# Performance Matched Discretionary Accrual Measures

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## Abstract

Prior research shows that extant discretionary accrual models are misspecified when applied to firms with extreme past performance. Nonetheless, use of discretionary accruals in tests of earnings management and market efficiency is commonplace in the literature. We examine the specification and power of the test based on a performance-matched discretionary accrual measure and compare it with traditional discretionary accrual measures (e.g., Jones and Modified-Jones Models). Performance matching is on return on assets and industry. Our results suggest that inferences about earnings management using a performance-matched discretionary accrual measure are likely to be more reliable than using a traditional measure of discretionary accruals.

# Performance Matched Discretionary Accrual Measures

## 1. Introduction

Use of discretionary accruals in tests of earnings management and market efficiency is widespread (see, for example, Defond and Jiambalvo, 1994, Rees, Gill and Gore, 1996, and Teoh, Welch, and Wong, 1998a and 1998b). Earnings management studies "examine whether managers act as if they believe users of financial reporting data can be misled into interpreting reported accounting earnings as equivalent to economic profitability" (Fields, Lys, and Vincent, 2001, p. 279). Naturally, earnings management research is of interest not only to academics, but also to practitioners and regulators.

Tests of hypotheses related to incentives for earnings management hinge critically on the researcher's ability to accurately estimate discretionary accruals. Unfortunately, as Fields et al. (2001, p. 289) note, accurate estimation of discretionary accruals does not appear to be accomplished using existing models. Fields et al. (2001, p. 289) point out that "The only convincing conclusion appears to be that relying on existing accruals models to solve the problem of multiple method choices may result in serious inference problems," where multiple method choices refers to earnings management using accruals.

Previous research examining the specification and power of commonly used discretionary-accrual models includes an influential study by Dechow, Sloan, and Sweeney (1995, p. 193) who conclude that "all models reject the null hypothesis of no earnings management at rates exceeding the specified test levels when applied to samples of firms with extreme financial performance." Since earnings management research typically examines non-random samples (e.g., samples that firms self-select into by, for example, changing auditors), earnings management studies must employ some means of mitigating the misspecification to reduce the likelihood of incorrect inferences (i.e., falsely rejecting the null hypothesis). In this vein, use of a control sample to address model misspecification is not uncommon in the literature.

Our objective in this paper is to test whether a performance-matched discretionary-accrual estimation approach is both well specified and powerful. Such an accrual measure would enhance the reliability of inferences drawn from earnings management studies and tests of market efficiency with respect to discretionary accruals. Well-specified tests reject the null hypothesis, when it is true, at the nominal significance level of the test (e.g., 1% or 5%). In the context of discretionary accrual models, power of a test refers to the likelihood that a test concludes non-zero discretionary accruals of a given magnitude (e.g., 1%, 2%, etc.) in a sample of firms. Powerful tests reject the null hypothesis with high probability when it is false.

A key feature of our study is that we examine properties of discretionary accruals adjusted for a performance-matched firm's discretionary accrual, where performance matching is on the basis of a firm's return on assets and industry membership. One motivation to match on return on assets (ROA) stems from evidence in Barber and Lyon (1996) that ROA matching provides well-specified and powerful tests for changes in operating performance measures (accruals are not examined). Our results suggest that performance matching is crucial to designing well-specified tests of earnings management. The importance of controlling for the effect of past performance in tests of earnings management is not surprising and has been recognized in some prior studies (e.g., Teoh et al., 1998a and 1998b). Nonetheless, our study is the first to thoroughly examine and document the specification and power of performance-based discretionary accrual measures across a wide variety of settings representative of those encountered in accounting.

The importance of controlling for past performance can also be seen from the simple model of earnings, cash flows, and accruals in Dechow, Kothari, and Watts (1998). This model shows that working capital accruals increase in forecasted sales growth and earnings because of a firm's investment in working capital to support growth. Therefore, if a firm's performance exhibits momentum or mean reversion (i.e., performance deviates from a random walk), then forecasted accruals would be non-zero. Earnings momentum might be observed because firms with high growth opportunities often exhibit persistent growth patterns. Similarly, accounting conservatism can produce earnings persistence (i.e., momentum) in the presence of good news and mean reversion in the presence of bad news (Basu, 1997). In addition, there is evidence of mean reversion conditional on extreme earnings performance (see Brooks and Buckmaster, 1976, for early evidence on mean reversion). As a result, forecasted accruals of firms that have experienced unusual performance are expected to be systematically non-zero. A correlation between performance and accruals is problematic in tests of earnings management because commonly used discretionary accrual models (e.g., the Jones (1991) and modified-Jones models) are severely mis-specified when applied to samples experiencing extreme performance (see Dechow, et al., 1995). As a result, previous research attempts to develop accrual models as a function of performance (see Kang and Sivaramakrishnan, 1995, Guay, et al., 1996, Healy, 1996, Dechow, Kothari, and Watts, 1998, Peasnell, Pope and Young, 2000, and Barth, Cram, and Nelson, 2001).

We control for the impact of performance on estimated discretionary accruals using a performance-matched firm's discretionary accrual. An alternative is to formally model accruals as a function of performance (see Fields et. al (2001) for a discussion of this issue). However, doing so requires imposing a specific functional form linking accruals to past performance in the cross-section. Since a suitable way to do this is not immediately obvious, we control for prior performance using a performance-matched firm's discretionary accrual. Using a performance-matched firm's discretionary accrual does not impose a particular functional form linking accruals to performance in a cross-section of firms. Instead, the assumption underlying performance matching is that, at the portfolio level, the impact of performance on accruals is identical for the test and matched control samples. Results below suggest that tests using a performance-matched approach to estimate discretionary accruals are better specified than those using a linear regression-based approach to control for the effect of past performance on accruals.

