

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 working capital accruals that naturally occur due to firm growth. This biases tests of earnings management in many settings where the partitioning variable is correlated with firm growth (such as stock splits, SEOs, stock acquisitions, and stock-based compensation). We show that there is a severe problem of falsely rejecting the null hypothesis of no earnings management in samples over-represented by high growth or low growth firms when using performance-adjusted discretionary accruals. In contrast, discretionary accrual models that control for both performance and firm growth are well specified and do not sacrifice power. Including adjustments for accruals' noise reduction and timely loss recognition roles further improves the model power.

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1. 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 firms' contracting characteristics (e.g., stock-based management compensation arrangements and debt contracting environment).¹ Much of the research to date fails to control for the effects of firm growth on estimates of discretionary accruals. 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 posits and finds that firms with greater expected earnings growth are likely to have greater accruals than firms with less expected earnings growth. Kothari, Leone, and Wasley (2005) examine the specification and power of Jones-type discretionary accrual models using *annual* data and show these accruals are correlated with firm performance. They find that both Jones model and modified-Jones model residuals adjusted by the residuals of same-industry firms matched on ROA yield reasonably well-specified tests of earnings management in most stratified random samples. Further, they conclude that "Performance-matched discretionary accruals exhibit only a *modest degree of misspecification* (emphasis added) when firms are randomly selected from an extreme quartile of stocks

¹ See Appendix 1 for a partial list of these studies.

ranked on firm characteristics such as the book-to-market ratio, firm size, sales growth, and earnings yield.” (Page 167).²

We survey the literature and find 32 published earnings management studies that analyze quarterly accrual data. Appendix 2 summarizes the main findings from this survey. Despite the warnings about possible misspecification due to failure to control for firm growth issued by McNichols (2000), a substantial portion of these studies follow the guidance provided in Kothari et al. (2005) and use performance (ROA)-matched Jones-type model discretionary accrual estimates. Only four studies include an explicit control for growth. Thus, the vast majority of quarterly earnings management studies implicitly assume that any distortion due to firm growth is minimal. We estimate that nearly three-fourths of these studies are subject to rather severe Type I specification bias due to their failure to control for firm growth when testing for earnings management. Hence, a rather substantial body of work that tests for earnings management in quarterly settings is subject to errors of inference that we point out below.

In this study, we estimate the extent of specification bias in tests of earnings management when one fails to control for firm growth. We show that quarterly current accruals vary dramatically when firms are sorted into deciles based on rolling annual measures of sales growth (SG, our growth proxy) and that this relation is non-linear. Further, we show that the effect of growth on accruals measurement dominates the effects of other firm characteristics found to be related to accruals, such as performance (ROA), size (MV), market-to-book (MB), and earnings-to-price (EP). Matching firms on performance and sales growth within 2-digit SIC industry and differencing the raw quarterly current accruals dramatically dampens the variation in accruals for firms ranked on performance and sales growth as one would expect. Interestingly, this matching also substantially dampens the variation in accruals that is related to size, market-to-book, and earnings-to-price. In other words, matching on performance and growth is likely to

² The degree of misspecification documented in Table 3 of Kothari et al. (2005) is lower than what one would typically encounter in most empirical settings because the sample size underlying these specification tests is 100 observations. We find that the median sample size in quarterly settings where researchers have tested for earnings management is around 2,500 observations. We estimate that the type I error rates are likely 3 to 12 times greater than the nominal alpha level of 0.05 when sample sizes are 1,000 observations and the sample is over-represented by high growth firms (see Figure 4 below and discussion in Section 4.2).

mitigate bias in discretionary accrual estimates in samples over-represented by firms with these extreme characteristics, which covers many settings analyzed in the accounting and finance literature.

Our study contributes to the extant literature on earnings management in several ways. First, it is one of the first studies to investigate the specification and power of alternative discretionary accrual models in quarterly settings.³ This is important to do because of the rapidly increasing number of quarterly earnings management studies over the past decade. Second, we demonstrate that the confounding effect of firm growth on tests of earnings management in quarterly settings is pervasive and that the growth effect on accruals dominates the effects of performance, size, market-to-book, and earnings-to-price. Third, in their comprehensive review of the literature on earnings quality, Dechow, Ge, and Schrand (2010) claim that the explanatory power of Jones-type models is low, explaining only about 10% of the variation in accruals. Moreover, they conclude that the ability of these models to reliably detect even relatively large amounts of earnings management (1% to 5% of total assets) is low. In contrast to these generalizations, we demonstrate that Jones-type models applied to current accruals in quarterly settings explain more than 40% of the cross-sectional variation in accruals within 2-digit SIC codes when these models are adjusted for contemporaneous operating cash flows (Ball and Shivakumar, 2006). After matching on performance and firm growth, our simulation analysis demonstrates detection rates of nearly 90% using Jones-type models that control for contemporaneous operating cash flows for earnings management as small as 0.25% of total assets with sample sizes typically encountered in most empirical settings.

Concerns arise that matching on sales growth may “throw the baby out with the bathwater” when revenues are manipulated. However, contrary to what one might expect, we demonstrate that matching on sales growth introduces very little downward bias (typically less than 5 basis points) in discretionary accrual estimates when earnings are managed through revenue manipulation. We also demonstrate that reversal methodology recently advanced by Dechow et al. (2012) as having greater power than matching procedures when applied in annual settings actually yields tests of lower power in quarterly settings

³ Jeter and Shivakumar (1999) demonstrate the misspecification of Jones-type models in quarterly settings where samples are over-represented by firms with high (low) operating cash flows.

where the number of quarters over which reversals occur is less certain and the analysis is confounded by seasonality.

The remainder of the paper is organized as follows. Section 2 documents that firm growth is a pervasive and correlated omitted variable in many settings where researchers test for earnings management. Section 3 demonstrates graphically the non-linear relation between rolling annual measures of sales growth (our proxy for firm growth) and quarterly current accruals, and we show that the effect of sales growth on accruals dominates the effect of ROA, MV, MB, and EP. We show that matching firms on performance and sales growth (ROA + SG) within 2-digit SIC industry and differencing the raw quarterly current accruals dramatically dampens the variation and non-linearity of current accruals for firms ranked on ROA and SG as well as these other three dimensions. We also provide numerical estimates of the bias in a variety of Jones-type discretionary accrual estimates typically encountered in the literature using a comprehensive sample of Compustat firm-quarters and from stratified sub-samples using extreme quintiles of firm-quarters partitioned by SG, ROA, MV, MB, and EP. Section 4 compares Type I error rates for alternative Jones-model tests of income-increasing and income-decreasing earnings management across all Compustat firm-quarters and in samples with varying degrees of over-represented firms from extreme quintiles of the firm characteristics noted above. Section 5 uses simulation analysis to compare Type II error rates and power of alternative discretionary accrual models in random samples over-represented by high growth firms. Section 6 presents simulation results that address the concern of whether matching on sales growth throws the baby out with the bathwater when earnings management is accomplished through revenue manipulation. Section 7 compares the ROA + SG matching procedure to the reversal methodology recently proposed by Dechow et al. (2012) and offers simulation results on the relative power of these two approaches in quarterly settings. Section 8 concludes and summarizes the implications of our findings for future earnings management research.

2. Firm growth and earnings management partitioning variables

2.1 *The correlation between alternative partitioning variables and firm growth measures*

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 general discretionary accruals 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 a 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. We examine the pervasiveness and magnitude of the bias that exists in extant earnings management studies that fail to control for firm growth in two steps. First, we show the association between five key partitioning variables and firms ranked on sales growth (SG), our proxy for firm growth. Next, we quantify the error in Jones-type discretionary accrual estimates that are not adjusted for growth in three event-driven settings and estimate the potential bias.

The five partitioning variables we consider are stock splits, SEOs, stock-for-stock acquisitions, percentage of stock-based (executive) compensation, and abnormal insider selling. Prior research has hypothesized and shown each of these partitioning variables to be significantly associated with upward earnings management. For the first three partitioning variables, we start with a comprehensive sample of firm-quarters from 1991 to 2007 from the Compustat and CRSP databases and merge it with samples of firms that announced stock splits, SEOs, and stock acquisitions.⁴ We require that the included firm-quarters have a CRSP share code of 10 or 11 and an asset value greater than \$10 million. We also require that the quarterly earnings announcement date is available in Compustat. We exclude financial firms. The sales growth is calculated as the sales during the quarter with the earnings announcement date preceding the event date of interest divided by the sales during the same quarter of the previous year, minus one ($[\text{Sales}_t / \text{Sales}_{t-4}] - 1$). The corresponding decile ranks are calculated each quarter using the data for all

⁴ The construction of the comprehensive sample of firm-quarters and the calculation of accrual measures is provided below in Section 3.1.

firm-quarters. Stock splits are identified from the CRSP database using distribution code of 5523 and a positive split factor, and SEOs and stock acquisitions are identified from the SDC database.

Panel A of Figure 1 shows the frequency distribution of 2,646 stock splits, 2,951 SEOs, and 1,193 stock acquisitions across sales growth (SG) deciles. As shown, there is a strong positive relation between all three partitioning events and SG with nearly 50% of these events falling into the upper two decile ranks (i.e., upper quintile) of firm growth.

[Insert Figure 1 here]

For the stock-based compensation and abnormal insider selling partitions, we start with a comprehensive sample of 41,383 firm-years (instead of firm-quarters) during 1991 to 2007 from the Compustat and CRSP databases and 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).⁵ The insider trading data pass through several filters commonly employed in previous literature.⁶ Stock based compensation is calculated as the Black-Scholes value of stock option grants plus the market value of restricted stock divided by total compensation and this quotient is multiplied by 100. Total compensation is defined as the value of stock options and restricted stock plus salary and bonus. Next, 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.

The left bars of Panel B of Figure 1 show the median stock-based compensation as a percentage of total compensation for firm-years ranked by sales growth decile and the right bars in this plot show the percent of all firm-years for which there was abnormal insider selling. Once again we see that both stock-based compensation and abnormal insider selling tend to be concentrated in high growth deciles. The

⁵ We use firm-years because executive compensation data is only available on an annual basis from ExecuComp.

⁶ We collect data as reported on form 4 filed with the SEC. We restrict to cleanse codes R and H, which indicate the highest level of confidence in data, and transaction codes P and S, which indicate open market or private purchase and sale of non-derivative or derivative security. We also restrict to transactions involving at least 100 shares.

clear take-away from these two figures is that failure to control for firm growth in these settings is likely to result in upward biased estimates of discretionary accruals and a bias in favor of finding earnings management.

2.2 Alternative Jones-type model discretionary accrual specifications

The two most popular models for estimating the discretionary component of 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 for current or working capital accruals ($CA_{i,t}$) are specified below:

Quarterly Jones Model:

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

In this expression, subscript i denotes firm and t denotes calendar quarter. $Q_{1,i,t}$ to $Q_{4,i,t}$ are fiscal quarter dummies that allow for possible fiscal quarter effects in accruals. It is important to note that the $\Delta SALES_{i,t}$ term in these models is the *quarterly change in sales measured relative to the previous quarter's sales*. Adjacent quarter changes in sales are likely dominated by seasonality effects and are too short making this term a poor proxy to capture true changes in firm growth. Consequently, below we suggest controlling for firm growth using a rolling window annual measure of sales growth calculated as $(Sales_t - Sales_{t-4}) / Sales_{t-4}$. We include $CA_{i,t-4}$, the current accruals from the same fiscal quarter in the preceding year, to control for other possible but unknown determinants of current accruals for the current fiscal quarter. All independent variables except the intercept term are scaled by lagged total assets. Using Compustat data, the regressions are run by calendar quarter for the cross-section of all firms belonging to the same industry as the sample firm (i.e., same two-digit SIC code). The Jones model discretionary accruals are calculated as the residuals $\varepsilon_{i,t}$ from Equation (1).⁷

⁷ Throughout this paper we adopt the one-step approach to estimating discretionary accruals that is the dominant approach in the literature subsequent to the Kothari, Leone, and Wasley (2005) paper. Under this approach, both treatment and control (benchmark) firm observations are included in the estimating equation used to determine non-discretionary accruals. This is in contrast to the two-step approach that uses only observations from the non-event or control firm sample to estimate parameters for determining non-discretionary accruals. These parameter estimates are then combined with observed values of the economic determinants of accruals for treatment firms in the event period to form expected (non-discretionary) accruals. The difference between the actual and expected accruals is

Quarterly Modified-Jones Model—Common Specification [Mod-Jones(C)]:

Mod-Jones(C) model discretionary accruals are calculated as the residuals $\xi_{i,t}$ from the following model. We examine the most common way of estimating the modified-Jones model that treats all credit sales in the event period and the estimation period as discretionary for both the treatment and control firms included in the regression (we refer to this as Mod-Jones(C)).⁸

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

where all notations have the same meaning as described above.⁹ $\Delta AR_{i,t}$ is measured over adjacent quarters.

Models that adjust for accruals' role in noise reduction and timely loss recognition:

Ball and Shivakumar (2006) posit that accruals serve two major purposes: (1) ameliorating transitory shocks to operating cash flows (CFO); and (2) promoting efficient contracting by providing timely loss recognition. They demonstrate how explicitly recognizing these two roles results in formulation of non-linear discretionary accruals models that offer substantial specification improvement over existing models. Models that adjust for accruals' noise reduction and timely loss recognition roles by including the contemporaneous CFO term explain substantially more cross-sectional variation in accruals than equivalent linear models, and better capture the true dynamics of the accrual process in quarterly settings (Jeter and Shivakumar, 1999). This has important implications for assessing the power of tests in detecting earnings management as we demonstrate below.

Ball and Shivakumar (2006) note that one reason why transitory operating cash flows occur is because firms' operating activities cause working capital items like inventory, receivables, and payables

used as the proxy for abnormal or discretionary accruals for treatment firms in the event period that is hypothesized to give rise to earnings management. The choice between the two approaches has little effect on Type I error rates, but the one-step approach can be slightly less powerful when there is clustering of data in calendar time or within industry.

⁸ We also estimate discretionary accruals using the original specification of the modified-Jones model proposed by Dechow, Sloan and Sweeney (1995), which treats all credit sales in the event period (but not in the estimation period or benchmark sample) as discretionary. For brevity, we do not table these results, but they are available from the authors upon request.

⁹ The Mod-Jones(C) model assumes nondiscretionary accruals [the fitted part of equation (2)] are related only to cash sales for all sample and benchmark firms included in the regression.

to vary over time. Current accruals adjust operating cash flow to produce an earnings number that is less noisy in measuring periodic performance and more efficient for contracting with lenders, managers, and others. Quarterly CFO measures are particularly noisy for businesses with strong seasonality. Quarterly accruals for inventories, receivables, and payables represent non-discretionary adjustments to reduce the transitory fluctuations in CFO that naturally occur in these seasonal businesses. Thus, adding the contemporaneous CFO in discretionary accruals models greatly enhances standard Jones-type models' ability to capture the true dynamics of the accrual process in quarterly settings (Jeter and Shivakumar, 1999).

Ball and Shivakumar (2006) note that another way that accrual accounting functions is to provide recognition of unrealized gains and losses. Timely gain and loss recognition occurs around the time of revision in expectations about future cash flows, which likely occurs prior to the actual realization of the cash flows, thus requiring an accrual. Because the recognition of gains and losses is asymmetric (Basu, 1997), they argue that the relation between accruals and cash flows cannot be linear. This implies that standard linear forms of Jones-type models like those examined above could be misspecified for the purpose of estimating discretionary accruals. Accordingly, we adopt the Ball and Shivakumar's proposed adjustments to the standard Jones model to capture the noise reduction and asymmetric loss recognition properties of accruals in quarterly settings as follows:

$$CA_{i,t} = \beta_0 + \beta_1 Q_{1,i,t} + \beta_2 Q_{2,i,t} + \beta_3 Q_{3,i,t} + \beta_4 Q_{4,i,t} + \beta_5 \Delta SALES_{i,t} + \beta_6 CA_{i,t-4} + \beta_7 CFO_{i,t} + \beta_8 DCFO_{i,t} + \beta_9 DCFO * CFO_{i,t} + \varepsilon_{i,t} \quad (3)$$

where $CFO_{i,t}$ is operating cash flows for firm i in quarter t and $DCFO_{i,t}$ is a dummy variable set to 1 if $CFO_{i,t} < 0$ and zero otherwise. All other variables are as previously defined in Equation (1). Henceforth, we refer to this specification as Jones + CFO. We supplement the modified-Jones model in a similar fashion and refer to this specification as Mod-Jones(C) + CFO.

Following Ball and Shivakumar (2006), models with CFO terms are estimated for each two-digit industry. This is unlike models without CFO terms that are estimated for each industry-quarter. The

difference arises due to a greater number of terms in the former case and the limited number of observations within many industry-quarters.

