow from operations ($CFO_{i,t}$). Thus, the baseline Jones and Mod-Jones models given by Equations (T1.1) and (T1.4) in Table 1 of the main paper are expanded to include property, plant, and equipment ($PPE_{i,t}$) scaled by assets ($ASSETS_{i,t-1}$) as an additional regressor. Table 1 also provides details of other models and partitioning variables used here and the aggregate sample of 203,090 firm-quarters. Because total accruals defined here are inversely related to CFO, we use lagged ROA (LROA, or $ROA_{i,t-4}$) as the measure of firm performance. This follows the caution in Kothari et al. (2005) regarding limitations of matching on current ROA (see their footnote 11). The numbers below represent the percentage of 250 samples of 200 firms each where the null hypothesis of zero discretionary accrual is rejected at the 5% level using one-tailed *t*-test for mean. We calculate that if the rejection frequency within any one run of 250 samples is below 2.4% or above 8.0%, then it is statistically significantly different from the model rejection frequency of 5% at the 5% confidence level in a two-tailed frequency test.

Partitioning variable →	All firms	ROA		SG		MB		MV		FD	
		Low	High	Low	High	Low	High	Low	High	Low	High
Figures in **bold** (***bold italic***) signify rejection rates that significantly exceed (fall below) the 5% significance level of the test and indicate that such tests are biased against (in favor of) the null hypothesis											
Panel A: H_1: Discretionary accruals < 0											
Jones	3.6	**18.8**	2.4	**46.4**	2.4	**31.2**	***1.6***	**12.0**	***0.8***	***0.4***	**34.0**
Jones with ROA matching	5.2	3.2	6.4	**30.8**	2.8	**20.0**	3.6	7.2	4.0	***1.2***	**14.0**
Jones with linear ROA, SG, and MB	4.4	**12.4**	4.8	**28.0**	3.2	**21.6**	5.2	**10.4**	***1.6***	***0.4***	**24.0**
Jones with ROA, SG, and MB quintile dummies	4.0	2.0	4.4	3.6	2.8	4.4	6.4	5.2	6.4	***1.2***	**15.6**
Mod-Jones	3.6	**23.2**	***0.8***	**76.0**	***0.0***	**33.6**	***1.6***	**15.2**	***0.8***	***0.4***	**36.0**
Mod-Jones with ROA matching	4.0	3.2	7.2	**51.2**	***0.4***	**19.6**	4.0	**9.2**	4.4	***0.8***	**14.4**
Mod-Jones with linear ROA, SG, and MB	4.4	**11.6**	4.0	**36.8**	2.8	**16.8**	4.4	**11.2**	***1.6***	***0.4***	**20.4**
Mod-Jones with ROA, SG, and MB quintile dummies	4.8	2.0	4.8	4.0	4.0	3.6	6.8	6.0	7.2	2.8	**12.4**
Panel B: H_1: Discretionary accruals > 0											
Jones	6.4	***1.2***	**14.8**	***0.0***	**14.0**	***0.4***	**14.4**	4.8	**19.2**	**46.0**	***0.4***
Jones with ROA matching	4.8	**8.8**	6.0	***0.0***	**10.0**	***0.8***	**9.6**	6.0	6.8	**12.8**	***1.2***
Jones with linear ROA, SG, and MB	5.6	***0.4***	**10.4**	***0.0***	7.6	***0.8***	**10.8**	4.4	**14.0**	**28.4**	***0.4***
Jones with ROA, SG, and MB quintile dummies	7.2	6.0	8.4	4.8	6.4	6.0	8.8	**8.4**	4.8	**14.8**	***1.2***
Mod-Jones	5.2	***0.8***	**25.6**	***0.8***	**40.0**	***0.4***	**16.4**	2.4	**22.4**	**54.0**	***0.4***
Mod-Jones with ROA matching	4.8	**9.6**	5.6	***0.0***	**27.2**	***0.8***	**10.4**	5.2	6.4	**15.6**	***0.8***
Mod-Jones with linear ROA, SG, and MB	4.0	***0.8***	**13.6**	***0.0***	**9.2**	***0.8***	**10.4**	5.2	**13.6**	**24.4**	***0.4***
Mod-Jones with ROA, SG, and MB quintile dummies	6.4	6.8	8.0	5.6	7.6	8.0	7.6	**8.8**	3.6	**8.4**	***1.2***



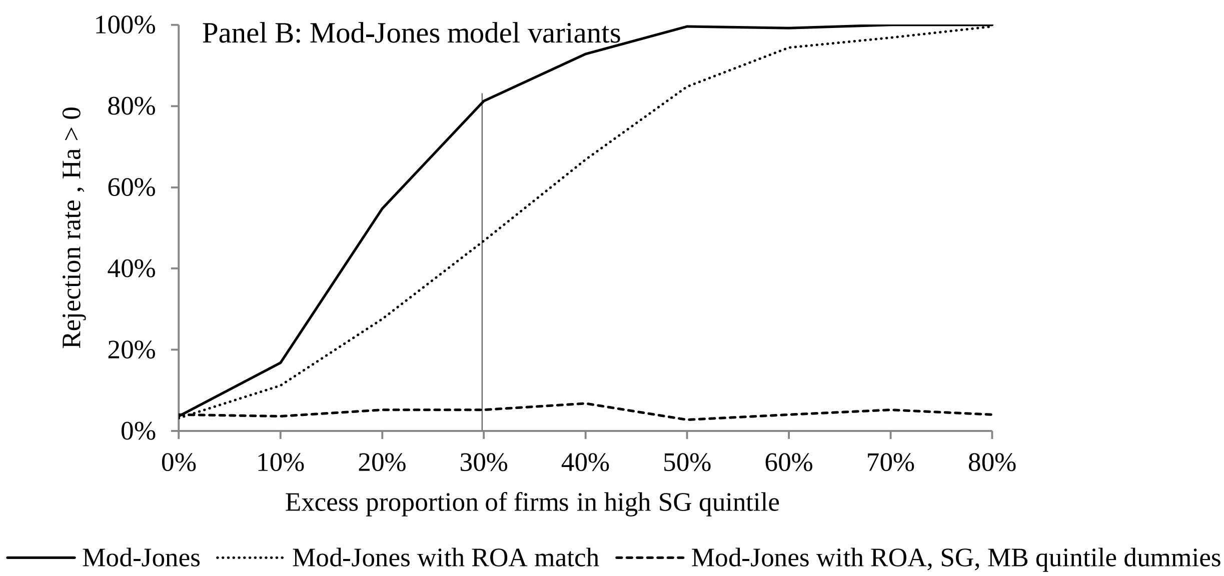


Figure IS-1. Specification tests of quarterly discretionary accrual measures as an increasing proportion of sample is drawn from the top SG quintile. This figure provides specification tests similar to Table 2 in the main paper, but with one difference. Whereas that table examines a sample size of 200 firm-quarters from the top SG quintile, this figure examines a sample size of 1,000 firm-quarters retrieved as follows. First, we randomly select an excess proportion of the sample from the top SG quintile as noted on the horizontal axis (for example, an excess proportion of 30% means that 50% of the sample is selected from the top SG quintile). Second, we randomly select the remaining sample from the other four SG quintiles. The vertical axis shows the percentage of 250 such samples for which the null hypothesis of zero discretionary accruals is rejected at the 5% level using one-tailed *t*-test for mean. The aggregate sample of 203,090 Compustat firm-quarters and the various discretionary accrual measures are described in Table 1 in the main paper.

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