While adjustment of discretionary accruals for those of performance-matched samples is not uncommon in the literature, researchers choose from a wide range of firm characteristics on which to match without systematic evidence to guide the choice of a matching variable. For example, previous research uses control firms matched on cash flows (Defond and Subramanyam, 1998), industry and net income (Teoh et al., 1998a), year and industry (Defond and Jiambalvo, 1994), industry and size (Perry and Williams, 1994), and control firm defined as the median performance of the subset of firms in the same industry with past performance similar to that of the treatment firm (Holthausen and Larcker, 1996) or median performance of the percentile of firms matched on return on assets (Kasznik, 1999). The contribution of our study is that it provides a systematic treatment of the specification (under the null) and power of the test of performance-based discretionary accrual measures. As such, our results should aid in the design of future earnings management and market efficiency studies that need to accurately measure discretionary accruals.

***Summary of results.*** The main result from our simulation analysis is that discretionary accruals estimated using the Jones or the modified-Jones model *and* adjusted for a performance-matched firm's discretionary accruals are well specified. We label these as performance-matched discretionary accruals. We report results using performance matching on the basis of industry and past (or current) year's return on assets.[1] Performance-matched discretionary accruals exhibit only a modest degree of mis-specification in certain stratified-random samples, but otherwise tests using them perform quite well, whereas in such samples traditional

[1] While other performance matching variables are possible, performance matching on the basis of lagged return on assets follows the approach taken in Barber and Lyon (1996) in their study of detecting abnormal operating performance. Barber and Lyon (1996) do not study accruals, discretionary or non-discretionary.

discretionary accrual measures are grossly mis-specified. An example of a stratified-random sample is a sample of randomly selected stocks from an extreme quartile of stocks ranked on the basis of their book-to-market ratio. We analyze many types of stratified-random samples (e.g., large vs. small firms, growth versus value stocks, high vs. low earnings yield stocks, high vs. low past sales growth, high vs. low cash flow from operations).

A caveat related to our analysis is that firms in stratified-random samples might be engaging in earnings management for contracting, political or capital market reasons. Thus, the well-specified rejection rate of the performance-matched approach might be an indication of a tendency to under-reject the null hypothesis (see Guay et al., 1996). However, the results of our power tests suggest that while this may be a concern, it is unlikely to be an overwhelming concern. Even so, our result that performance-matched measures are well specified is helpful insofar as a researcher calibrates discretionary accruals relative to those estimated for a matched sample that has not experienced the treatment event (also see section 2). The ROA performance-matched accrual measures' superior performance compared to other measures of discretionary accruals parallels the result in the context of operating performance measures and long-horizon stock returns (see Barber and Lyon, 1996 and 1997, Lyon, Barber, and Tsui, 1999, and Ikenberry, Lakonishok, and Vermaelen, 1995).

Other aspects of our findings are that rejection rates are quite similar across different stratified-random samples and are moderately higher as the sample size increases and as the horizon increases from one year to three or five years. For example, when the sample size is 100 firms and discretionary accruals equal 2% of assets, the tests conclude significant discretionary abnormal accruals approximately 30-50% of the time for various stratified-random samples. The rejection frequency jumps to about 90% if the discretionary accruals are 4% of assets.

To provide evidence of the potential bias engendered by using discretionary accrual models without performance matching, we estimate discretionary accruals for a sample of firms making seasoned equity offers, SEOs. In essence we replicate Teoh et al. (1998a) using measures of discretionary accruals (based on the Jones Model) with and without performance matching. The magnitudes of discretionary accruals are attenuated upon performance matching. Unlike Teoh et al., we fail to find a reliable reversal of estimated discretionary accruals around SEOs when performance-matched discretionary accruals are used.

Our results provide guidance to researchers in selecting a discretionary accrual measure in an actual empirical setting. More specifically, our findings suggest that researchers will be on firmer ground if they used a performance-matched accrual measure. Conversely, researchers who do not use such a measure are likely to draw inferences that are unreliable at best and incorrect at worst.

Section 2 provides the motivation for using a performance-matched approach to develop well-specified tests of discretionary accruals and section 3 describes the simulation procedure. Section 4 summarizes the results on the specification of the test (i.e., rejection frequencies when the null hypothesis of zero abnormal performance is true) and section 5 reports results for the power of the test (i.e., rejection rates when we add 1% to 10% discretionary accrual to each sample firm's estimated discretionary accrual). Section 6 reports the results of a wide range of sensitivity analyses. In section 7 we present the results of replicating a study examining discretionary accruals over a multi-year horizon surrounding seasoned equity issues. Section 8 summarizes and discusses recommendations for future research.

## 2. Motivation for performance matching

In this section we describe the relation between firm performance and accruals. This provides a framework and the motivation for developing a control for firm performance when estimating discretionary accruals and for comparing estimated discretionary accruals between samples of firms.