2.3 Adjustments for performance and firm growth

The residuals from the above alternative specifications adjusted for like residuals from firms matched on ROA and/or sales growth (SG) form the basis for our subsequent specification and power tests. For ROA adjustment, we choose the matching firm that is from the same two-digit industry with the closest ROA during quarter $t-4$. We match on ROA_{t-4} rather than ROA_t because of the mechanical relation between ROA_t and CA_t when CFO_t is included in the model (see Kothari et al., 2005). For ROA + SG adjustment we arrange all same-industry firms during quarter $t-4$ into five ROA quintiles and choose the matching firm that has the closest SG from quarter $t-4$ to t in the relevant quintile. We calculate ROA as the net income divided by total assets, and SG as the sales during quarter t divided by sales during quarter $t-4$ minus one $[(Sales_t - Sales_{t-4}) / Sales_{t-4} = (Sales_t / Sales_{t-4}) - 1]$. Thus, this is a rolling annual window measure of sales growth. All accrual measures and partitioning variables are winsorized at the 1% and 99% levels.

Most studies that test for earnings management make no explicit adjustment for accruals' role in noise reduction and timely loss recognition. Thus, we begin by calculating the Jones and Mod-Jones(C) model abnormal accruals from Equations (1) and (2) without adjustment for CFO. We adjust these discretionary accrual estimates for performance (growth) by subtracting the discretionary accruals of the firm from the same 2-digit SIC industry with the closest ROA_{t-4} (SG) match. Finally, we calculate Jones model and Mod-Jones(C) model discretionary accruals and adjust for both performance (ROA) and sales growth (SG) by subtracting the Jones or Mod-Jones(C) model residuals of the ROA + SG matched firm from the same model residuals of the treatment firm as described above. This provides eight discretionary accrual estimates: (1) Jones model, (2) Jones with ROA matching, (3) Jones with SG matching, (4) Jones model with ROA + SG matching, (5) Mod-Jones(C) model, (6) Mod-Jones(C) with ROA matching, (7) Mod-Jones (C) with SG matching, and (8) Mod-Jones(C) model with ROA + SG matching.

Panel A of Table 1 provides summary results for tests of upward earnings management for each of these eight discretionary accrual estimates around the three events-related partitioning variables enumerated above—stock splits, SEOs, and stock acquisitions. Each cell reports the average discretionary accrual estimate stated as a percentage of the beginning-of-quarter total assets and related t-statistic. As shown, both baseline models [Jones and Mod-Jones(C)] yield highly significant positive abnormal accruals for all three events, with values ranging from 0.188% to 0.616% of total assets. ROA matching generally reduces the average abnormal accrual, but for stock splits and SEOs the magnitudes remain highly significant for both models. Matching on SG considerably reduces average discretionary accruals using Jones model (between -0.023% and 0.052% of total assets, insignificant in all three cases) as well as Mod-Jones(C) model (between -0.004% and 0.165% of total assets, insignificant for stock splits and stock acquisitions but significant at 5% level in one-tailed tests for SEOs). Finally, matching on both ROA and SG also results in much lower average abnormal accrual estimates for the stock split and stock acquisitions samples and none of the mean values are significantly different from zero. However, the SEO sample produces ROA + SG matched discretionary accruals that are significantly positive for both model specifications. Thus, consistent with the prior findings of Teoh, Welch, and Wong (1998) and Rangan (1998), there does appear to be upward earnings management associated with SEOs, although the degree of upward management appears to be considerably less than previously documented (especially when using the Mod-Jones(C) model). Overall, SG or ROA + SG matching yield discretionary accruals that are smaller in magnitude than with ROA matching for samples that are over-represented by high growth firms.

[Insert Table 1 here]

Across all three samples, the bias in test results is most severe for the Mod-Jones(C) and Mod-Jones(C) + ROA matching estimates, which are the most popular models used in prior research. For the stock split and stock acquisition samples, the bias for these two discretionary accruals models is particularly acute. Panel B of Table 1 shows why. As shown there and as demonstrated in Figure 1, these two samples are heavily populated with high growth firms. The average SG decile rank is 7.55 for the stock acquisition sample and 7.25 for the stock split sample. Thus, studies that fail to control for growth

when testing for earnings management in these settings are likely to reject the null hypothesis of no earnings management, when, in fact, the null is true. Panel B of Table 1 also shows the average decile ranks of firms along ROA, MB, MV, and EP dimensions. Note that along each dimension the average decile rank for each event is significantly different from the population average decile rank of 5.50, and in some cases more so than for SG. Yet, correcting for ROA and SG or SG alone yields insignificant abnormal accruals in the case of stock splits and stock acquisitions. Below we show that, in general, matching on ROA and SG effectively mitigates the effects of these other firm characteristics on accruals measurements.

3. Quarterly current accruals and discretionary accrual measures in the aggregate sample and across deciles of SG, ROA, MB, MV, and EP

The previous section provides evidence on Type I error rates in samples where the partitioning variable is highly correlated with firm growth. To provide a sense of the potential bias in more general settings, in this section we demonstrate how quarterly raw current accruals and alternative discretionary accrual measures vary across deciles of firm-quarters sorted by SG, ROA, MB, MV, and EP.

3.1 A comprehensive sample of firm-quarters

Most of our tests in this paper 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 five partitioning variables—SG, ROA, MB, MV, and EP are available. Following Hribar and Collins (2002), we calculate current accruals from the cash flow statement as $-(CHGAR+CHGINV+CHGAP+CHGTAX+CHGOTH)$. The bracketed quantities in this expression represent the changes in accounts receivable, inventories, accounts payable, taxes payable, and other items.^{10, 11} We undo the year-to-date nature of these quarterly cash flow statement items and

¹⁰ Notice a positive (negative) value of *CHGAR* and *CHGINV* represents a decrease (increase) in accounts receivable and inventories, while a positive (negative) value of *CHGAP*, *CHGTAX*, and *CHGOTH* represents an increase (decrease) in accounts payable, taxes payable, and other items. These variables carry names of *RECCHY*, *INVCHY*, *APALCHY*, *TAXCHY*, and *AOLOCHY* in the current version of Compustat. We recode missing values of *RECCHY*, *INVCHY*, *APALCHY*, and *TAXCHY* as zero 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 zero. In other tests, we obtain *CFO* by undoing the year-to-date nature of the Compustat variable *OANCFY*.

¹¹ Unlike the other four items, *CHGOTH* is not all current accruals. It includes current items such as deferred revenues and expenses, but can also include gains (losses) on sales of fixed assets, asset impairment charges, foreign

compute the quantities for the quarter under consideration. 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 codes between 60 and 69); (3) The CRSP share code is 10 or 11 (which excludes ADRs, REITs, units, 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 one.

We begin by showing in Panel A of Figure 2 a two-dimensional plot of raw quarterly current accruals for firms ranked into deciles along five dimensions that prior research has shown to be related to accruals: SG, ROA, MB, MV, and EP. The plotted lines are the average raw quarterly current accruals for each decile-rank of the associated dimension. Two aspects of this plot are noteworthy. First, the dominant factor associated with variation in raw accruals is firm growth. The SG line shows the most variation in current accruals (steepest slope) across all the various firm dimensions ranging from -0.67% of lagged total assets for decile 1 to 1.26% of lagged total assets for decile 10. *Thus, firm growth appears to be the most important factor to control for when testing for earnings management in quarterly settings.* The second most important factor appears to be MB, which is a commonly-used proxy for expected future growth, followed by firm performance (ROA). The second important feature of this plot is that the relation between SG and raw quarterly current accruals is non-linear. The non-linearity is particularly apparent in the lowest (highest) two deciles (i.e., in the bottom and top quintiles), a point that we will come back to later in our discussion. Thus, adding a linear annual SG term in quarterly discretionary accrual models will not provide an effective control for the effects of firm growth on quarterly accruals measurements. While there is some non-linearity along other firm dimensions, this non-linearity does not appear to be as acute as it is for SG.

[Insert Figure 2 here]

Panel B of Figure 2 shows the difference in raw quarterly current accruals where firms are matched within 2-digit SIC along ROA and SG dimensions as outlined in Section 2.4 above. The difference between Panels A and B is striking. The variation in the differenced accruals across decile

currency translation gains (losses), and restructuring charges. We include this item as part of current accruals because often items missing values of other items may be included here. (See previous footnote.)

ranks is much smaller, ranging from -0.29% to +0.20% for all five firm dimensions, and the non-linearity is no longer as acute.

Figure 3 shows discretionary accrual estimates for the four alternative Jones (Panel A) and Mod-Jones (Panel B) models described in Section 2.2 across SG deciles. The striking feature of these graphs is that abnormal accruals based on differencing either by SG or ROA + SG hover around zero across all SG decile ranks. However, both Jones and Mod-Jones discretionary accrual models exhibit significant non-zero discretionary accruals for high (low) SG deciles and this is particularly problematic for the Mod-Jones(C) model. As is apparent from the plots, matching on ROA within 2-digit SIC and taking the difference in Jones or Mod-Jones discretionary accrual estimates does little to eliminate the bias due to firm growth (SG).

[Insert Figure 3 here]

3.2 Distributional statistics for accruals in the aggregate sample

Panel A of Table 2 shows the distributional statistics of various accrual measures for the aggregate sample. Current accruals calculated from the statement of cash flows scaled by lagged assets have mean and median values of 0.44% and 0.32%. The positive mean and median values are consistent with positive firm growth and the associated increasing working capital requirements over time. Current accruals also show considerable cross-sectional variation, with a standard deviation of 4.36%. Some of this variation is explained by Jones and Mod-Jones(C) models, but a large part remains unexplained. The residual accruals from the Jones and Mod-Jones(C) models have standard deviation of 3.60% and 3.61%, respectively, which average 83% of the 4.36% standard deviation of raw accruals. By construction, the residual accruals from the Jones and Mod-Jones(C) models have mean values close to zero and a symmetric distribution around zero (unlike raw accruals that are slightly skewed to the right of the median as shown by lower and upper quartiles). Matching on either ROA or SG increases the cross-sectional standard deviation of the resultant accrual difference measures by a factor of about $\sqrt{2}$.¹² Finally,

¹² This is explained as follows. Suppose the Jones model (or modified-Jones model) residuals for sample firm and matching firm are denoted by $\epsilon_{i,t}$ and $\epsilon_{i,t,m}$. The matching procedure calculates discretionary accruals as $\epsilon_{i,t} - \epsilon_{i,t,m}$. In a random sample, on average, the standard deviation of the two residuals are approximately equal, so the

although not shown in Table 2, the average adjusted- R^2 of Jones and Mod-Jones(C) model regressions in equations (5) and (6) is on the order of 0.26 when estimated within 2-digit SIC industry codes.

Panel B of Table 2 provides mean and median values of raw current accruals and the eight abnormal accrual measures identified earlier for the subsamples of firm-quarter observations in high and low quintiles of each firm characteristic. We start by examining Jones or Mod-Jones(C) model residuals with no matching or with ROA matching, which are the most commonly used models in prior studies. If these models are well specified, the resultant abnormal accruals should have a mean near zero. We term non-zero values of these measures as ‘biases’ and examine how these ‘biases’ are mitigated by SG or (in particular) ROA + SG matching.

The largest biases occur in SG partitions, ranging from -0.43% to -0.86% of lagged assets in the low SG quintile and from 0.33% to 0.78% in the high SG quintile. In both cases the biases are largely mitigated by SG or ROA + SG matching, to a maximum absolute value of 0.08% (i.e., 8 basis points). Across ROA partitions, the biases are negligible in the low ROA quintile but a substantial 0.22% of lagged assets in the high ROA quintile for the Mod-Jones(C) model with no matching. This bias is reduced to 0.02% by ROA + SG matching. For the MB partitions, we find biases ranging from -0.31% to -0.39% in the low MB quintile and from 0.13% to 0.24% in the high MB quintile without SG or ROA + SG matching. These biases across MB partitions are quite substantial. Because MB is often used as a proxy for future expected growth, the biases in abnormal accrual estimates for extreme MB partitions further emphasize the relation between firm growth and accruals. Note that the relation is weaker with MB, a long-term forward-looking growth measure, than with SG, a short-term historical growth measure. ROA + SG matching mitigates most of these biases in the high MB quintile (maximum absolute value of 0.06%) and some of these biases in the low MB quintile (maximum absolute value of 0.23%).

Looking across firm size (MV) partitions in Panel B of Table 2, the biases are negligible in the high MV quintile but somewhat more significant in the low MV quintile. These biases are largely mitigated by ROA + SG matching. We observe similar but somewhat more pronounced evidence of bias

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.

across EP partitions. ROA + SG matching tends to have little effect on the EP bias when using the Jones model, but substantially reduces the bias for low EP samples when using the Mod-Jones (C) model. Overall, averaged across all ten partitions, the bias is reduced to an absolute value of 0.09% for Jones model with ROA + SG matching and around 0.07% for Mod-Jones(C) model with ROA + SG matching. That is a significant improvement from corresponding values of 0.19% and 0.32% with no matching and 0.17% and 0.26% with ROA matching. Of course, this rough comparison understates the importance of the incremental SG matching in practical situations where the dominant distinguishing firm characteristic affecting accruals is firm growth.

[Insert Table 2 here]

4. Specification tests (Type I errors) of discretionary accrual models using quarterly data

4.1 Results for highly concentrated samples of low (high) growth firms and other firm characteristics

In this section we replicate a typical research design employed to detect earnings management around specific corporate events in order to test the specification (Type I error rates) of the same eight discretionary accrual measures starting with Jones-type models as analyzed in Section 3.2 above (i.e., Jones or Mod-Jones(C) model, with no matching or ROA, SG, or ROA + SG matching). Instead of real events we select a random sample of 200 observations taken from either the aggregate sample of Compustat firm-quarters or from the bottom (Low) or top (High) quintile of firm-quarters ranked by SG, ROA, MB, MV, and EP. The choice of 200 observations is somewhat arbitrary. While it is less than the typical sample size in most event studies, 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. Later we repeat the specification tests for these accrual measures with larger samples, but a lower concentration of observations in extreme deciles.

We repeat the above sampling procedure 250 times with replacement. Because the 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%, we measure the percentage of the 250 trials that the null hypothesis of no earnings management (zero

abnormal accruals) is rejected in favor of the alternate hypothesis of either positive or negative abnormal accruals using a one-tailed *t*-test of means. With 250 replications, there is a 95% probability that the measured rejection rate will lie between 2.4% and 8.0% if the discretionary accrual measure is not misspecified and the null is true.

Table 3 presents the simulation results using accruals taken from the cash flow statement. Panel A (B) shows the rejection rates against the alternative hypothesis that discretionary or abnormal accruals are negative (positive). The first column provides rejection frequencies for samples drawn from the aggregate sample, 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 SG, ROA, MB, MV, and EP. The key findings are as follows:

[Insert Table 3 here]

1. For samples drawn from the aggregate set of Compustat firm-quarters, the rejection rates lie between the bounds of 2.4% and 8.0% in all 16 cases (which has a probability of $0.95^{16} = 0.44$). This is not surprising because roughly half of each draw of 200 observations should have ROA and SG values above or below the corresponding mean value for all same-industry firms. Thus, any performance or growth-related bias in discretionary accruals estimates will likely cancel out. Overall, these tests serve as an important validation-check of our simulation procedures.
2. As shown in Table 3, Jones and Mod-Jones(C) models suffer from large Type I errors in samples selected from low and high SG quintiles of Compustat firm-quarters. In low SG samples the researcher erroneously concludes in favor of downward earnings management, and in high SG sample erroneously concludes in favor of upward earnings management. Looking across models, the Mod-Jones(C) model is associated with the highest Type I errors, with rejection rates as high as 91.2% (86.0%) in the low (high) SG partitions. The rejection rates are the lowest for Jones model, 41.2% (34.8%) in the low (high) SG partition, still high in absolute terms. ROA matching moderates the over-rejection rates, but they remain high in absolute terms. When the alternative hypothesis is that discretionary accruals are negative, the Jones and Mod-Jones(C) models with ROA matching give rejection rates of 26.8% and 71.6% in the bottom SG quintile. Similarly, when the alternative hypothesis is positive discretionary accruals, the two models with ROA matching give rejection rates

of 20.8% and 62.8% in the top SG quintile. Thus, similar to the evidence based on summary statistics in Table 2, tests of earnings management based on performance-adjusted (ROA matched) Jones and Mod-Jones(C) models are highly misspecified when samples have extreme growth characteristics.¹³

3. As expected, both Jones and Mod-Jones(C) models with ROA + SG matching yield reasonably well-specified results in either high or low SG partitions and under either alternative hypothesis (i.e., downward or upward earnings management). SG matching alone comes close, but gives abnormally high rejection rates of 8.8% and 10.0% in two out of eight tests.
4. Both ROA and ROA + SG matching give well-specified results in low and high ROA partitions with either model and under either alternative hypothesis while SG matching gives slightly misspecified results in two out of eight tests. However, ROA + SG matching outperforms ROA matching in MB partitions, with rejection rates in the range of 0.8% to 10.8% in the former case and 0.4% to 19.2% in the latter case. A similar pattern can be observed for MV partitions. Both ROA + SG and ROA matching give somewhat elevated rejection rates in EP partitions, ranging from 0.8% to 26.0% with the first measure and 0.0% to 27.6% with ROA matching only.