Economic intuition, extant models of accruals, earnings, and cash flows, and empirical evidence all suggest that accruals are correlated with a firm's contemporaneous and past performance.[2] While the Jones and modified-Jones discretionary accrual models attempt to control for contemporaneous performance, empirical assessments of these models suggest that estimated discretionary accruals are significantly influenced by a firm's contemporaneous and past performance (e.g., Dechow, Sloan, and Sweeney, 1995).

***Properties of earnings, cash flows and accruals.*** To formalize a relation between firm performance and accruals, we begin with a simple version of the model of earnings, cash flows and accruals discussed in Dechow et al. (1998). Ignoring the depreciation accrual and assuming (i) sales, $S_t$, follow a random walk, (ii) cash margin of sales is a constant percentage $\pi$, (iii) $\alpha$ fraction of sales are on credit, and (iv) all expenses are cash, Dechow et al. show that:

$$CF_t = \pi S_t - \alpha \varepsilon_t \tag{1}$$

$$A_t = \alpha \varepsilon_t, \text{ and} \tag{2}$$

$$X_t = CF_t + \alpha \varepsilon_t = \pi S_t, \tag{3}$$

where CF is cash flow, A is accrual, $\varepsilon_t = S_t - S_{t-1}$ is change in sales (or sales shock if earnings follow a random walk), and X is accounting earnings. In this simple setting forecasted accruals are zero because sales follow a random walk. Moreover,

$$E_t(A_{t+1}) = E_t(\alpha \varepsilon_{t+1}) = 0 \,, \tag{4}$$

and the forecast of future cash flows is current earnings,

$$E_t(CF_{t+1}) = E_t(\pi S_{t+1} - \alpha \varepsilon_{t+1}) = \pi S_t = X_t. \tag{5}$$

[2] See, for example, Guay, Kothari, and Watts (1996), Healy (1996), Dechow, Kothari, and Watts (1998), Dechow, Sloan, and Sweeney (1995), and Barth, Cram, and Nelson (2001).

The above analysis suggests that as long as the assumptions about the parameters and about the random walk property for sales, and therefore earnings, are descriptive, forecasted accruals are zero.[3] However, as seen from eq. (4), if forecasted sales changes are not zero (i.e., sales depart from a random walk) or when profit margins or other parameters affecting accruals change, then forecasted earnings changes as well as accruals are non-zero. Forecasted sales and earnings changes can be positive or negative depending on whether performance is expected to mean revert or expected to exhibit momentum. Extreme one-time increases or decreases in performance are likely to produce mean reversion, whereas growth stocks might exhibit momentum for a period of time. Mean reversion or momentum in sales and earnings performance is quite likely for firms exhibiting unusual past performance. This predictability in future performance generates predictable future accruals. Unless the discretionary accrual models adequately filter out this performance-related predictable component of accruals, there is a danger of spurious indication of discretionary accruals.[4] Previous research (e.g., Dechow et al., 1995, and Guay et al., 1996) suggests the likelihood of a spurious indication of discretionary accruals is extremely high in samples experiencing unusual past performance.

***Controlling for the effect of performance on accruals.*** One means of controlling for the influence of firm performance on estimated discretionary accruals is to develop better models of discretionary accruals. In this spirit, we augment the Jones (1991) and modified-Jones discretionary models to include past return on assets. This approach is in addition to the use of a performance-based discretionary accrual measure that adjusts the Jones and modified-Jones

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[3] This conclusion also holds for models that better capture the complexity of accounts payables and fixed costs (see Dechow et al., 1998). However, the result cannot be demonstrated as cleanly as in the case of the simple model we present here.

[4] In the presence of mean reversion, momentum, and/or other departures from a random walk property of sales, the inclusion of sales change as an explanatory variable in a discretionary accrual regression model is not sufficient to forecast all of the firm's non-discretionary accruals related to sales.

model discretionary accrual of a given firm by subtracting the corresponding discretionary accrual on a firm matched on the basis of prior year return on assets and industry.

The choice of matching on past return on assets is guided by the modeling of earnings, cash flows and accruals summarized above. In particular, eq. (4) for the prediction of accruals suggests that when sales changes are predictable, earnings changes will also be predictable and forecasted accruals will be non-zero.[5] In samples of firms that are not random with respect to prior firm performance, earnings changes are predictable and accruals are also expected to be non-zero. Intuitively, either the inclusion of past firm performance as an explanatory variable in the discretionary accrual model or adjustment of a firm's estimated discretionary accrual by that of a (performance) matched firm would serve to mitigate the likelihood that the resulting estimated discretionary accruals would systematically be non-zero (i.e., lead to invalid inferences about accrual behavior). Selection of return on assets as a performance measure is logical because assets are typically used as a deflator in the discretionary accrual models and earnings performance deflated by assets is (net) return on assets.

The relative efficacy of including a performance variable in the discretionary accrual regression model versus the matched-firm approach is an empirical issue. The regression approach imposes stationarity of the relation through time or in the cross-section, and perhaps more importantly, does not accommodate potential non-linearity in the relation between the magnitude of performance and accruals. It is well known that the mapping of current performance into future performance, or the mapping of performance into returns, is non-linear (e.g., Brooks and Buckmaster, 1976, Beaver, Clarke, and Wright, 1979, Freeman and Tse, 1992, and Basu, 1997). Unless the discretionary accrual models are modified to address non-linearity,

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[5] As the simple model suggests, an alternative to return on assets would be to match on past sales growth. However, matching on return on assets serves to incorporate other factors contributing to the firm's accrual generating process, which our simple model does not capture, but which are likely to affect the magnitude of nondiscretionary accruals.

the regression approach might not be effective at controlling for non-zero estimated discretionary accruals in stratified-random samples. Conversely, the matched-firm approach does not impose restrictions on the functional form of the relation between performance and accruals. Nonetheless, the success of the matched-firm approach hinges on the precision with which matching can be done and the homogeneity in the relation between performance and accruals for the matched firm and the sample firm. As a result, we examine both the regression approach and the matched-firm approach to control for past performance.

***Does controlling for past performance over-correct for performance-related accruals?*** One may be tempted to argue that use of industry and performance-matched control firms might remove discretionary accruals resulting from the treatment firms' earnings management activities, and thus the researcher might fail to reject the null hypothesis when it is false. This concern arises because matched (control) firms in the industry might have similar incentives to manage earnings when compared to the treatment firms. While such a concern is not entirely misplaced, we believe controlling for performance-related accruals is nevertheless warranted. In an earnings management study, researchers typically infer whether an event (e.g., a seasoned equity offer) influences reported earnings performance in the pre- and post-event years. If the treatment firms' earnings performance in the post-event period is indistinguishable from that of control firms, then the conclusion would be that the firms experiencing the event do not manage earnings any more or less than the matched firms that do not experience the event. Of course, it is possible that both treatment and control firms manage earnings. However, this is not central to the researcher's study, which seeks to discern whether the *event* contributes to earnings management for reasons beyond other known or observable factors like past performance. Therefore, it behooves researchers to match on performance in ascertaining whether an event influences reported earnings performance.

Another interpretation of this issue is that if control firms face similar incentives to manage earnings, then they should really be in the treatment group. Thus, this issue may have more to do with a researcher's (in)ability to correctly identify his/her treatment group, rather than constituting a weakness of the performance-matched approach to measuring discretionary accruals.

## 3. The simulation procedure

This section describes the baseline simulation procedure that we use to provide evidence on the specification and power of the tests using alternative measures of discretionary accruals. We discuss stratified-random and random sample construction (section 3.1), discretionary accrual measures (section 3.2), and the test statistics under the null hypothesis of zero discretionary accruals (section 3.3). Section 3.4 presents descriptive statistics and serial correlation properties of all the discretionary accrual measures. These descriptive statistics are important as they provide some preliminary evidence of the potential biases inherent to traditional measures of discretionary accruals. Such misspecification contributes to test statistic misspecification in actual empirical studies.

### 3.1 Sample selection

We begin with all 572,728 firm-year observations from the COMPUSTAT Industrial Annual, and Research files from 1962 through 1999. From these, we exclude firm-year observations that do not have sufficient data to compute total accruals (described in section 3.2) or the variables needed estimate the Jones models. This reduces the sample to 175,287 firm-year observations. We next exclude all firm-year observations where there are fewer than ten observations in any two-digit SIC code in any given year. This is designed to exclude observations for which the regression-model-based discretionary accrual estimates are likely to be imprecise. This step reduces the sample to 170,197 observations. In much of our analysis, we match firms on the basis of performance (described below) and analyze stratified samples. The final sample size as a result of performance matching and excluding firm-year observations that do not contain variables required for constructing stratified samples (e.g., book-to-market, market size, earnings yield and sales growth) is 122,798 observations.

We report baseline simulation results for 250 samples of 100 firms each. We draw samples without replacement either from the "all-firms" population or from stratified subsets of the population. The stratified subsets are firms in the lowest and highest quartiles of firms ranked on book-to-market ratio, past sales growth, earnings-to-price ratio, size measured as the market value of equity, and operating cash flow. To construct these stratified subsets, each year we rank all firm-year observations on the basis of each partitioning characteristic (e.g., book-to-market or size) measured at the beginning of the year. We then pool across all the years the observations in the respective upper or lower quartile to obtain stratified subsets from which samples can be drawn. From each subset, we then randomly select 250 samples of 100 firms.

**3.2 Discretionary accrual measures**

Previous research (e.g., Dechow et al. 1995) suggests that among the various discretionary accrual models, the Jones (1991) and the modified-Jones models (see Dechow et al.) perform the best. We therefore use discretionary accruals estimated using these two models. We also estimate a discretionary current accrual measure (i.e., the discretionary portion of accruals without the depreciation accrual) that is increasingly being used in accounting research (see Teoh et al., 1998a and 1998b). We estimate the performance-matched Jones-model discretionary accrual as the difference between the Jones model discretionary accrual and the corresponding discretionary accrual for a performance-matched firm. We similarly estimate the performance-matched modified-Jones model discretionary accrual. To compare the effectiveness of performance matching, versus a regression-based approach, we estimate an additional discretionary accrual measure where we include the previous year's return on assets (ROA) in the Jones-Model regression.