We summarize the evidence from Table 3 as follows:

- a. ROA + SG matching outperforms ROA matching in 20 cases and is outperformed in only 3 cases in a total of 40 tests reported for SG, ROA, MB, MV, and EP partitions.¹⁴
- b. Looking at each measure by itself, ROA + SG matching gives well-specified rejection rates in 24 out of 40 tests. The rejection rates are too low in 7 tests and too high in 9 tests. In the latter case, the rejection rates range between 8.4% and 26.0%, with an average value of 13.4%. In comparison, ROA matching gives well-specified rejection rates in 17 tests, too low in 11 tests,

¹³ Notice ROA matching leaves almost unchanged the magnitudes of modified-Jones model residuals in low and high SG partitions in Table 2, but it decreases the rejection rates in the same partitions in Table 3. This highlights the limitation of examining only the rejection rates in simulation models. The rejection rates depend on the magnitudes of biases as well as their standard deviations. Table 2 shows that any kind of matching increases the cross-sectional standard deviation of modified-Jones model residuals by a factor of about $\sqrt{2}$. Thus, ROA-matching decreases the rejection rates in Table 3 even though it leaves unchanged the magnitudes of biases in Table 2.

¹⁴ We compare the two measures as follows. First, if both measures give well-specified rejection rates in the range of 2.4% to 8.0%, we call it a tie. Second, if one measure gives rejection rates within this range and the other does not, then we say that the former measure outperforms the latter measure. Third, if both measures give rejection rates outside the range, we calculate which one is closer to the range and say that it outperforms the other.

too high in 12 tests, and in the last 12 tests the rejection rates range between 9.6% and 71.6% with an average value of 27.2%.

- c. We conclude that in a wide variety of circumstances Jones-type models with ROA + SG matching yield better specified tests of earnings management in quarterly settings compared to the ROA matching procedure proposed by Kothari et al. (2005). There is considerable parallel between the magnitudes of biases in Table 2 and the rejection rates in Table 3. Thus, the caveat at the end of Section 3.2 also applies to the current discussion-- the rough comparison of rejection rates across all partitions understates the importance of ROA + SG matching in practical situations where the dominant distinguishing firm characteristic affecting accruals is firm growth.

4.2 Results for samples with varying proportions of high growth firms

The specification tests in Table 3 show the Type I error rates when a relatively small sample (200 observations) is drawn entirely from firm-quarters in the high (low) growth quintiles as well as samples drawn from quintiles of other firm characteristics related to accruals. The earlier analysis assumes that the partitioning variable used to identify cases of earnings management has a 100% overlap with firms with extreme growth (or any other firm characteristic). However, the partitioning variable in most studies of earnings management rarely coincides perfectly with firm growth. Rather, the samples often 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. For example, the histograms in Figure 1 suggest that samples used in studies that test for earnings management around SEOs or stock acquisitions are more likely to be over-represented by high growth firms than are studies that test for earnings management around stock splits, and that roughly 50% of these samples come from the highest growth quintile.

To assess how varying the proportion of high growth firms in a sample can impact Type I error rates in sample sizes more commonly used in testing for earnings management, we conduct the following simulation. We begin by taking 250 stratified random samples (with replacement) of 1,000 firm-quarters,

and for each of the 250 trials we vary the proportion of firms drawn from the high sales growth quintile.¹⁵ We estimate the mean abnormal accrual (μ) for each sample conditional on each of the eight models shown in Table 3. Using a significance level of 5%, we measure the percentage of the 250 trials that the null hypothesis of $\mu = 0$ is rejected in favor of the alternative hypothesis of $\mu > 0$ using a one-tailed t -test of the mean. Figure 4 shows the rejection rates (Type I error rates) across samples with an increasing proportion of firms-quarters drawn from the high SG quintile.¹⁶ The origin on the x -axis (0) represents random samples of 1,000 firm-quarters with no excess proportion of firm-quarters drawn from the high SG quintile. Thus, 20% of the firm-quarters in each of these random samples would be expected to come from the high SG quintile. The 30% point on the x -axis represents samples that have 2.5 times the normal representation of high SG quintile firms. Thus, these samples would have roughly 50% of the 1,000 observations coming from the high SG quintile while the remaining 50% are evenly distributed across the lower four SG quintiles. Note that samples comprised of 50% high quintile SG firms roughly mirror the proportion of high SG firms found in SEO and stock acquisition samples reported in Panel A of Figure 1.

For parsimony, in the remainder of the paper we focus on six models, which are Jones or Mod-Jones(C) model with no matching, ROA matching, or ROA + SG matching. The results in Figure 4 show that all six models yield rejection rates of right around 5% when there is no excess representation of high SG firm-quarters in the sample (i.e., 0 point on x -axis). As the excess proportion of high SG firm-quarters increases, Type I error rates for the Jones and the Mod-Jones(C) models, with and without adjustment for ROA, increase rather dramatically. For example, in samples with 30% excess representation of firm-quarters from the high SG quintile (i.e., samples with 50% of the observations coming from the high SG quintile), a true null hypothesis of no earnings management ($\mu = 0$) is rejected roughly 28% and 73% of the time when using the Jones and Mod-Jones(C) models, respectively. Adjusting these models by

¹⁵ Note that a sample size of 1,000 firm-quarters is roughly comparable to sample sizes used in prior studies to test for earnings management around stock splits, SEOs, and stock acquisitions.

¹⁶ The plots are virtually identical when varying the proportion of the sample from the low SG quintile and testing the alternative hypothesis of $\mu < 0$.

matching on ROA reduces the Type I error rates, but they are still excessive at 13% and 48%, respectively.¹⁷

In comparison, Jones and Mod-Jones(C) models with ROA + SG matching yield well specified tests (rejection rates hover around 5%) across all levels of excess representation of high SG firms in the sample. The overall results show that with realistic representation of firm-quarters across SG quintiles that mirror the distribution of common events and with realistic sample sizes of 1,000 observations the Jones and Mod-Jones(C) model results *without ROA + SG matching* are considerably misspecified.

[Insert Figure 4 here]

Figure 5 repeats the analyses in Figure 4 for the versions of the Jones and Mod-Jones(C) models that adjust for accruals' role in reducing the noise in quarterly operating cash flows due to seasonality and for non-linearities due to asymmetric timeliness of loss recognition (Ball and Shivakumar, 2006). Although not widely adopted in the literature, we present the results for these models for completeness and to demonstrate that the increased power that results from using these models (demonstrated in Section 5 below) potentially comes at the expense of high Type I error rates. Specifically, Figure 5 shows that rejection frequencies for samples with excess representation of high growth firms are well above the 5% nominal rate for all versions of the models that fail to control for firm growth. However, as before, the Jones and the Mod-Jones(C) models with CFO adjustment yield well specified tests (rejection frequencies that hover around 5%) when matching on both ROA and SG.

[Insert Figure 5 here]

Finally, although not tabulated or plotted, we replicated all our specification tests of Table 3 and Figures 4 and 5 starting with raw accruals calculated using the balance sheet method for calculating accruals.¹⁸ Hribar and Collins (2002) document that this method is subject to severe biases when there are nonoperating events such as acquisitions, divestitures, and foreign currency translations during the event

¹⁷ As pointed out in a previous footnote, the reduction in rejection rates with ROA matching may represent a lower mean or a higher standard deviation of discretionary accrual measures.

¹⁸ Under this method, the raw accruals are calculated as $\Delta CA - \Delta CL - \Delta CASH + \Delta STDEBT$, where ΔCA is the change in current assets during the quarter, ΔCL is the change in current liabilities, $\Delta CASH$ is the change in cash and cash equivalents, and $\Delta STDEBT$ is the current maturities of long-term debt and other short-term debt included in current liabilities.

period. Despite their warning, this method continues to be used in many studies. We find that without matching for firm growth the various discretionary accrual measures reported in this paper are subject to even greater misspecification when raw accruals are calculated using the balance sheet method.

5. Power of tests based on alternative discretionary accrual measures

5.1 Power of tests in random samples with no over-representation of high growth firms

In this section we address two distinct questions: (1) How does controlling for firm growth affect the power of tests to detect earnings management in quarterly settings; and (2) How does adjustment of Jones-type models for accruals' noise reduction and timely loss recognition roles affect the power of these tests? Strictly speaking, power tests should be carried out on sampling distributions where all competing measures are known to have similar Type I errors. From Table 3 and Figure 4, we know that a sampling distribution drawn from the aggregate sample of Compustat firm-quarters is the only one we have examined that meets this requirement (i.e., samples not over-weighted with high or low growth firms). So we report power test results based on samples drawn from this aggregate sample. We artificially add a seed of 0.25% of lagged total assets to raw working capital accruals of each randomly picked firm-quarter and compute the following four discretionary accrual measures without CFO adjustment: Jones with ROA matching, Jones with ROA + SG matching, Mod-Jones(C) with ROA matching, and Mod-Jones(C) with ROA + SG matching. Note that this seed is considerably smaller than the $\pm 1\%$ to 10% of total asset seeds used in simulations tests in Kothari et al. (2005) and the 1% to 5% seeds in Dechow et al. (1995).

We next repeat the process using versions of these models with CFO adjustment (i.e., versions of models that adjust for accruals' noise reduction role and asymmetric timely loss recognition) as outlined above. As before, our inferences are based on a *t*-test for mean discretionary accruals and a one-tailed significance level of 5%. For brevity, we report only tests of the null hypothesis of zero discretionary accruals against the alternative hypothesis of positive discretionary accruals, which is the more common alternative hypothesis in the finance and accounting literature. For any given seed level, the probability of rejecting the null hypothesis depends on the sample size. Therefore, we run 250 simulations for each

measure with sample sizes ranging between 200 and 2,000 firm-quarters in increments of 200 observations. The results are summarized in Figure 6.

[Insert Figure 6 here]

First, keeping aside the issue of CFO adjustment, there is no reason to believe that any one of the four competing Jones-type model specifications considered in this figure is more powerful than the others when samples are drawn from the broad cross-section of Compustat firm-quarters. The key determinant of power is the cross-sectional standard deviation of an accrual measure. Because each measure calculates the difference between Jones or Mod-Jones(C) model residuals of a sample firm and a matching firm from the same industry, and because Table 2 shows that Jones and Mod-Jones(C) model residuals have nearly identical standard deviations, all four models should have comparable power. This prediction is confirmed in the lower grouping of plots depicted in Panel A of Figure 6. The differences in power across the alternative models are minor and may be attributed to random simulation errors. Averaged across all models without CFO adjustments, sample sizes of 1,200, 1,600, and 2,000 firm-quarters lead to average rejection rates of 42%, 51%, and 61%, respectively, with a seed level of +0.25% of lagged assets. In contrast, for annual data Kothari et al. (2005) report rejection rates of 14.0% for performance (ROA_{t-1})-matched Jones model and 14.8% for performance-matched Mod-Jones(C) model for +1% seed with a much smaller sample size of 100 observations.

Next, we consider the impact of adjusting for contemporaneous operation cash flows (CFO adjustment) in discretionary accrual models as suggested by Ball and Shivakumar (2006). We do so to show that this adjustment, which has *not* been commonly used in prior research, makes a considerable difference in the explanatory power of Jones-type discretionary accrual models and in power of detection. The upper grouping of plots in Panel A of Figure 6 shows that the same four models but with CFO adjustments yield average rejection rates of 58%, 70%, and 78% across samples sizes of 1,200, 1,600, and 2,000 firm-quarters, respectively. Thus, samples of 1,200 to 2,000 or more observations, which are common in many research settings, have roughly 60% to 80% probability of detecting earnings manipulation of 0.25% of lagged assets with quarterly data when CFO adjustments are made to control for the accruals' noise reduction and timely loss recognition roles. As before, there is no significant

difference across models depending on Jones versus Mod-Jones(C) specifications or matching on ROA or ROA + SG. The main factor that improves the model power is the inclusion of CFO adjustments for accruals' noise reduction role and non-linearities due to asymmetric timely loss recognition as suggested by Jeter and Shivakumar (1999) and Ball and Shivakumar (2006).

5.2 Sample distribution and mean versus median tests

All tests of discretionary accrual models reported so far have used a *t*-test of mean abnormal accruals or accrual differences. This test is commonly used in the literature, and it underlies all cross-sectional regressions that include discretionary accruals as the dependent variable of interest. It is also the primary test employed by Kothari et al. (2005) in their examination of discretionary accrual models using annual data. The *t*-test is a parametric test, and generally speaking parametric tests are more powerful than nonparametric tests when the underlying variable is normally distributed. However, this generalization breaks down when the underlying variable is not normally distributed. In such cases, nonparametric tests such as the Wilcoxon signed-rank test for median can be more powerful than the *t*-test for mean (Blair and Higgins, 1985).

We examine the skewness and kurtosis of different discretionary accrual measures using the aggregate sample of 203,090 firm-quarters to measure the departures from normality. For the Jones model without (with) CFO adjustment the skewness equals -0.07 (-1.03) and the *excess* kurtosis (which subtracts three from the scaled fourth moment of distribution) equals 2.06 (5.33).¹⁹ The greater departure from normality with CFO adjustment indicates that this procedure works better for some industries than for others.²⁰ The skewness of both measures is corrected when we subtract the corresponding value for an

¹⁹ Skewness of a variable with values x_i , $i = 1, 2, \dots, n$ is defined as $\sum_{i=1}^n \frac{(x_i - \mu)^3}{n\sigma^3}$, where μ is the population mean and σ is the standard deviation. Kurtosis is defined as $\sum_{i=1}^n \frac{(x_i - \mu)^4}{n\sigma^4} - 3$. (It is sometimes known as excess kurtosis due to "minus 3".) For a normal distribution, skewness and kurtosis should both equal zero, while winsorizing should reduce the kurtosis to slightly less than zero. A negative (positive) skewness indicates a distribution tilted to the left (right), and a negative (positive) kurtosis indicates thinner (thicker) tails than a normal distribution. Given the very large number of observations in the aggregate sample, tests of normality always reject it. So we focus on the magnitudes of skewness and kurtosis to measure the economic magnitude of departure from normality.

²⁰ For example, the CFO adjustment should work better for businesses with greater seasonality, higher discretion over cash versus credit sales, and frequent loss recognition. In support of this conjecture we first find that, averaged across 38 industries (i.e., two-digit SIC codes), equation (5) gives an adjusted- R^2 of 0.20 for Jones model without CFO adjustment and equation (7) gives an adjusted- R^2 of 0.42 for Jones model with CFO adjustment. The

ROA or ROA + SG matching firm, but the kurtosis remains significantly different from zero. With ROA matching the kurtosis of Jones model discretionary accruals without (with) CFO adjustment equals 1.13 (3.50). With ROA + SG matching it equals 1.17 (3.51). The evidence is quite similar when we examine the variants of the Mod-Jones(C) model.

Panel B of Figure 6 shows the power of different discretionary accrual models to detect artificially induced earnings management of 0.25% of lagged total assets, but using the Wilcoxon signed rank test for median instead of the t -test for mean in Panel A. We find that the median test is more powerful for all discretionary accrual models. However, the increase in power is greater for models that include CFO controls than for models that do not include CFO controls. This is not surprising in view of the above evidence that CFO adjustment results in greater departures from normality for all discretionary accrual measures. More specifically, *without* CFO controls, the Jones and Mod-Jones(C) models, with ROA or ROA + SG matching, have rejection rates of 54%, 64%, and 74% in sample sizes of 1200, 1600, and 2000 firm-quarters when we use the Wilcoxon signed rank test for median. These rejection rates are 12% to 13% higher than corresponding rejection rates with the t -test for mean. In comparison, *with* CFO controls, the same models have rejection rates of 78%, 89%, and 95% with the median test, which are 17% to 20% higher than for the mean test (despite the already higher baseline rejection rates with t -test for mean). In absolute terms, including CFO terms in Jones-type models combined with ROA + SG matching enables a researcher to detect earnings management of 0.25% of total assets with a probability hovering around 95% when the sample size is around 2,000 observations.²¹ Note that our findings here stand in stark contrast to the general conclusion reached in a recent literature survey paper by Dechow et al. (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% of total assets) are seeded in the data.

incremental R^2 is 0.22. (The difference between average adjusted- R^2 values of 0.20 in this section and 0.26 in Section 3.2 can be attributed to running the regressions by industry versus industry-quarter. The latter gives a better fit.) There is considerable variation in incremental R^2 across industries. The three lowest incremental R^2 values are 0.09, 0.10, and 0.11 (for chemical and allied products, communications, and eating and drinking establishments), and the three highest incremental R^2 values are 0.45, 0.42, and 0.35 (for wholesale trade – durable goods, motion pictures, and automotive dealers and gasoline service stations). These differences can create additional heterogeneity and departures from normality in CFO-adjusted discretionary accruals in samples drawn from the aggregate dataset of Compustat firm-quarters.

²¹ In untabulated results, we also find that the median test is well-specified in the presence of ROA + SG matching.

6. Does adjusting for firm growth throw the baby out with the bathwater?

The simulations presented in the preceding sections infuse earnings management seeds into aggregate working capital accruals. A natural question arises as to whether one “throws the baby out with the bathwater” if firms manage earnings through revenue manipulation and abnormal accruals are estimated using Jones-type models with the ROA + SG matching procedure. Essentially, the concern is that if a part of the treatment firm’s sales growth is due to revenue manipulation, then one will end up choosing a control firm matched on sales growth that is too high. As a result, all or part of the earnings management that is accomplished through revenue manipulation may be negated when the matching firm’s Jones-type-model residuals are subtracted from the residuals of the corresponding sample firm. Moreover, the Jones model uses $\Delta Sales$ (scaled by total assets) as a main explanatory variable, which likely removes most of the earnings management that occurs through revenue manipulation. Note that this does not happen with the Mod-Jones(C) model because ΔAR is subtracted from $\Delta Sales$, which means that any earnings management that occurs through revenue manipulation remains as part of the residual discretionary accrual from that model. This section reports simulation results designed to address the baby and bathwater concern.²² We show below that the resultant bias in discretionary accrual estimates from SG matching is very modest in most realistic settings and much less serious than biases that result from failure to control for firm growth.

To provide a benchmark for the amount of revenue manipulation seeded into the data, we use descriptive statistics on annual sales growth of a sample of firms reporting restatements from 1997 to 2002 identified in a recent study by Badertscher, Collins, and Lys (2012).²³ For firms reporting a difference between originally reported and restated sales, the mean (median) difference in annual sales growth in their study is 5.02% (5.16%). So for the simulations in this section we introduce a revenue management seed of 5.0% of four-quarter lagged sales, $S_{i,t-4}$. For benchmarking and comparability purposes, we also investigate cases where the seed is 0.0% and 2.5% of lagged sales. It follows that the

²² For an alternative approach to isolating discretionary and non-discretionary revenues in tests of earnings management see Stubben (2010).

²³ The sample comes from a study of restatements published by the Government Accountability Office (GAO 2002). We thank Brad Badertscher for providing us with these descriptive statistics.

manipulated or overstated sales in period t becomes $S'_{i,t} = S_{i,t} + \text{seed} * S_{i,t-4}$ and sales growth becomes $SG' = [(S_{i,t} + \text{seed} * S_{i,t-4}) - S_{i,t-4}] / S_{i,t-4} = SG + \text{seed}$. Assuming that all overstated sales are on credit, the accounts receivable in turn becomes $AR'_{i,t} = AR_{i,t} + \text{seed} * S_{i,t-4}$. In all expressions a superscript ' attached to any quantity denotes a manipulated value. Finally, the effect of this amount of sales overstatement $(S'_{i,t} - S_{i,t})$ on bottom-line earnings is calculated as $(1 - \tau) * (S'_{i,t} - S_{i,t}) * GM_{i,t}$, where τ is the marginal corporate tax rate (35%) and $GM_{i,t}$ is the average gross margin for all firms with the same 2-digit SIC code during the same quarter.²⁴ These amounts normalized by lagged assets are presented in column (3) of Table 4 and provide the benchmark for assessing the degree of bias using alternative methods for calculating discretionary accruals that result from revenue overstatement.^{25,26}

Table 4 presents our test results of whether Jones-type discretionary accrual models with ROA + SG matching throw the baby out with the bathwater when the source of earnings management is revenue manipulation. Panel A presents variations of the Jones model with three different matching procedures, and Panel B presents the corresponding variations of the Mod-Jones(C) model. The model presented in column (4) uses regressors that include the inflated revenue amounts and matches only on ROA. This form of the model represents the most popular form used in the literature to date. The model presented in columns (5) uses regressors that include the inflated revenue amounts and matches on $ROA + SG'$, the inflated sales growth amount. The model presented in columns (6) uses regressors that include the inflated revenue amounts but matches on $ROA + SG$, the sales growth without the manipulated portion. Although sales growth without manipulation is unobservable to the researcher, this model provides a useful benchmark for evaluating bias in discretionary accruals estimates that result from matching on inflated sales numbers, which is the difference in the bias in model (6) versus model (5) presented in column (10) of Table 4.

²⁴ We assume that when revenues are overstated, then the cost of sales is also overstated by $(1 - GM_{i,t}) * (S'_{i,t} - S_{i,t})$.

²⁵ As always, we normalize all quantities appearing in Jones-type-models (in particular, the adjacent-quarter change in sales and accounts receivable and current accruals) by lagged assets.

²⁶ We denote the adjacent quarter change in sales, which is the primary explanatory variable in the Jones model, as $\Delta S'_{i,t} = S'_{i,t} - S_{i,t-1}$.

For all tests reported in this table we draw 1,000 samples of 1,000 firm-quarters of which 500 observations are drawn from the top SG quintile and the remaining 500 observations are drawn randomly from the remaining SG quintiles.²⁷ Recall that this incidence of over-representation of high SG firm-quarters is roughly similar to what we find for the SEO and stock acquisition samples depicted in Figure 1. Regarding the extent of revenue manipulation, we first consider the most extreme case where 100% of the sample firms overstate sales revenue, which is presented in Subpanels A1 and B1. More realistic cases are presented in the remaining subpanels and are based on studies of restatements by the United States Government Accountability Office (GAO) issued in 2002 (2006). These studies indicate that 37.9% (20.1%) of restatements involve some type of revenue manipulation. Therefore, in Subpanels A2 and B2 (A3 and B3) we report simulations in which the source of earnings management is revenue overstatement for 40% (20%) of the observations. For the remaining 60% (80%) of observations in these subpanels, we assume that the source of earnings management is expense understatement in an amount equivalent to the accruals overstatement resulting from sales overstatement in the other 40% (20%) of the observations. Column (3) shows the magnitude of the resultant earnings effect stated as a percentage of lagged assets, which is either 0.158% or 0.316% depending on the amount of assumed revenue manipulation. The table legend shows the remaining simulation details.

6.1. Variations of Jones model (Panel A of Table 4)

Recall that the variations of the basic Jones model effectively treat all earnings manipulation through revenues as nondiscretionary because the observed change in sales ($\Delta S'_{i,t}$) is the primary regressor, which effectively removes any revenue manipulation imbedded in $\Delta S'_{i,t}$ from the discretionary accruals estimate. Thus, the discretionary portion of accruals that is used to test for earnings management is understated (i.e., biased downward towards zero when we insert a positive seed). This will become evident in the tabled results discussed below.

²⁷ Whereas all tests elsewhere in this paper employ 250 replications, in this table we employ 1,000 replications. This is because the baby with the bathwater issue turns out to be of a smaller magnitude in many cases and requires more precise measurement.

Row 1 in Subpanel A1 of Table 4 uses a seed of 0.0%. In other words, there is no earnings (or revenue) management. We investigate this situation to illustrate the bias in discretionary accruals estimates that results when there is an over-representation of high growth firms in the sample and one does not control for firm growth. Note that the Jones model with *ROA* matching yields discretionary accruals of 0.118% of lagged assets when there is no earnings management seeded into the data. In comparison, estimates of discretionary accruals based on *ROA + SG'* or *ROA + SG* matching procedures yield unbiased estimates of discretionary accruals (bias of less than 1 basis point – see columns 8 and 9).

Row 3 in Subpanel A1 presents results for an extreme case scenario where every sample observation is seeded with excess sales revenue equal to 5.0% of $S_{i,t-4}$ and, as a result, earnings are overstated by 0.316% of lagged assets. Jones model with *ROA* matching (column 4) gives discretionary accruals of 0.332% of lagged assets, not much different from the induced amount of earnings management, which is 0.316% of lagged assets. This result is deceiving, however, because it results from a downward bias from using an overstated $\Delta S'_{i,t}$ regressor (which means that the effects of upward revenue manipulation are removed from the discretionary accruals estimate) offset by an upward bias due to failing to control for the effects of firm growth on discretionary accrual estimates. These offsetting effects add up to an upward bias of less than 2 basis points. One should not erroneously conclude from this that Jones model with *ROA* matching gives unbiased estimates of discretionary accruals. It is simply a chance result of two opposite biases cancelling each other. The net result is a deceptively low total bias which is reported in Column (7).

Next we consider the Jones model with *ROA + SG'* matching (column 5). This model corrects the upward bias that results from failing to control for overrepresentation of high growth firms in the sample, but introduces a downward bias due to using an overstated $\Delta S'_{i,t}$ regressor and matching control firms with treatment firms based on inflated *SG'* values. This method results in a total bias of -0.156% of lagged total assets reported in Column (8). But the bias introduced by matching on *SG'* relative to the conceptually correct but un-implementable *ROA + SG* matching yields a very small difference of only 0.034% of lagged assets reported in Column (10). Thus, most of the downward bias in the Jones with *ROA + SG'* discretionary accrual estimates is due to using overstated $\Delta S'_{i,t}$ as the regressor in the Jones

model. The amount of downward bias that results when $\Delta S'_{i,t}$ is overstated by 5% is -0.122% (-12.2 basis points) as shown in column (9) of row (3). Note that this source of bias is eliminated when using the Mod-Jones (C) model because $\Delta AR'$ is subtracted from $\Delta Sales'$ (see results in next section).

More realistic scenarios are presented in Subpanels A2 and A3 where the source of earnings management through revenue manipulation only occurs for part of the sample and expense understatement occurs for the remaining observations in the sample. We start with Row 6 where for 40% of observations sales are overstated by 5.0% of $S_{i,t-4}$, and for the remaining 60% of observations expenses are understated to create an equivalent amount of earnings management of 0.316% of lagged assets. Relative to Subpanel A1, the Jones model with ROA matching leads to a larger upward bias in discretionary accruals of 0.096% of lagged assets (see column 7). This larger bias is because revenue manipulation is washed away for only 40% of the sample due to using observed (overstated) change in adjacent-quarter sales. This leaves a greater net upward bias due to failing to control for firm growth. The Jones with $ROA + SG'$ matching gives a smaller bias of -0.058% of lagged assets, and the difference between $ROA + SG'$ and $ROA + SG$ matching is a negligible 0.014% of lagged assets. Once again, the bias introduced by matching on inflated SG' is minimal.

Row 9 shows the results when revenue manipulation is the source of earnings management for 20% of observations. In this case, the bias in Jones model discretionary accruals with ROA matching increases to 0.123%, the bias with $ROA + SG'$ matching decreases to -0.025%, and the difference between $ROA + SG'$ matching and $ROA + SG$ matching is close to zero.

Overall, with a realistic mix of revenue and expense manipulation as the two sources of earnings management, we find that Jones model with $ROA + SG'$ matching, an implementable approach, stands up well relative to other approaches for estimating discretionary accruals when sales revenue is manipulated by 5% of four-quarter lagged sales. If the revenue manipulation is only half of this amount (i.e., the 2.5% seed cases in Rows 2, 5, and 8), this approach does much better for reasons explained in a footnote to Table 4. The bias in discretionary accrual estimates due to the effect of matching on SG' is negligible, often less than 5 basis points in realistic settings (see column 10). Next, we show that variations of Mod-Jones(C) model give results that are even more favorable to the $ROA + SG'$ matching procedure.

[Insert Table 4 Here]

6.2. Variations of Mod-Jones(C) model (Panel B of Table 4)

Subsequent to Dechow, Sloan, and Sweeney (1995), it is well recognized that if revenue manipulation is the likely source of earnings management, then Mod-Jones(C) model provides less biased estimates of discretionary accruals compared to variations of the Jones model. This is because Mod-Jones(C) model includes $(\Delta S'_{i,t} - \Delta AR'_{i,t})$ as a regressor. When revenue is manipulated, both terms in this expression are overstated by the same amount, so the difference between them is unaffected by revenue manipulation and the downward bias in discretionary accruals discussed in the previous section is eliminated. However, the upward bias due to failure to control for firm growth is exacerbated with Mod-Jones(C) model and ROA matching. This is because the entire change in accounts receivable is treated as discretionary accruals, which impacts high growth firms more than average growth firms. This bias depends mainly on how the sample is distributed across SG quintiles and it is largely independent of the source and magnitude of earnings management as evident from Column (7) across all nine rows of Panel B. It is also substantial in magnitude, averaging around 0.350% of lagged assets for our sample distribution.

The cases where revenues are managed upward by five percent for 100%, 40%, and 20% of the sample observations are presented in rows 12, 15, and 18 in Panel B of Table 4. Mod-Jones(C) with $ROA + SG'$ matching gives reasonably unbiased estimates of discretionary accruals that differ from known discretionary accruals by between -0.031% and 0.024% of lagged assets (depending on the mix of sales overstatement and expense understatement). In comparison, Mod-Jones(C) with $ROA + SG$ matching gives discretionary accruals that are upward biased by amounts ranging between 0.039% and 0.042% of lagged assets in each case. The difference between discretionary accruals obtained by these two matching procedures ranges between 0.015% and 0.073% (see column 10) and it is much smaller than the upward bias of around 0.350% of lagged assets created by ignoring sales growth matching altogether. This finding alleviates the concern that in cases of revenue overstatement, sales growth matching throws out a large part of discretionary accruals (the baby) with non-discretionary accruals (the

bathwater). Even in the worst case scenario considered in Row 12 (where 100% of the observations are subject to revenue manipulation) the bias due to matching on an inflated revenue amount as shown in column (8) is -0.031%, which is only one-tenth of the bias due to failing to control for firm growth (0.339%). Finally, with half the revenue manipulation (i.e., 2.5% seed in Rows 11, 14, and 17) the bias due to matching on an inflated revenue amount becomes less than a third of the bias reported in rows 12, 15, and 18, while the bias due to failing to control for firm growth remains comparable.

We draw three conclusions from this discussion. First, if revenue manipulation is a serious concern in samples with an over-representation of growth firms, then the Mod-Jones(C) model is a better starting point as recognized in the previous literature. Second, if the residuals from this model are not adjusted further by subtracting the corresponding residuals of a performance and sales growth matching firm, then the estimated discretionary accruals are likely to contain a strong upward bias in samples that are over-represented by high growth firms. In contrast, performance and sales growth matching produces well specified results, even if sales growth has been overstated due to revenue manipulation. Finally, matching on an inflated sales growth figure introduces minimal downward bias to abnormal accrual estimates when using Mod-Jones (C) models to estimate discretionary accruals.

7. Comparison of ROA + SG matching methodology with reversal methodology

Dechow et al. (2012) propose a new methodology of detecting earnings management that exploits the reversal property of discretionary accruals. The following equation sets forth the specification for this methodology:

$$CA_{i,t} = a + b PART_{i,t} + c PARTR1_{i,t} + d PARTR2_{i,t} + Usual\ Jones - type\ model\ terms + \varepsilon_{i,t} \quad (4)$$

In this framework, *PART* is a dummy variable that takes the value one for a period during which the accruals are managed, and zero otherwise. *PARTR1* and *PARTR2* are dummy variables that take the value one during first and second reversal periods, and zero otherwise. If the accruals are expected to reverse only during the first period, then the second reversal term is dropped. Using a pooled sample of *firm-years*, Dechow et al. test whether the condition $b - (c + d) = 0$ can be rejected in favor of $b -$

$(c + d) > 0$ for upward earnings management and $b - (c + d) < 0$ for downward earnings management.²⁸

Dechow et al. suggest that the reversal methodology has two advantages over typical cross-sectional matching methodology. First, the reversals methodology corrects model misspecification related to a variety of firm characteristics without having to identify the source of misspecification. This is based on the assumption that factors associated with the non-discretionary part of accruals during the earnings management and reversal periods remain constant and approximately cancel each other. Second, they suggest that the reversals methodology is more powerful than procedures that use matching to control for factors correlated with the partitioning variable. This is based on the assumption that the earnings management and reversal periods can be identified reasonably accurately, in which case $b - (c + d)$ is approximately twice the value of b (the numerator of test statistic) while the standard error of this difference (the denominator) is approximately $\sqrt{3}$ times the standard error of b . By comparison, the numerator for the matching procedure, b , is unchanged and the denominator increases by a factor of $\sqrt{2}$ in cross-sectional methodology as outlined earlier in this paper (the result of differencing Jones-type model residuals).

Applying the reversal methodology in quarterly settings faces several challenges. First, specifying the number of quarterly periods over which the hypothesized earnings management will reverse is problematic. Accelerated revenue recognition may be expected to reverse in one or two subsequent quarters, while capitalizing a cost that should be expensed or taking excessive asset write-downs are likely to reverse over a much longer horizon. Faced with this uncertainty, a researcher may err on the side of including too many periods, which lowers the power of the reversal methodology because the standard error of the test statistic increases as a function of $\sqrt{T}$ where T is the combined number of earnings management and reversal periods. In addition, including too many periods in the reversal horizon will contribute to greater misspecification (Type I error) because there is no guarantee that factors contributing

²⁸ It is important to note that Dechow et al (2012) conduct their tests of the reversal methodology only in annual settings and they do not assert that the methodology would be equally effective in quarterly settings. We include a brief comparison of the reversal and matching procedure in a quarterly setting here for completeness. A more comprehensive comparison of reversal and matching methodologies is the subject of on-going research by Collins, Pungaliya and Vijh (2012).

to non-discretionary accruals in the earnings management period and the reversal periods will cancel out. On the other hand, including too short of reversal period fails to fully exploit the advantages of the reversal methodology by lowering the numerator of the test statistic below what it would otherwise be. Finally, instances of earnings management in quarterly settings typically span multiple quarters (GAO 2002, 2005). Thus, originating earnings management and reversals of previous periods' earnings management will tend to cancel out, which greatly complicates the specification for testing.