Details of estimating the discretionary accrual models are as follows. We define total accruals (TA) as the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt minus depreciation and amortization, scaled by lagged total assets.[6] The Jones model discretionary accrual is estimated cross-sectionally each year using all firm-year observations in the same two-digit SIC code.

$$TA_{it} = \beta_0/ASSETS_{it-1} + \beta_1\Delta SALES_{it} + \beta_2 PPE_{it} + \varepsilon_{it}, \quad (6)$$

where $\Delta SALES_{it}$ is change in sales scaled by lagged total assets, $ASSETS_{it-1}$, and $PPE_{it}$ is net property, plant and equipment scaled by $ASSETS_{it-1}$. Assets as the deflator, including for the constant, in eq. (6) is intended to mitigate heteroskedasticity in residuals. White (1980) statistics for the annual, cross-sectional, industry models show that deflation reduces, but does not eliminate heteroskedasticity.[7]

We use residuals from the annual cross-sectional industry regression model in (6) as the Jones model discretionary accruals. Following prior studies that estimate the modified-Jones model cross-sectionally, to obtain modified-Jones model discretionary accruals, we subtract the change in accounts receivable ($\Delta AR_{it}$) from $\Delta SALES_{it}$ prior to estimating model (6).[8] This differs from the procedure advocated by Dechow et al. (1995) in a *time-series* setting. They assume that sales are not managed in the estimation period, but that the entire change in accounts receivable in the event year represents earnings management. Therefore, Dechow et al., use the parameters from the Jones model estimated in the pre-event period for each firm in their sample, but apply those to a modified sales change variable defined as ($\Delta SALES_{it}$ - $\Delta AR_{it}$) to estimate discretionary accruals in the event period. While their procedure is reasonable in a *time-series* setting it is less so when discretionary accruals are estimated cross sectionally. We do not have a "pre-event"

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[6] With reference to COMPUSTAT data items, total accruals = (ΔData4 - ΔData1 - ΔData5 + ΔData34 - Data14)/lagged Data6.

[7] While eq. (6) does not include an intercept, we repeat estimation of all models with an intercept in the regressions. The deflation in this case is intended to mitigate problems stemming from an omitted size variable (see Brown, Lo, and Lys, 1999). We find that the tenor of the results from the simulation analysis is unaffected.

[8] See DeFond and Park (1997), Subramanyam (1996) and Guidry, et al (1999) as examples.

period where we can assume that changes in accounts receivable are unmanaged. Instead, we make the assumption that all changes in accounts receivable arise from earnings management and estimate the Jones model using modified sales changes ( $\Delta SALES_{it}$ - $\Delta AR_{it}$ ).

We estimate a third model that is similar to the Jones model, but it also includes lagged ROA. This model is:

$$TA_{it} = \delta_0/ASSETS_{it-1} + \delta_1 \Delta SALES_{it} + \delta_2 PPE_{it} + \delta_3 ROA_{it-1} + \upsilon_{it}, \quad (7)$$

where $ROA_{it-1}$ is return on assets in period t-1. This discretionary accrual measure provides a comparison between the effectiveness of performance matching versus including a performance measure in the accruals regression.

***Performance matching.*** We match each firm-year observation with another from the same two-digit SIC code industry and year with the closest return on assets (ROA), where ROA is net income divided by lagged total assets. Matching on ROA can be on the basis of ROA in the year contemporaneous with the year for which a discretionary accrual is being calculated or in the year prior to the year for which a discretionary accrual is being calculated (e.g., Teoh et al., 1998a). There are pros and cons of these two alternatives, which are discussed when we present descriptive statistics for estimated discretionary accruals. Throughout the paper we present results using matching on ROA in both contemporaneous and lagged year relative to the discretionary accrual estimation year. We define the Jones-model performance-matched discretionary accrual for firm i in year t as "The Jones-model discretionary accrual in year t minus the matched firm's Jones-model discretionary accrual for year t." Performance-matched modified-Jones model discretionary accrual is defined similarly.

### 3.3 Test statistics

For each of the 250 randomly selected samples (per event condition), we assess the significance of the mean discretionary accrual using a t-test. The t-test is defined as the equal-weighted sample mean discretionary accrual divided by an estimate of its standard error. We assume cross-sectional independence in the estimated discretionary accruals of the sample firms. This assumption seems justified given that we construct samples by selecting firms without regard to time period or industry membership (i.e., our samples are not clustered by industry and/or calendar time). The test statistic is:

$$\overline{DA}/(s(DA)/\sqrt{N}) \sim t_{N-1}, \tag{9}$$

*where*

$$\overline{DA} = \frac{1}{N}\sum_{i=1}^{N} DA_{it}, \tag{10}$$

*and*

$$s(DA) = \sqrt{\sum_{i=1}^{N}(DA_{it} - \overline{DA})^2 / N - 1} \tag{11}$$

where $DA_{it}$ is the discretionary accrual of firm i in year t (based on one of the alternative discretionary accrual models described above), $\overline{DA}$ is the mean discretionary accrual for the sample, *s(DA)* is the estimated standard deviation for the distribution of DA for the sample, and *N* is the number of firms in the sample.

### 3.4 Descriptive statistics and serial correlations for discretionary accrual measures under the null hypothesis

***Descriptive statistics***. Table 1 reports descriptive statistics for total accruals and several discretionary accrual measures for the aggregate sample of 122,798 firm-year observations (panel A) and for various stratified-random samples (panel B). Total accruals average –3.03% of total assets. The negative value is due largely to the depreciation accrual. The inter-quartile range is from –8% to 2%, but the standard deviation is 11.62%, which means the distribution of total accruals is fat-tailed relative to a normal distribution.

Average discretionary accruals in table 1, panel A are often negative on average. Since these are regression residuals, they are expected to average to zero. However, two factors influence their averages. First, since we estimate the Jones and modified-Jones discretionary accrual models without an intercept, the fitted residuals will not sum to zero. Second, we winsorize extreme observations for all discretionary accrual measures by setting the values in the bottom and top one percent of observations of each measure to the values of the 1st and 99th percentiles of their respective distributions.