In sum, firms have considerable discretion over how they go about managing accruals during a chosen quarter and these choices have a substantial impact on the subsequent reversal process. Further, this discretion is likely to differ across industries, which makes it difficult to know how many quarters to include as reversal quarters. Seasonality considerations further complicate how the reversal process will unfold. A full investigation of specification and power issues of reversals methodology using quarterly data is beyond the scope of this paper. Here we describe a simple experiment to compare the power of Jones and Mod-Jones(C) models with ROA + SG matching with the power of Dechow et al. (2012) reversal methodology employing the same models. As explained earlier, power tests are best carried out over the neutral sample of all 203,090 firm-quarters for which misspecification issues arising from firm characteristics like firm growth are of minimal concern. From this comprehensive neutral sample we randomly select sample sizes of $N = 600, 1,000, \text{ or } 2,000$ firm-quarters and inflate their raw accruals by 0.25% of total assets. Following the evidence in Baber, Kang, and Li (2011),²⁹ we assume reversals take place over the subsequent quarters with the indicated frequencies: one quarter (43%), two quarters (29%), three quarters (21%), and four quarters (7%). Further, if reversals take place over n quarters, we assume that $1/n^{\text{th}}$ of the total reversal occurs each quarter from 1 to n , following the earnings management quarter. Finally, we assume that the following proportion of the original earnings management reverses during the

²⁹ Baber, Kang, and Li (2011) model the reversal process of quarterly accruals and show that if period t discretionary accruals (d_t) reverse fully in period $t + n$, where $n \geq 1$, then the minimum value of k 'th order autocorrelation ρ_k , is achieved when $k = n$. Using this proposition, they measure the length of reversal process as the lag at which the quarterly accruals have the most negative autocorrelation. Examining a large sample of firms, they find that in only 41% of all cases does the most negative autocorrelation occur during the first four quarters (i.e., $n \leq 4$). Restricting their analysis to the first four quarters, the most negative autocorrelation occurs at the first lag in 43% of cases, second lag in 29% of cases, third lag in 21% of cases, and fourth lag in 7% of cases.

specified reversal horizon: 100%, 50%, and 30%. We merge these seeded firm-quarters and reversal quarters with the remaining firm-quarters and carry out the following regression:

$$CA_{i,t} = a + b PART_{i,t} + c PARTR1_{i,t} + d PARTR2_{i,t} + e PARTR3_{i,t} + f PARTR4_{i,t} + Usual Jones - type model terms + \varepsilon_{i,t} \quad (5)$$

We repeat the procedure 250 times and record the frequency with which the null hypothesis of $b - (c + d + e + f) = 0$ can be rejected in favor of the alternate hypothesis of $b - (c + d + e + f) > 0$ with 5% significance level.

The results are shown in Table 5 and are briefly summarized here. Across all three sample sizes, the reversal methodology with quarterly data has lower power than Jones and Mod-Jones(C) models with ROA + SG matching without CFO adjustment. The differences in power become more dramatic as the sample size increases and as the proportion of original earnings management that reverses over the subsequent four quarters decreases. For example, for a sample size of $N = 2,000$ the Jones model with ROA + SG matching has a rejection rate of 63.2% with mean test and 75.6% with median test. In comparison, the reversal methodology with Jones model has a rejection rate of 39.6% with 100% reversal, 24.0% with 50% reversal, and 19.2% with 30% reversal. Similar differences are seen for Mod-Jones(C) model.

[Insert Table 5 Here]

8. Conclusions

Numerous studies in accounting and finance investigate potential earnings management in a variety of settings. Typically, researchers test whether some measure of discretionary accruals averaged across a sample of firms is significantly different from zero in the predicted direction. The choice of the discretionary accrual measure thus becomes critically important. Following the evidence of Jones (1991) and Dechow, Sloan, and Sweeney (1995), residuals from Jones or modified-Jones models have been the popular starting point in many studies. More recently, following the evidence of Kothari, Leone, and Wasley (2005) that accruals are correlated with firm performance, these residuals are performance-adjusted by subtracting similar residuals for ROA matched firms from the same industry.

In this paper we demonstrate the rather severe misspecification (in terms of Type I error rates) that exists in tests of earnings management in quarterly settings that use Jones-type model discretionary accrual estimates, even after performance matching, and we show how matching on both performance and growth measures results in well-specified tests. We extend the analysis in McNichols (2000) in several ways. First, we identify multiple partitioning variables used in prior earnings management research (stock splits, SEOs, stock acquisitions, equity-based compensation, and insider trading) and demonstrate how these partitioning variables are correlated with firm growth measures. We show that the resulting measurement error can lead to substantial over rejection of the null hypothesis of no earnings management in these settings.

Next, using stratified random samples of firms with no known earnings management, we show that the traditional discretionary accrual measures based on Jones or modified-Jones models with ROA matching are highly misspecified in both high growth and low growth subsamples of firm-quarters. The modified-Jones model as commonly estimated in the literature with ROA matching is particularly misspecified, with rejection rates of the null hypothesis of no earnings management as high as 72% and 63% (compared to theoretical 5%) in low SG and high SG quintiles.

Finally, using simulations we demonstrate that Jones-type model discretionary accrual estimates adjusted for accruals' noise reduction role and asymmetric timely loss recognition and matched on both performance (ROA) and sales growth (SG) yield well specified tests with reasonable power (70% or greater for parametric *t*-test of mean and 90% or greater for non-parametric Wilcoxon signed rank test of median) of detecting modest amounts (0.25% of total assets) of earnings management in sample sizes commonly found in the literature. These detection rates are much higher than those documented in previous studies (Dechow et al., 1995, and Kothari et al., 2005) that use annual data. Moreover, matching on SG does not introduce serious bias in discretionary accrual estimates when earnings management is accomplished through revenue manipulation. Thus, our findings suggest that, going forward, researchers should adjust for both performance and firm growth when testing for earnings management, particularly in settings where the partitioning variable deemed to give rise to earnings management is likely to be correlated with firm growth. In addition, adjusting discretionary accrual models for accruals' noise

reduction and timely loss recognition roles (Ball and Shivakumar, 2006) appears warranted, particularly in quarterly settings where seasonality is likely to affect the dynamics of the accrual process.

We conclude with an important qualification. We do not interpret our findings as evidence that a performance and sales growth-matched discretionary accrual measure is the best measure in every conceivable setting that tests for earnings management using quarterly data. Rather, our findings suggest that performance and growth-matched discretionary accrual measures are useful in mitigating Type I errors in cases where the partitioning variable of interest is correlated with firm growth, which we find is quite often. The approach outlined in this paper provides additional controls for what is considered ‘normal’ accruals given the level of firm performance and firm growth. If firms with exceptionally high (low) performance and growth systematically manage earnings up (down), then our estimates of abnormal accruals will be biased towards zero. What we can say is that firms found to have abnormally high or low levels of earnings management are those that manage more than expected given their levels of performance and growth (which is often the relevant question in studies of earnings management around corporate events).

Appendix 1

Literature on earnings management detected using discretionary accrual models

This is necessarily a partial list

A1.1 Event studies of earnings management around IPOs and SEOs

Rangan (1998), Teoh, Welch, and Wong (1998), Shivakumar (2000), Kim and Park (2005), Fan (2007), Ball and Shivakumar (2008)

A1.2 Event studies of earnings management around stock acquisitions

Erickson and Wang (1999), Louis (2004), Botsari and Meeks (2008), Gong, Louis, and Sun (2008a), Anilowski, Macias, and Sanchez (2009), Pungaliya and Vijn (2009)

A1.3 Event studies of earnings management around stock repurchases

Hribar, Jenkins, and Johnson (2006), Gong, Louis, and Sun (2008b)

A1.4 Event studies of earnings management around proxy contests

DeAngelo (1988), Collins and DeAngelo (1990)

A1.5 Event studies of earnings management around stock splits

Louis and Robinson (2005)

A1.6 Event studies of earnings management to maintain dividend payment

Daniel, Denis, and Naveen (2008)

A1.7 Cross-sectional relation between earnings management and performance-based executive compensation

Gaver, Gaver, and Austin (1995), Holthausen, Larcker, and Sloan (1995), Balsam (1998), Guidry, Leone, and Rock (1999), Baker, Collins, and Reitenga (2003), Cheng and Warfield (2005), Bergstresser and Philippon (2006), Burns and Kedia (2006), Efendi, Srivastava, and Swanson (2007), Cohen, Dey, and Lys (2008), Cornett, Marcus, and Tehranian (2008), McAnally, Srivastava, and Weaver (2008), Jiang, Petroni, and Wang (2010)

A1.8 Cross-sectional relation between earnings management and option grants, option exercises, option repricings, and stock trading

Beneish and Vargus (2002), Bartov and Mohanram (2004), Coles, Hertz, and Kalpathy (2006)

A1.9 Cross-sectional studies of earnings management to avoid debt covenant violations

Dechow, Sloan, and Sweeney (1996), Beneish (1999)

Appendix 2

A survey of research methodologies of detecting earnings management and empirical findings in previous literature that examines quarterly accrual 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* (7), *Journal of Accounting and Economics* (6), *Accounting Review* (5), *Journal of Accounting Research* (4), *Journal of Financial Economics* (4), *Contemporary Accounting Research* (2), *International Journal of Accounting* (1), *Journal of Business Finance and Accounting* (1), *Journal of Finance* (1), and *Journal of Financial and Quantitative Analysis* (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 ^a
Raw accrual measure	Balance sheet approach: 15 Cash flow statement: 10 Both: 3
Discretionary accrual model	Jones: 13 Modified Jones: 14 ROA Adjustment: 11 Growth adjustment: 4^b
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: 13 Modified-Jones model and evidence of earnings management: 14
Article concludes in favor of earnings management	Yes: 32 No: 0

^a The 32 quarterly earnings management studies summarized in this table are included in our references and are identified by an asterix before the authors' names. Details on how each of these studies is classified in constructing this summary table are available from the authors on request.

^b Generally this growth adjustment is made by adding a linear growth term.

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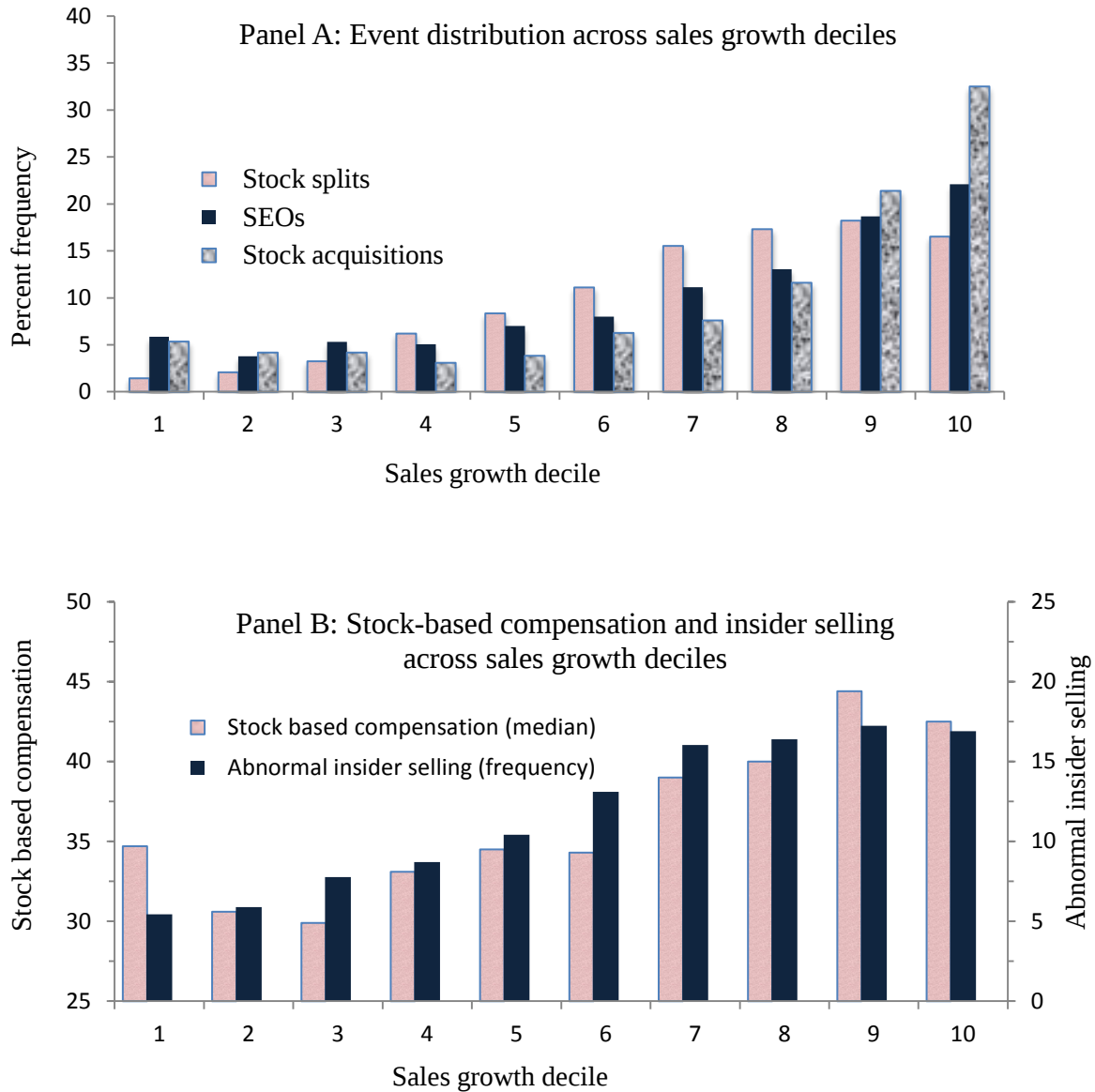


Figure 1: Typical sample distributions across sales growth deciles underlying studies of earnings management. In Panel A, we start with a comprehensive sample of 203,090 firm-quarters during 1991:Q1 to 2007:Q4 from the Compustat and CRSP databases as described in Section 3.1. We merge this sample with samples of firms that announced stock splits, SEOs, and stock acquisitions. Stock splits are identified from the CRSP database using 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. In Panel B, We start with a comprehensive sample of 41,383 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). 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. Sales growth in both panels is calculated as sales during the year ending before the current year divided by sales during the previous year, minus one.

Figure 2: Firm characteristics and accruals: The effects of ROA+SG matching. The sample starts with all 203,090 Compustat firm-quarters during 1991-Q1 to 2007-Q4 for which data on the analyzed firm characteristics are available. This sample is further described in Table 2, which also describes the calculation of raw quarterly current accruals. Firm characteristics are defined as follows. SG is sales growth from quarter $t-4$ to t , ROA is return on assets for quarter $t-4$ calculated as net income divided by beginning assets, MB is market-to-book equity as of quarter $t-1$, MV is market value of equity as of quarter $t-1$, and EP is earnings-to-price calculated as net income for quarters $t-4$ to $t-1$ divided by ending stock price. Panel A shows raw quarterly current accruals, and Panel B shows raw quarterly current accruals after subtracting the corresponding measures for ROA + SG matched firms. In the latter case we arrange all same-industry firms during quarter $t-4$ into five ROA quintiles and choose the matching firm that has the closest SG from quarter $t-4$ to t in the relevant quintile.

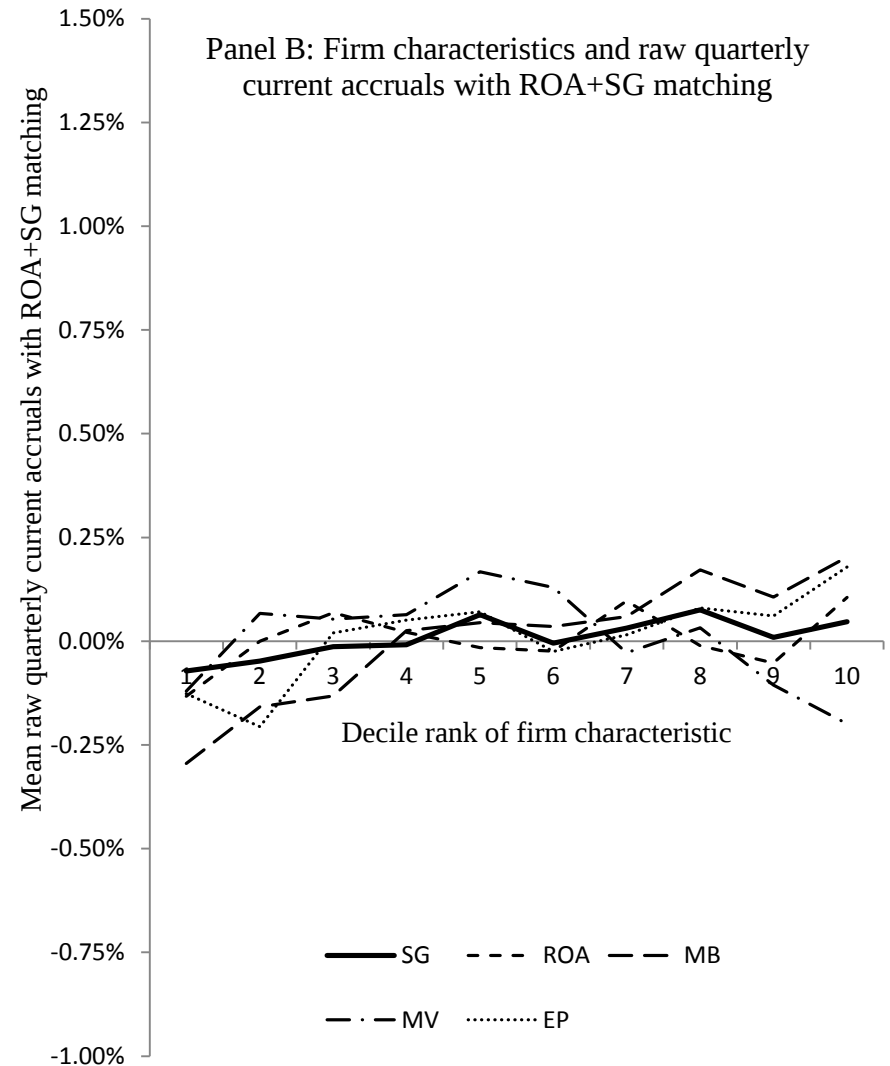
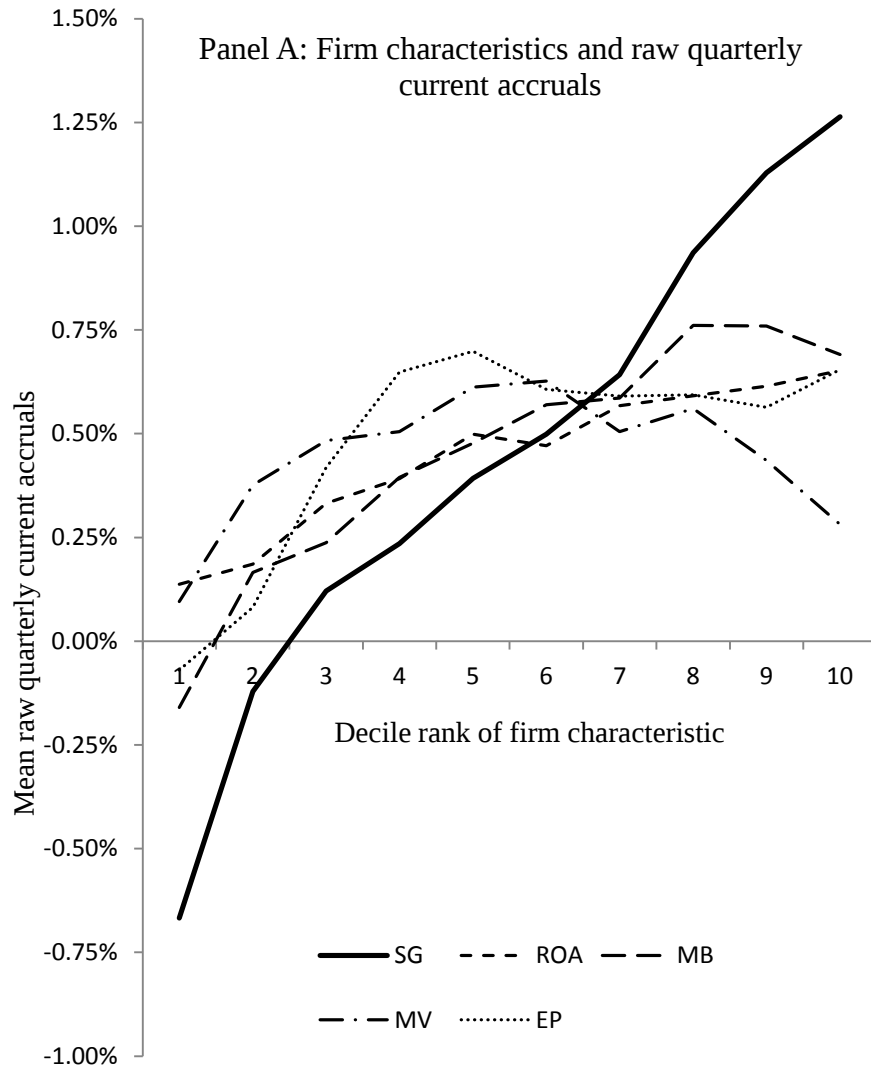


Figure 3: Discretionary accrual measures across SG deciles – Variants of Jones and Mod-Jones(C) models. The sample starts with all 203,090 Compustat firm-quarters during 1991-Q1 to 2007-Q4 for which data on the analyzed firm characteristics are available. This sample is further described in Table 2, which also describes the application of Jones and Mod-Jones(C) models to raw quarterly current accruals. Four variants of each model are presented, the first one without any matching firm adjustment, and the next three with matching firm adjustment to control for ROA, SG, or both ROA and SG effects. ROA is return on assets for quarter $t-4$ calculated as net income divided by beginning assets, and SG is sales growth from quarter $t-4$ to t . For ROA or SG matching we choose a same-industry firm with the closest ROA or SG. For ROA + SG matching we arrange all same-industry firms into five ROA quintiles and choose the matching firm that has the closest SG in the relevant ROA quintile.

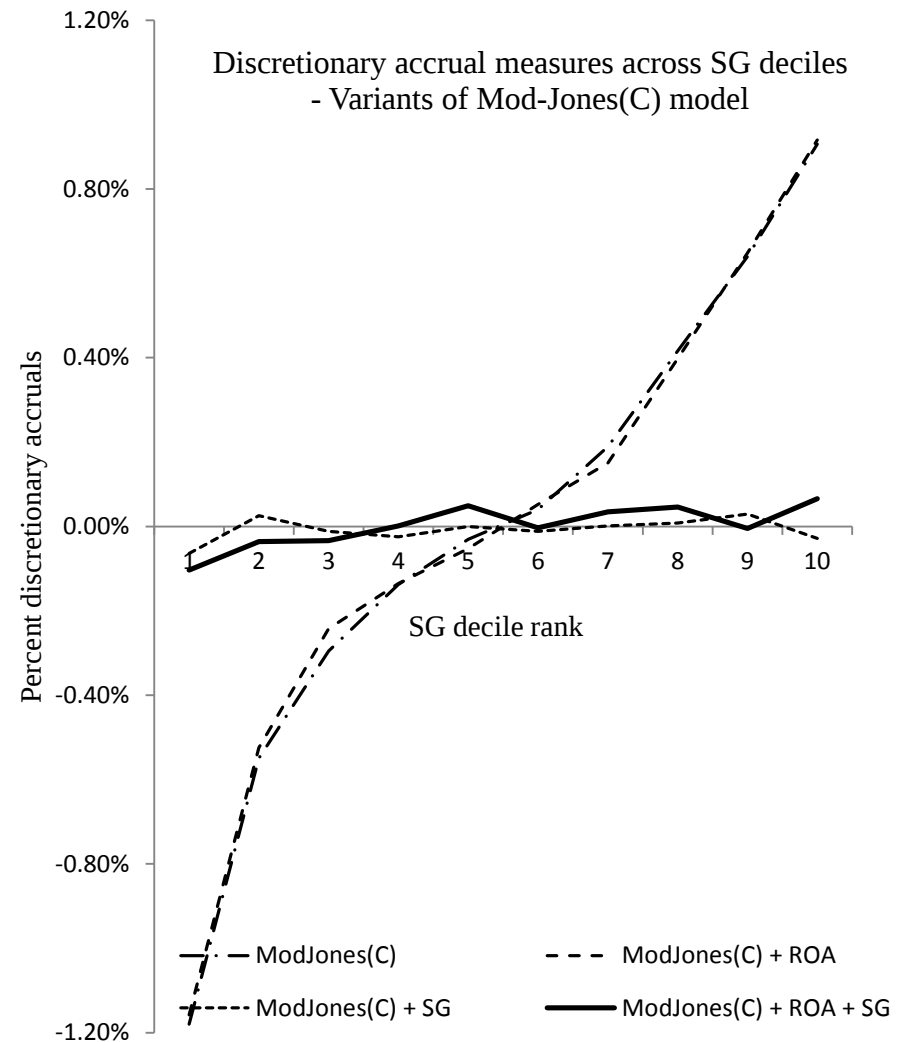
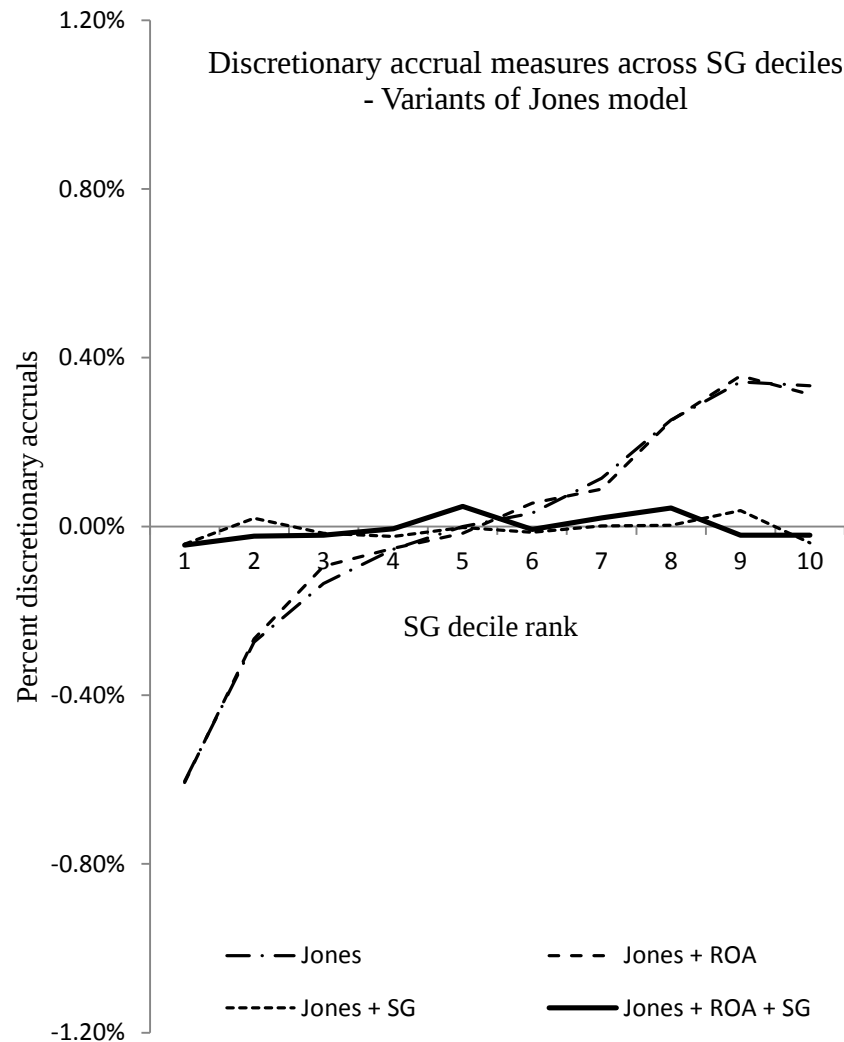
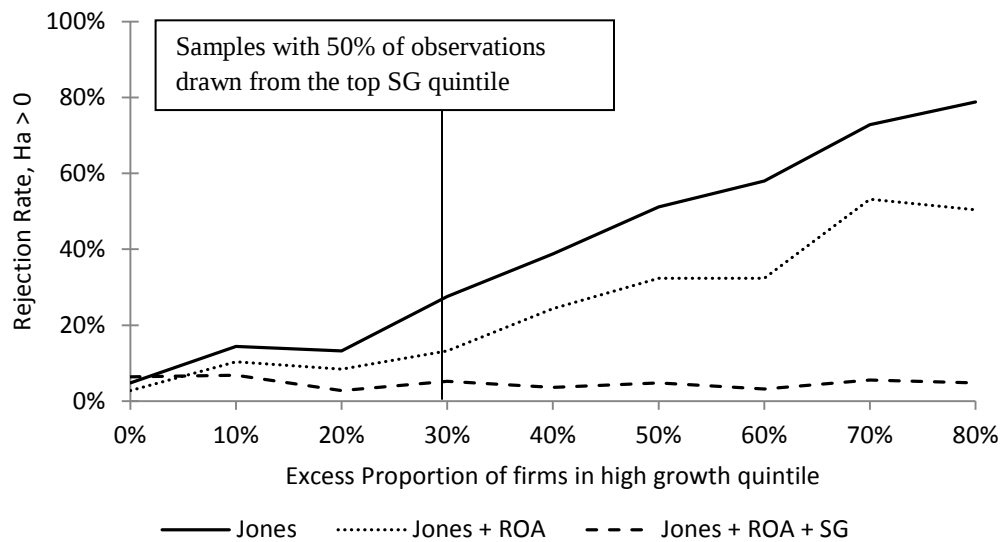


Figure 4. Specification tests of discretionary accrual measures using quarterly data as an increasing proportion of the sample is drawn from the top quintile of sales growth. This figure provides specification tests similar to Table 3, but with one major difference. Whereas Table 3 examines a sample size of 200 firm-quarters from the top SG quintile, this figure examines a sample size of 1,000 firm-quarters distributed as follows. First, we randomly select an excess proportion of the sample from the top SG quintile as noted on the x-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 remaining four SG quintiles. The vertical axis shows the percentage of 250 such samples where 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 is described in Section 3.1 and Table 2. The calculation of Jones and Mod-Jones(C) models, and the partitioning variable are described in Section 2.2 and Table 2.

Panel A: Jones model variants



Panel B: Mod-Jones(C) model variants

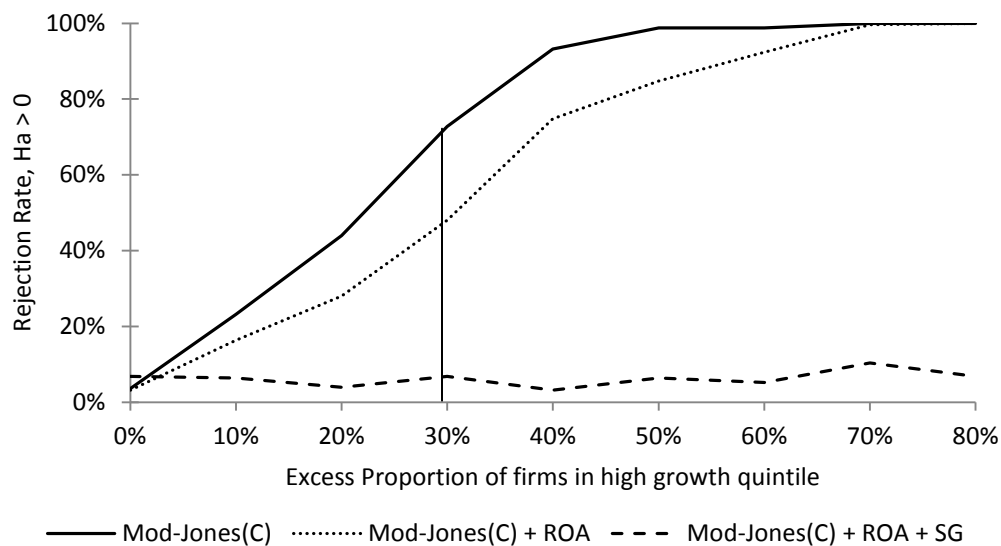
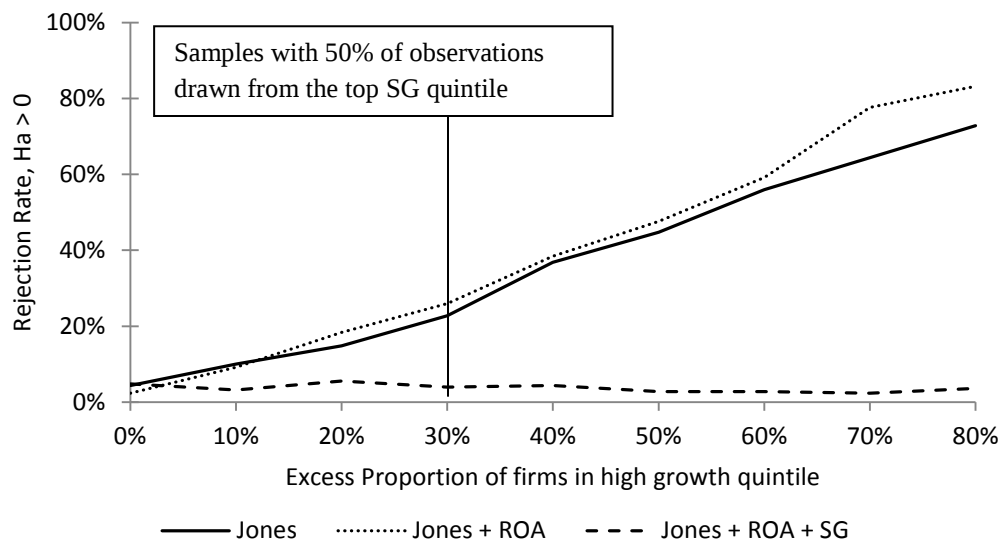


Figure 5. Specification tests of discretionary accrual measures using quarterly data as an increasing proportion of the sample is drawn from the top quintile of sales growth: Models with CFO adjustment (see Ball and Shivakumar, 2006). This figure is similar to Figure 4, except that all Jones-type models include CFO adjustment as described in Section 2.2 and Table 2. Specifically, we examine a sample size of 1,000 firm-quarters distributed as follows. First, we randomly select an excess proportion of the sample from the top SG quintile as noted on the x-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 remaining four SG quintiles. The vertical axis shows the percentage of 250 such samples where 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 is described in Section 3.1 and Table 2.