Performance-matched Jones and performance-matched modified-Jones model discretionary accruals, with matching either on contemporaneous or lagged year's ROA, exhibit smaller means compared to those without performance matching. However, holding constant the sample size, performance matching results in increasing the standard deviation from about 10% for the Jones model discretionary accrual to about 14-16% for the performance-matched Jones model discretionary accrual. This represents about a 40-50% increase in the variability of the performance-matched accrual. However, this is approximately the increase one would expect if the estimated discretionary accrual of the sample firm were uncorrelated with the matched firm's estimated discretionary accrual.[9] Thus, while performance matching is likely to improve the specification because performance-matched discretionary accruals appear less biased, there is a trade-off of diminished power. However, the adverse impact on power should be muted at a portfolio level because of diversification across firms. At any rate, the power of the test is an empirical issue, so it remains to be seen how adversely the higher standard deviation affects the overall power of the test using the performance-matched discretionary accrual measures.

**[Table 1]**

[9] Assuming independence, the variance of the difference between two random variables with identical variances is twice the variance of the individual random variables. Therefore, the standard deviation would be the square root of two or 1.41 times the standard deviation of the individual random variable.

Consistent with the claims in previous research, descriptive statistics in panel B document the discretionary accrual models' inadequacy in generating zero-mean estimates when applied to stratified-random samples.[10] For example, the average discretionary accrual using the modified-Jones model for growth stocks (i.e., the bottom quartile of stocks ranked on book-to-market ratio at the end of each year) is -1.42% of assets and it is -4.14% of assets for the stocks in the lowest quartile of stocks ranked on earnings yield. The benefit from performance matching is apparent by comparing the average discretionary accruals estimated using measures with and without performance matching. For example, the small stocks' average discretionary accrual using the lagged-year performance-matched modified-Jones model is -0.59% compared to -2.08% using the modified-Jones model without performance matching. The average using matching on the basis of contemporaneous year's ROA is –0.31%. While a similar observation can be made for many of the stratified-random samples, average performance-matched discretionary accrual for the operating cash flow samples is substantially different depending on whether matching is on the contemporaneous or lagged year's ROA. However, matching on contemporaneous ROA for the extreme operating cash flow samples mechanically influences the performance-matched discretionary accrual. Holding the ROA constant, high operating cash flow stocks must necessarily have low accruals compared to the matched ROA firm. Thus, we expect a negative average for the contemporaneously performance-matched discretionary accrual for high operating cash flow stocks and positive for the low operating cash flow stocks, and this is what is observed in table 1, panel B. This mechanical relation is not true when matched on lagged ROA.

Overall, estimated performance-matched discretionary accruals are closer to zero than those without performance matching. While the bias is not eliminated, it is the case that the

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[10] Stratified samples are constructing based on characteristics measured in the earnings management year. For example, book-to-market is calculated using market and book values at the end of the period in which discretionary accruals are calculated.

greater the bias, the more likely it is that the null hypothesis of zero discretionary accrual will be spuriously rejected.

***Serial correlations***. Under the ***null hypothesis*** of zero abnormal discretionary accruals, well-specified models should generate discretionary accrual estimates (i.e., errors from the models) that are approximately serially uncorrelated regardless of a firm's past performance.[11] In contrast, if past performance leads to biased estimates of discretionary accruals, then for stratified-random samples estimated discretionary accruals are likely to be negatively serially correlated. The null hypothesis is a maintained assumption applicable to the population and stratified-random samples in the research testing for earnings management around specific events (e.g., an SEO).

We estimate serial correlation in various discretionary accrual measures for the entire sample as well as stratified-random subsamples of firms. Serial correlations are from the following cross-sectional regressions estimated annually from t = 1959 to 1993:

$$X_{it} = \alpha + \beta X_{it-1} + \varepsilon_{it} \qquad (12)$$

where $X_{it}$ ($X_{it-1}$) is the (lagged) value of the variable of interest. We set $X_{it}$ to be the return on assets, total accruals, Jones- and modified-Jones model discretionary accrual, performance-matched Jones- and modified-Jones model accruals. Performance-matched measures are with matching either in the contemporaneous year or in the lagged year. A serial correlation estimate from a cross-sectional regression assumes that it is identical across the firms in the cross-section (see Fama and French, 2000). In practice, the estimated coefficient is the cross-sectional average of the serial correlations of the firms included in the regression. The advantage of using eq. (12) to estimate serial correlation is that a long time series of historical data for individual firms to

[11] We note that a modest degree of serial correlation in estimated discretionary accruals is expected in part because past performance might be correlated with earnings management, which a well-specified discretionary-accrual model would detect and generate negative serial correlation as the managed accruals reverse.

estimate a time-series model is not necessary. Variation in serial correlation across firms can be captured by estimating the model for subsamples that are, *a priori,* likely to be homogeneous in the serial correlation. We adopt this approach.

Table 2 reports the average of the 36 annual cross-sectional serial correlation estimates (i.e., slope coefficients from eq. 12) for each X variable and for each subsample. Statistical significance is based on t-tests for zero mean, where the Fama-MacBeth (1973) standard error in calculating the t-statistic incorporates the Newey-West (1987) autocorrelation correction for five lags.