Panel A: Jones model variants, with CFO adjustment



Panel B: Mod-Jones(C) model variants, with CFO adjustment

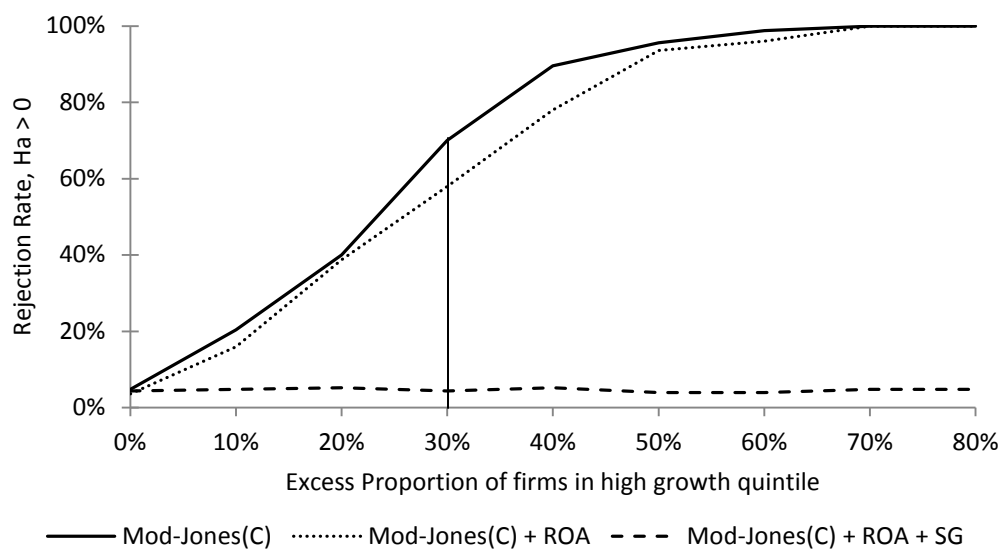


Figure 6. Power of discretionary accrual measures to reject the null hypothesis of no earnings management in favor of the alternate hypothesis of positive earnings management in samples drawn from the aggregate dataset of all Compustat firm-quarters. The aggregate sample includes all 203,090 Compustat firm-quarters described in Section 3.1 and Table 2. The figure shows the percentage of 250 random samples of between 200 and 2,000 firm-quarters each where the null hypothesis of zero discretionary accrual is rejected at the 5% significance level using one-tailed t -test for mean. The higher the rejection rate, the more powerful the discretionary accrual measure in detecting earnings management. Panel A reports model power using t -test for mean, and Panel B reports model power using Wilcoxon signed-rank test for median. For each sample firm-quarter we increase the raw current accrual derived from the cash flow statement by 0.25% of lagged total assets. All discretionary accrual measures with and without CFO adjustment are described in Section 2.2 and Table 2.

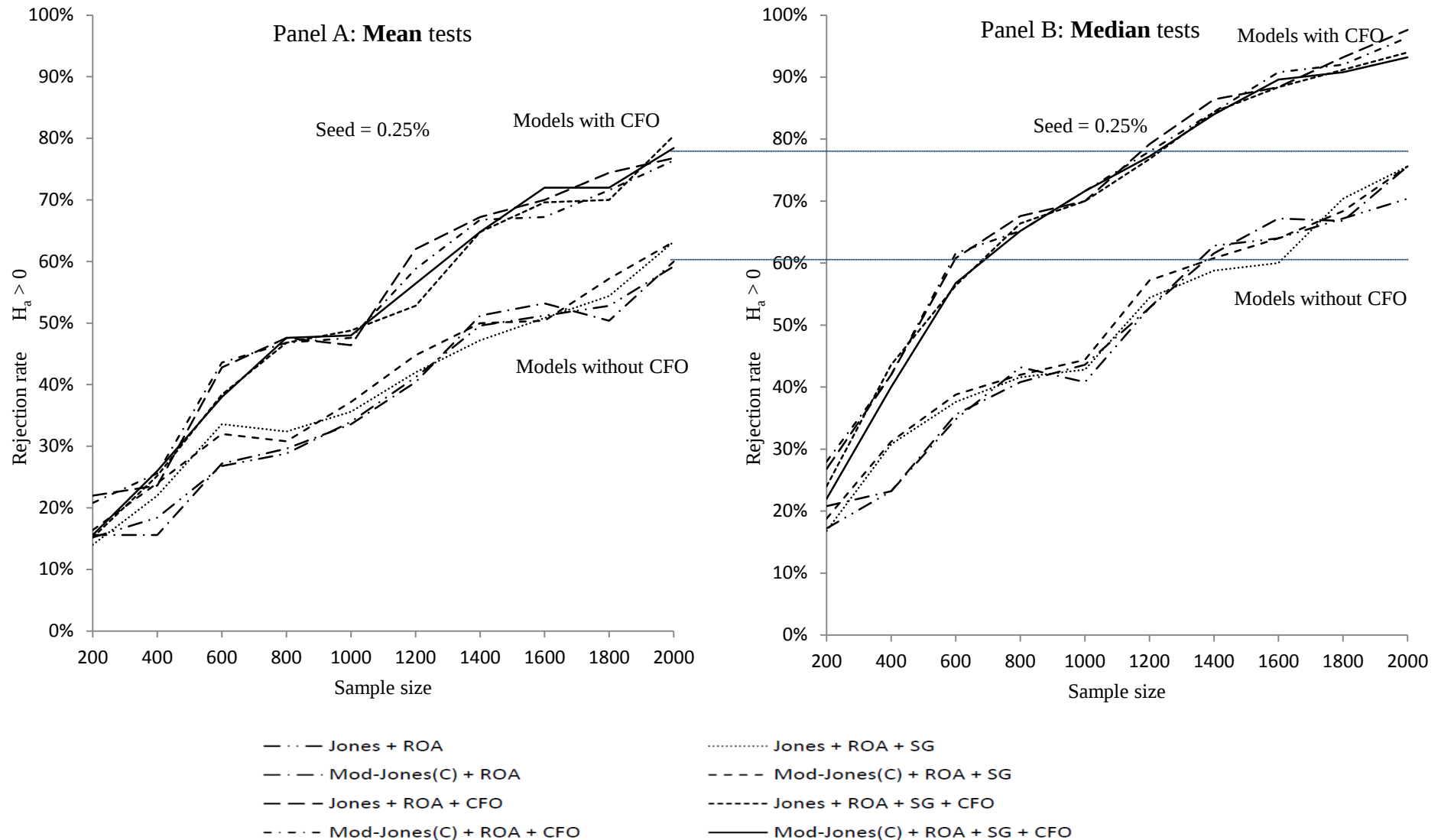


Table 1
Biases in discretionary accruals estimated using quarterly data and
without sales growth (SG) matching before select events

We start with a comprehensive sample of 203,090 firm-quarters during 1991 to 2007 from the Compustat and CRSP databases as described below in Section 3.1 and Table 2 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 several accrual measures using Compustat data for quarter t , which is the fiscal quarter with an earnings announcement date immediately preceding the event date. Raw accruals are calculated using the cash flow statement as described in Section 3.1 and Table 2, and discretionary accruals are first calculated as Jones or Mod-Jones(C) model residuals as described in Section 2.2 and Table 2. ROA, SG, or ROA + SG matched discretionary accruals are next calculated as the difference between Jones model or Mod-Jones(C) model residuals for a sample firm and its matching firm. For ROA matching we choose a same-industry firm with the closest ROA, and for SG matching we choose a same-industry firm with the closest SG. For ROA + SG matching we arrange all same-industry firms into five ROA quintiles and choose the matching firm that has the closest SG in the relevant ROA quintile. We calculate ROA as the net income divided by total assets during quarter $t-4$, and SG as sales during quarter t divided by sales during quarter $t-4$ minus one. Panel A reports the mean values of various discretionary accrual measures as well as their t -statistics (in parentheses). Panel B reports the mean SG, ROA, MB, MV, and EP decile ranks for the three event samples relative to the distribution of all Compustat firms during quarter t . MB is market-to-book equity as of last quarter-end, MV is market value of equity as of last quarter-end, and EP is earnings-to-price calculated as net income for quarters $t-4$ to $t-1$ divided by ending stock price. The notations *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels in one-tailed tests. In Panel B the significance levels are based on the difference between the average decile ranks and 5.50 (which is, by construction, the average decile rank for the aggregate sample).

Description	Stock splits	SEOs	Stock acquisitions
<i>Panel A: Mean discretionary accrual measures and t-statistics in parentheses</i>			
Jones model	0.188% (2.58)***	0.276% (4.19)***	0.281% (2.48)***
Jones model with ROA matching	0.192 (1.84)**	0.204 (2.08)**	0.069 (0.40)
Jones model with SG matching	-0.023 (-0.23)	0.052 (0.56)	-0.013 (-0.08)
Jones model with ROA + SG matching	0.032 (0.30)	0.202 (2.07)**	-0.027 (-0.16)
Mod-Jones(C) model	0.467 (6.47)***	0.554 (8.25)***	0.616 (5.56)***
Mod-Jones(C) model with ROA matching	0.406 (3.93)***	0.471 (4.75)***	0.341 (2.02)**
Mod-Jones(C) model with SG matching	0.066 (0.67)	0.165 (1.76)**	-0.004 (-0.03)
Mod-Jones(C) model with ROA + SG matching	0.068 (0.65)	0.314 (3.24)***	-0.053 (-0.31)
<i>Panel B: Mean decile ranks of firm characteristics</i>			
Sales growth (SG)	7.25***	7.06***	7.55***
Return-on-assets (ROA)	7.28***	5.30***	6.21***
Market-to-book (MB)	7.09***	6.79***	7.53***
Market value (MV)	7.32***	6.69***	7.91***
Earnings-to-price (EP)	6.43***	5.12***	4.69***
N	2,646	2,951	1,193

Table 2

Descriptive statistics for various accrual measures and partitioning variables used in the simulation exercise

The sample and methodology are described in Sections 3.1 and 2.2 and reproduced in this table. The 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. 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 codes between 60 and 69); (3) The CRSP share code is 10 or 11 (which excludes ADRs, REITs, units, 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 one. The final sample consists of 203,090 firm-quarters. The calculation of the various accrual measures follows several steps. First, we compute current 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 *TAXCHY*), and other items (item *AOLOCHY*), all taken from the cash flow statement. We undo the year-to-date nature of these quarterly cash flow statement items and compute the quantities for the current quarter. In addition, we recode missing values of *RECCHY*, *INVCHY*, *APALCHY*, and *TAXCHY* as zero 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 zero. Second, we carry out the following cross-sectional regression:

$$CA_{i,t} = \beta_0 + \beta_1 Q_{1,i,t} + \beta_2 Q_{2,i,t} + \beta_3 Q_{3,i,t} + \beta_4 Q_{4,i,t} + \beta_5 \Delta SALES_{i,t} + \beta_6 CA_{i,t-4} + \varepsilon_{i,t}. \quad (T2.1)$$

In this expression, subscript i denotes firm and t denotes quarter. $Q_{1,i,t} - Q_{4,i,t}$ are the fiscal quarter dummies, $\Delta SALES_{i,t}$ is the quarterly change in sales measured over adjacent quarters, and $CA_{i,t-4}$ is the current accrual from the same quarter in the preceding year. The residuals $\varepsilon_{i,t}$ from Model (T2.1) constitute the **Jones** model discretionary accruals. We estimate the following cross-sectional regression for the Mod-Jones(C) model:

$$CA_{i,t} = \lambda_0 + \lambda_1 Q_{1,i,t} + \lambda_2 Q_{2,i,t} + \lambda_3 Q_{3,i,t} + \lambda_4 Q_{4,i,t} + \lambda_5 (\Delta SALES_{i,t} - \Delta AR_{i,t}) + \lambda_6 CA_{i,t-4} + \xi_{i,t}. \quad (T2.2)$$

The residuals $\xi_{i,t}$ from Model (T2.2) constitute the Mod-Jones(C) model discretionary accruals. All variables are scaled by lagged total assets, and the regressions are run by the calendar quarter across all same-industry firms (i.e., with the same two-digit SIC code as the sample firm). Third, we calculate the ROA, SG, or ROA+SG matching discretionary accruals as the difference between Jones model or Mod-Jones(C) model residuals for a sample firm and its matching firm. For ROA matching we choose a same-industry firm with the closest ROA, and for SG matching we choose a same-industry firm with the closest SG. For ROA + SG matching we arrange all same-industry firms into five ROA quintiles and choose the matching firm that has the closest SG in the relevant ROA quintile. We calculate ROA as the net income divided by total assets during quarter $t-4$, and SG as the sales during quarter t divided by sales during quarter $t-4$ minus one. The partitioning variables are SG, ROA, MB, MV, and EP. MB is market-to-book equity as of last quarter-end, MV is market value of equity as of last quarter-end, and EP is earnings-to-price calculated as net income for quarters $t-4$ to $t-1$ divided by ending stock price. All accrual measures and partitioning variables are winsorized at the 1% and 99% levels. Panel A presents the descriptive statistics for the aggregate sample of 203,090 firm-quarters, and Panel B presents the same for subsamples formed by the highest and lowest quintiles of each partitioning variable.

Table 2 continued ...

Panel A: Descriptive statistics of discretionary accrual measures scaled by lagged total assets for the aggregate sample of 203,090 firm-quarters

Description	Mean	Standard deviation	Lower quartile	Median	Upper quartile
Current accruals	0.44%	4.36%	-1.47%	0.32%	2.35%
Jones model	0.00	3.60	-1.71	-0.00	1.72
Jones model with ROA matching	0.00	5.10	-2.74	0.00	2.75
Jones model with SG matching	-0.01	5.07	-2.76	-0.00	2.74
Jones model with ROA+SG matching	-0.00	5.07	-2.71	0.00	2.72
Mod-Jones(C) model	-0.00	3.61	-1.72	-0.02	1.70
Mod-Jones(C) model with ROA matching	0.00	5.11	-2.74	0.01	2.74
Mod-Jones(C) model with SG matching	-0.01	5.03	-2.72	0.00	2.71
Mod-Jones(C) model with ROA+SG matching	0.00	5.01	-2.68	0.00	2.69

Panel B: Mean (median) discretionary accrual measures scaled by lagged total assets for stratified subsamples

Description	SG		ROA		MB		MV		EP	
	Low	High	Low	High	Low	High	Low	High	Low	High
Current accruals	-0.39% (-0.15)	1.20% (0.82)	0.17% (0.18)	0.64% (0.48)	0.00% (0.07)	0.72% (0.48)	0.24% (0.23)	0.36% (0.24)	0.01% (0.11)	0.61% (0.42)
Jones model	-0.44 (-0.28)	0.34 (0.23)	-0.00 (0.01)	0.06 (0.00)	-0.32 (-0.19)	0.16 (0.07)	-0.21 (-0.15)	0.01 (-0.02)	-0.26 (-0.13)	0.11 (0.03)
Jones model with ROA matching	-0.43 (-0.31)	0.33 (0.25)	0.02 (0.01)	-0.01 (-0.00)	-0.31 (-0.24)	0.13 (0.08)	-0.19 (-0.18)	-0.03 (-0.00)	-0.21 (-0.16)	0.08 (0.06)
Jones model with SG matching	-0.01 (0.00)	-0.00 (-0.00)	0.01 (0.03)	0.01 (0.01)	-0.20 (-0.13)	0.09 (0.04)	-0.13 (-0.09)	-0.06 (-0.05)	-0.17 (-0.09)	0.10 (0.06)
Jones model with ROA+SG matching	-0.04 (-0.01)	-0.02 (0.00)	-0.02 (0.00)	0.01 (0.00)	-0.23 (-0.17)	0.06 (0.04)	-0.16 (-0.13)	-0.02 (-0.01)	-0.22 (-0.14)	0.12 (0.06)
Mod-Jones(C) model	-0.86 (-0.60)	0.77 (0.50)	-0.08 (-0.07)	0.22 (0.09)	-0.39 (-0.27)	0.24 (0.10)	-0.27 (-0.22)	0.04 (-0.03)	-0.30 (-0.19)	0.06 (0.00)
Mod-Jones(C) model with ROA matching	-0.84 (-0.64)	0.78 (0.61)	0.02 (0.01)	-0.01 (0.00)	-0.33 (-0.24)	0.18 (0.12)	-0.21 (-0.19)	-0.03 (-0.01)	-0.17 (-0.14)	-0.01 (0.01)
Mod-Jones(C) model with SG matching	-0.02 (-0.00)	0.00 (0.00)	-0.09 (-0.07)	0.15 (0.11)	-0.18 (-0.12)	0.09 (0.03)	-0.11 (-0.11)	-0.07 (-0.04)	-0.16 (-0.10)	0.08 (0.04)
Mod-Jones(C) model with ROA+SG matching	-0.08 (-0.04)	0.03 (0.03)	-0.03 (0.00)	0.02 (0.02)	-0.18 (-0.13)	0.05 (0.03)	-0.10 (-0.10)	-0.06 (-0.04)	-0.12 (-0.05)	0.06 (0.04)

Table 3

Specification tests of discretionary accrual measures using quarterly data

This table reports 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. 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 2. That table also describes the calculation of various accrual measures. The partitioning variables are as follows. SG is sales growth from quarter $t-4$ to t , ROA is return on assets for quarter $t-4$ calculated as net income divided by beginning assets, MB is market-to-book equity as of quarter $t-1$, MV is market value of equity as of quarter $t-1$, and EP is earnings-to-price calculated as net income for quarters $t-4$ to $t-1$ divided by ending stock price. 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% 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	SG		ROA		MB		MV		EP	
		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)											
<i>Panel A: H_1: Discretionary accruals < 0</i>											
Jones model	4.8	41.2	0.0	5.2	6.4	9.2	4.8	22.8	1.2	48.8	0.0
Jones with ROA matching	5.2	26.8	0.4	6.4	6.0	5.2	3.2	15.6	1.2	27.6	0.4
Jones with SG matching	4.0	8.8	2.8	4.4	4.8	3.6	6.4	14.0	2.0	23.6	0.8
Jones with ROA+SG matching	6.0	4.8	3.6	6.0	6.0	4.0	5.6	15.6	1.6	26.0	0.8
Mod-Jones(C) model	3.2	91.2	0.0	10.8	3.2	12.4	2.8	29.2	0.4	56.0	0.0
Mod-Jones(C) with ROA matching	4.8	71.6	0.0	6.8	5.2	7.6	2.8	18.4	0.4	26.8	0.0
Mod-Jones with SG matching	2.4	7.6	3.2	8.8	3.2	5.2	4.8	13.2	2.4	20.8	0.4
Mod-Jones(C) with ROA+SG matching	4.8	6.0	3.6	6.0	5.2	3.2	5.2	10.0	1.2	18.4	1.6
<i>Panel B: H_1: Discretionary accruals > 0</i>											
Jones model	3.6	0.0	34.8	3.2	10.0	0.0	24.0	4.4	4.8	0.8	17.2
Jones with ROA matching	6.0	0.8	20.8	2.8	4.8	0.8	13.6	4.0	4.0	1.2	13.2
Jones with SG matching	4.8	5.2	5.6	5.6	6.4	3.2	10.8	7.6	3.6	2.4	16.4
Jones with ROA+SG matching	4.0	3.6	2.8	5.2	4.4	0.8	10.8	8.4	4.8	1.6	12.0
Mod-Jones(C) model	4.0	0.0	86.0	0.4	20.8	0.0	33.6	2.0	10.8	1.2	16.4
Mod-Jones(C) with ROA matching	6.8	0.0	62.8	5.2	6.8	0.4	19.2	4.4	5.6	4.0	9.6
Mod-Jones with SG matching	4.4	5.2	10.0	2.4	10.4	3.6	10.4	7.2	2.8	2.0	13.6
Mod-Jones(C) with ROA+SG matching	5.6	3.6	6.4	3.6	4.4	2.0	7.6	8.4	4.0	2.4	10.8

Table 4

Simulation test results when earnings are managed through revenue manipulation

This table compares the biases in discretionary accruals estimates resulting from Jones-type models+ ROA matching with the biases resulting from Jones-type models with ROA + (overstated or true) SG matching when the source of earnings management is a mix of sales (revenue) overstatement and expense understatement. Panel A shows the variations of Jones model, and Panel B shows the variations of Mod-Jones(C) model. In all tests we draw samples of 1000 observations at random such that 50% of observations are from the top SG quintile and the remaining 50% are from the other four SG quintiles. Given space constraints, we denote sales for firm i during quarter t by $S_{i,t}$. Column (2) shows the fixed amount of sales overstatement as a percent of $S_{i,t-4}$, and the subpanel titles show whether this overstatement is for 100%, 40%, or 20% of observations. Thus, in the third row of subpanels A1 and B1, $S'_{i,t} = S_{i,t} + 0.05 \cdot S_{i,t-4}$, $SG'_{i,t} = \frac{S'_{i,t} - S_{i,t-4}}{S_{i,t-4}}$, and $AR'_{i,t} = AR_{i,t} + 0.05 \cdot S_{i,t-4}$ for 100% of observations (i.e., all overstated sales are on credit). A superscript ' attached to any quantity denotes a manipulated value. The resulting accruals overstatement for each observation subject to sales overstatement is calculated as $(1 - \tau) \cdot (S'_{i,t} - S_{i,t}) \cdot GM_{i,t}$, where τ is the marginal corporate tax rate (35%) and $GM_{i,t}$ is the average gross margin for all firms with the same 2-digit SIC code during the same quarter. For the remaining 0%, 60%, or 80% observations the source of earnings management is through expense understatement. For these observations the accruals are directly overstated by the same amount as the average of all other observations with induced sales overstatement, but without the corresponding sales overstatement. The resulting average accrual overstatement for all observations is shown in Column (3). Given that a researcher observes only $S'_{i,t}$, Columns (4) to (6) report the results of Jones model or Mod-Jones(C) model using this estimate of current sales and one of the three matching procedures described below. First, the models are estimated as follows:

Jones Model:
$$CA_{i,t} = \beta_0 + \beta_1 Q_{1,i,t} + \beta_2 Q_{2,i,t} + \beta_3 Q_{3,i,t} + \beta_4 Q_{4,i,t} + \beta_5 \Delta S'_{i,t} + \beta_6 CA_{i,t-4} + \varepsilon_{i,t}.$$

Mod-Jones(C) Model:
$$CA_{i,t} = \lambda_0 + \lambda_1 Q_{1,i,t} + \lambda_2 Q_{2,i,t} + \lambda_3 Q_{3,i,t} + \lambda_4 Q_{4,i,t} + \lambda_5 (\Delta S'_{i,t} - \Delta AR'_{i,t}) + \lambda_6 CA_{i,t-4} + \xi_{i,t}.$$

where $\Delta S'_{i,t} = S'_{i,t} - S_{i,t-1}$ and $\Delta AR'_{i,t} = AR'_{i,t} - AR_{i,t-1}$. The remaining variables on right side are defined in Table 2 and Section 2.2. All variables are normalized by lagged assets. Second, the Jones or Mod-Jones(C) model residuals are adjusted by the corresponding residuals for ROA matching, ROA + SG' (overstated sales growth) matching, and ROA + SG (true but unobservable sales growth) matching firms. The detailed matching procedure is also described in Table 2. Columns (7) to (9) report the biases in discretionary accrual measures reported in Columns (4) to (6) by using the true accrual overstatement in Column (3) as the benchmark. The last Column (10) reports the difference between discretionary accruals calculated using ROA + SG (true sales growth) matching and ROA + SG' (overstated sales growth) matching. Thus, this column addresses the question of whether our matching procedure throws the baby out with the bathwater (which is the primary focus of our analysis). All results are based on 1000 simulation runs and the precision of discretionary accrual estimates is the order of 0.005% to 0.010%.

Table 4 continued ...

Panel A: Variations of Jones model

Row number	Seeding process		Discretionary accrual measures			Biases			
	Induced sales overstatement, i.e., $S'_{i,t} - S_{i,t}$ as a percent of $S_{i,t-4}$, which also equals $SG'_{i,t} - SG_{i,t}$	Resulting accruals overstatement as a percent of assets, i.e., $CA'_{i,t} - CA_{i,t}$	Jones with overstated regressor $\Delta S'_{i,t}$ and ROA matching	Jones with overstated regressor $\Delta S'_{i,t}$ and $ROA + SG'$ (overstated sales growth) matching	Jones with overstated regressor $\Delta S'_{i,t}$ and $ROA + SG$ (true sales growth) matching	Difference between (4) and (3)	Difference between (5) and (3)	Difference between (6) and (3)	Difference between (6) and (5)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Subpanel A1: For 100% of firm-quarters $S_{i,t}$ is overstated as shown (i.e., source of earnings manipulation is through sales overstatement)</i>									
1.	0.0%	0.000%	0.118%	-0.009%	-0.009%	0.118%	-0.009%	-0.009%	0.000%
2.	2.5	0.158	0.250	0.109	0.111	0.092	-0.049	-0.047	0.002
3.	5.0	0.316	0.332	0.160	0.194	0.016	-0.156	-0.122	0.034
<i>Subpanel A2: For 40% of firm-quarters selected at random $S_{i,t}$ is overstated as shown (i.e., source of earnings manipulation is through sales overstatement), for the remaining 60% of firm-quarters $S_{i,t}$ is not overstated but $CA_{i,t}$ is directly overstated by 0.316%, 0.158%, or 0.000% of assets (i.e., source of earnings manipulation is through expense understatement)</i>									
4.	0.0	0.000	0.118	-0.009	-0.009	0.118	-0.009	-0.009	0.000
5.	2.5	0.158	0.290	0.150	0.151	0.132	-0.008	-0.007	0.001
6.	5.0	0.316	0.412	0.258	0.272	0.096	-0.058	-0.044	0.014
<i>Subpanel A3: For 20% of firm-quarters selected at random $S_{i,t}$ is overstated as shown (i.e., source of earnings manipulation is through sales overstatement), for the remaining 80% of firm-quarters $S_{i,t}$ is not overstated but $CA_{i,t}$ is directly overstated by 0.316%, 0.158%, or 0.000% of assets (i.e., source of earnings manipulation is through expense understatement)</i>									
7.	0.0	0.000	0.118	-0.009	-0.009	0.118	-0.009	-0.009	0.000
8.	2.5	0.158	0.304	0.164	0.164	0.146	0.006	0.006	0.000
9.	5.0	0.316	0.439	0.291	0.298	0.123	-0.025	-0.018	0.007

Table 4 continued ...

Panel B: Variations of Mod-Jones(C) model

Row number	Seeding process		Discretionary accrual measures			Biases			
	Induced sales overstatement, i.e., $S'_{i,t} - S_{i,t}$ as a percent of $S_{i,t-4}$, which also equals $SG'_{i,t} - SG_{i,t}$	Resulting accruals overstatement as a percent of assets, i.e., $CA'_{i,t} - CA_{i,t}$	Mod-Jones(C) with overstated regressor $(\Delta S'_{i,t} - \Delta AR'_{i,t})$ and ROA matching	Mod-Jones(C) with overstated regressor $(\Delta S'_{i,t} - \Delta AR'_{i,t})$ and $ROA + SG'$ (overstated sales growth) matching	Mod-Jones(C) with overstated regressor $(\Delta S'_{i,t} - \Delta AR'_{i,t})$ and $ROA + SG$ (true sales growth) matching	Difference between (4) and (3)	Difference between (5) and (3)	Difference between (6) and (3)	Difference between (6) and (5)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Subpanel B1: For 100% of firm-quarters $S_{i,t}$ is overstated as shown (i.e., source of earnings manipulation is through sales overstatement)</i>									
10.	0.0%	0.000%	0.298%	0.010%	0.010%	0.298%	0.010%	0.010%	0.000%
11.	2.5	0.158	0.507	0.187	0.211	0.349	0.029	0.053	0.024
12.	5.0	0.316	0.655	0.285	0.358	0.339	-0.031	0.042	0.073
<i>Subpanel B2: For 40% of firm-quarters selected at random $S_{i,t}$ is overstated as shown (i.e., source of earnings manipulation is through sales overstatement), for the remaining 60% of firm-quarters $S_{i,t}$ is not overstated but $CA_{i,t}$ is directly overstated by 0.316%, 0.158%, or 0.000% of assets (i.e., source of earnings manipulation is through expense understatement)</i>									
13.	0.0	0.000	0.298	0.010	0.010	0.298	0.010	0.010	0.000
14.	2.5	0.158	0.506	0.199	0.209	0.348	0.041	0.051	0.010
15.	5.0	0.316	0.654	0.325	0.356	0.338	0.009	0.040	0.031
<i>Subpanel B3: For 20% of firm-quarters selected at random $S_{i,t}$ is overstated as shown (i.e., source of earnings manipulation is through sales overstatement), for the remaining 80% of firm-quarters $S_{i,t}$ is not overstated but $CA_{i,t}$ is directly overstated by 0.316%, 0.158%, or 0.000% of assets (i.e., source of earnings manipulation is through expense understatement)</i>									
16.	0.0	0.000	0.298	0.010	0.010	0.298	0.010	0.010	0.000
17.	2.5	0.158	0.506	0.204	0.208	0.348	0.046	0.050	0.004
18.	5.0	0.316	0.654	0.340	0.355	0.338	0.024	0.039	0.015

Notes:

1. The numbers reported in the second row of Column (10) are always less than half of the numbers reported in the third row of the same column in all subpanels even though the induced sales overstatement is exactly 2.5% in the second row and 5.0% in the third row. This is a discreteness issue. In many cases with 2.5% sales overstatement in the second row the matching procedure ends up picking the same firm as with no sales overstatement in the first row. Hence, there is no difference between $ROA + SG$ and $ROA + SG'$ matching (given the sparse population of firms within any quarter for a given 2-digit SIC code).
2. Although each of the two terms in the regressor $(\Delta S'_{i,t} - \Delta AR'_{i,t})$ for Mod-Jones(C) is overstated by $0.05 \cdot S_{i,t-4}$, the difference is not overstated.

Table 5

**Comparison of power of ROA + SG matching methodologies and
Dechow et al. (2011) reversal methodology in quarterly setting**

This table reports the percentage of 250 samples of $N = 600$, 1000, or 2000 firms each where the null hypothesis of zero discretionary accrual is rejected at the 5% level using one-tailed t -test for mean and Wilcoxon signed-rank test for median. These samples are drawn at random from the universe of 203,090 Compustat firm-quarters as described in Table 2. That table also describes the calculation of Jones and Mod-Jones(C) methodologies with ROA + SG matching. The t -test for mean and the Wilcoxon signed-rank test for median are further described in Figure 6. The Dechow et al. (2011) reversals methodology is described as follows. We pick $N = 600$, 1000, or 2000 firm-quarters at random from the universe of 203,090 firm-quarters and increase their raw accruals by 0.25%. Following the evidence in Baber, Kang, and Li (2011), we assume reversals take place over the subsequent quarters with the indicated frequencies: one quarter (43%), two quarters (29%), three quarters (21%), and four quarters (7%). Further, if reversals take place over n quarters, we assume that $1/n^{\text{th}}$ of the total reversal occurs each quarter from 1 to n , following the earnings management quarter. Finally, we assume that the following proportion of the original earnings management reverses during the specified reversal horizon: 100%, 50%, and 30%. We mix these seeded quarters and reversal quarters with the remaining sample of firm-quarters and carry out the following regression:

$$CA_{i,t} = a + b PART_{i,t} + c PARTR1_{i,t} + d PARTR2_{i,t} + e PARTR3_{i,t} + f PARTR4_{i,t} + \text{Usual Jones - type model terms} + \varepsilon_{i,t} \quad (\text{T5.1})$$

$PART$ is a dummy variable that takes the value one for the earnings management quarter and zero otherwise. Similarly, $PARTR1 - PARTR4$ are dummy variables that take the value one for each of the next four quarters and zero otherwise. The subscripts i and t denote the firm and the quarter. The usual model terms are the same as included in equations (T2.1) and (T2.2) of Table 2 for Jones and Mod-Jones(C) models. We repeat the procedure 250 times and record the frequency with which the null hypothesis of $b - (c + d + e + f) = 0$ can be rejected in favor of the alternate hypothesis of $b - (c + d + e + f) > 0$.

Model/methodology	N = 600	N = 1000	N = 2000
Jones with ROA+SG matching – mean test	33.6	35.6	63.2
Jones with ROA+SG matching – median test	37.6	42.8	75.6
Jones with reversals methodology – 100% reversal	18.0	28.0	39.6
Jones with reversals methodology – 50% reversal	11.2	16.8	24.0
Jones with reversals methodology – 30% reversal	8.8	13.6	19.2
Mod-Jones(C) with ROA+SG matching – mean test	32.0	37.2	63.2
Mod-Jones(C) with ROA+SG matching – median test	38.8	44.4	75.6
Mod-Jones(C) with reversals methodology – 100% reversal	22.0	28.8	43.6
Mod-Jones(C) with reversals methodology – 50% reversal	12.4	20.8	27.6
Mod-Jones(C) with reversals methodology – 30% reversal	10.8	16.8	23.6