**[Table 2]**

Return on assets is positively autocorrelated for the entire sample as well as all the subsamples. The serial correlation is lower for extreme earnings yield and cash flow yield portfolios, which is consistent with mean reversion in extreme earnings (e.g., Brooks and Buckmaster, 1976) and cash flows. Serial correlation in total accruals is positive for the all-firm sample, but it is small or zero for value stocks, low earnings and cash flow yield stocks, low past sales growth stocks, and small firms. This means unusual past performance imparts a transitory component to accruals. On balance, the discretionary accrual models are successful in mitigating the serial correlation as seen from the correlation estimates for discretionary accrual estimates. Performance matching further dampens the serial correlation. For example, serial correlation in the modified-Jones model discretionary accruals is -0.115 for the low sales growth stocks, which is reduced to -0.066 or -0.049 by performance matching on ROA in period t-1 or t. Corresponding numbers for small stocks are -0.074 and -0.026 or -0.042. Overall, performance matching reduces the severity of the specification biases afflicting the popularly applied Jones- and modified-Jones discretionary accrual models. The extent to which this improvement manifests itself in the specification and power of the tests using discretionary accrual models is the empirical issue addressed in the next section.

## 4. Results: Specification of the tests using alternative discretionary accrual models

This section reports results on the specification of the test under the null hypothesis of zero discretionary accruals using the various discretionary accrual models described above. We report the percentage of times out of 250 simulated samples the null hypotheses of non-negative and non-positive discretionary accruals are rejected at the 5% level of significance (upper or lower one-tailed test). These rejection rates measure each metric's Type I error rate. If the rejection rate for a discretionary accrual measure falls between 2% and 8%, then the test is well specified. The 2% to 8% range represents the 95% confidence interval for the expected rejection rate of 5%, the nominal significance level of the test. If the actual rejection rate falls outside the 2% to 8% range, the test is deemed to reject the null hypothesis too infrequently or excessively.[12]

### 4.1. Rejection rates under the null hypothesis

The numbers in panel A of table 3 report rejection rates for one-tailed tests of the alternative hypothesis of negative discretionary accruals where the horizon is one year. The striking result is that rejection rates using the Jones and modified-Jones models far exceed the nominal significance level of the test (i.e., 5%) in many cases. Even after including ROA in the Jones and modified Jones accrual models, rejection rates often exceed 8%. For example, the rejection frequency with ROA in the Jones model is 21.2% for growth stocks and 59.2% for low earnings yield stocks. In contrast, the performance-matched discretionary accrual measures based on the Jones or modified-Jones models generally exhibit less extreme rejection frequencies, which tend to be closer to the nominal significance level of the test.

**[Table 3]**

***Results without performance matching.*** High rejection rates using the Jones and modified-Jones models are not surprising as Dechow et al. (1995) report similar evidence for

[12] Results using a 1% significance level lead to virtually identical inferences and are not reported to conserve space.

samples selected from extreme deciles of stocks ranked according to earnings and cash flow performance. By extending their results we find that even if firms are sampled from less extreme populations (i.e., quartiles in our study) and based on a variety of economic characteristics, the Jones and modified-Jones models excessively reject the null hypothesis of no discretionary accruals. For example, in the absence of performance-matching or controlling for ROA in the accrual regressions, high rejection rates are obtained for samples selected from quartiles of low sales growth (from 33.6% to 70.4%), low EP ratio (from 84.8% to 88.4%), small firms (from 34.4% to 44.4%) and low operating cash flow (from 61.6% to 68.0%).

In sample of low sales growth firms the rejection rate is quite high, 70.4%, based on the modified-Jones model. This result is somewhat surprising considering that sales growth is one of the explanatory variables in the modified-Jones model. One explanation for the result is that the relation between accruals and sales growth might be nonlinear. Alternatively, modified-Jones model's treatment of entire increase in credit sales as discretionary might contribute to mis-specification that is correlated with extreme sales performance.

Misspecification problems are attenuated but not eliminated when past ROA is included in the Jones- and modified-Jones accrual regressions. Rejection rates remain high for samples selected from quartiles of low sales growth (from 28.0% to 60.8%), low EP ratio (59.2% to 66.0%), small firm size (from 24.4% to 27.2%) and low operating cash flow (37.6% to 40.8%).[13]

***Performance matching.*** Table 3's rejection rates based on performance-matched discretionary accrual measures reveal a lesser degree of misspecification compared to other models. For example, performance-matched Jones model discretionary accruals based on

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[13] Untabulated results show that discretionary accruals calculated as the Jones or modified-Jones model discretionary accrual minus the industry mean or median Jones or modified-Jones model discretionary accrual do not cure the problem of excessive rejection rates of these models. Previous research (e.g., DeFond and Park, 1997) uses industry-adjustment as a means of mitigating the likelihood of spurious rejection. Our results suggest that such attempts are unlikely to be successful. These results are not reported in the table to save space (they are available upon request).

matching on period t ROA indicate negative discretionary accruals close to 5% of the time in all cases (the nominal significance level of the test) except when sampling is restricted to large market capitalization stocks and high operating cash flow stocks. In the latter two cases the rejection frequencies of 16.8% and 20.0% deviate from the expected rejection rate of 5%. The high rejection rate for the high operating cash flow firms is not surprising nor unexpected and is obtained mechanically because earnings is the sum of operating cash flows and accruals. Since we match on earnings performance (i.e., ROA) in the contemporaneous period, treatment firms selected from the high operating cash flow quartile, by construction, have lower accruals than the matched firms that do not always belong to the high operating cash flow quartile. This mechanical relation is absent when matching is on ROA in the lagged period. The rejection rate in that case is 12.4% for the high operating cash flow quartile. While no one discretionary accrual measure is immune from mis-specification in all settings, overall, across the variety of event conditions simulated in table 3, the performance matched discretionary accrual measures generally perform better than the other measures we examine (and those that have been used in prior research).

***Jones versus modified-Jones model.*** The results show that the differences between the rejection rates of the Jones and modified-Jones models are generally small except in the case of low sales growth samples. For example, for samples from the low operating cash flow quartiles, the rejection rate using the Jones measure is 61.6% compared to 68.0% using the modified-Jones model. The difference of 6.4% between the two rejection frequencies is not huge, but it is statistically significant.[14] The much higher rejection frequency of 70.4% for the low sales growth quartile firms using the modified-Jones model compared to 33.6% for the Jones model is likely because the modified-Jones model assumes that all credit sales represent accrual manipulation.

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[14] Assuming independence, a difference of about three percent between the rejection rates using two models is statistically significant.

As we note earlier, the credit-sales related assumption causes the modified-Jones model discretionary accrual to be positively correlated with sales growth. Therefore, for samples from low sales growth quartile firms, the performance-matched modified-Jones-model discretionary accrual is likely to be systematically negative, as seen from the excessive rejection rate. Thus, unless the researcher is confident that credit sales represent accrual manipulation, the modified-Jones-model is expected to spuriously conclude earnings management. The results in table 3, panel A also indicate that performance-matched Jones and modified-Jones models are similar everywhere except for the low sales growth samples. Thus, performance matching does not eliminate the bias in the modified-Jones model that stems from the correlation between estimated discretionary accrual and sales growth.

***Rejection rates for the alternative hypothesis of positive discretionary accruals.*** Simulation results of testing for positive discretionary accruals appear in panel B of table 3. They indicate that, in the case of several sample firm characteristics, some models of discretionary accruals exhibit excessively low Type I error rates. For example, all models except contemporaneous matching on ROA performance conclude positive abnormal accruals too infrequently for low earnings yield and cash flow yield samples. The modified-Jones model exhibits some tendency to reject the null hypothesis too often. For example, the rejection rates are about 12% to 24% of the time in high earnings yield, high cash flow yield, and high sales growth samples. Inclusion of ROA in the Jones and Modified Jones accrual models does little to change model specification. Fortunately, performance matching almost invariably eliminates the specification problems with the Jones and modified-Jones models (with the exception of performance-matched modified-Jones model in the case of high sales growth samples).

***Summary.*** In summary, under the null hypothesis, the results indicate that under a wide variety of sampling conditions, performance-matched Jones or modified-Jones models are well specified when testing for discretionary accruals over a one-year horizon. As expected on the basis of previous research, the Jones and modified-Jones models, with or without an adjustment for industry mean or median performance, are severely misspecified. The misspecification leading to Type I errors is apparent primarily in tests of negative discretionary accruals, whereas under-rejection frequently occurs when testing for positive discretionary accruals.

**5. The power of performance-matched discretionary accrual measures**

Table 4 summarizes the results of comparing the power of the Jones and modified-Jones models with and without performance matching. We report rejection frequencies for random and stratified-random samples of 100 firms with plus/minus 1%, 2%, 4%, or 10% accrual added to each firm's estimated discretionary accrual. The percentage accrual added to the data is accrual as a percentage of the firm's total assets. For each sample the indicated seed level is added to total accruals before estimating the respective discretionary accrual models. We assume that half of the abnormal accrual arises from credit sales and also add half of the seed to the change in sales and change in accounts receivable before estimating the discretionary accrual models.

Three main conclusions emerge from the results in table 4. First, performance-matched models' power is lower than the Jones and modified-Jones models. This result is not surprising because descriptive statistics in table 1 show that performance-matched discretionary accruals are more variable than those without performance matching. However, the *apparently* higher power of the Jones and modified-Jones models (e.g., in case of low earnings and cash flow yield and low sales growth samples) is misleading because these models are not well specified under the null hypothesis in that rejection rates are excessive (i.e., significantly exceed the 5% level of the test). For example, the Jones model's rejection rate for samples from the low operating cash flow quartile firms increases from 61.6% without any accrual added (i.e., under the null) to 90.4% when 2% accrual is added to the sample firms. Finally, using samples of 100 firms, performance-matched models would detect negative discretionary accrual of 2% about 20% to 60% of the time and of 4% discretionary accrual 35% to 90% of the time depending upon the stratified-random sample being examined.

**[Table 4]**

## *6.* Sensitivity analyses

We perform a variety of additional tests. These tests confirm the main conclusion that performance matching improves test statistic specification. Below we briefly summarize the motivation for and main findings from those tests.

### 6.1 Sample size

Many earnings management studies estimate average discretionary accruals for fairly large samples (e.g., over 1,000 in tests of earnings management in the initial public offerings studies like Teoh et al., 1998b). We therefore examine specification and power using samples of 200 and 300 firms. In general, misspecification is exacerbated in larger samples using all the models applied to stratified-random samples, with very high rejection rates under the null hypothesis for the Jones- and modified-Jones models. The results also indicate (not surprisingly) that the power of the test rises quite rapidly with sample size (e.g., with 300 firm samples the rejection rates approach 100% for performance-matched samples).[15] Overall, and consistent with results reported above, the performance-matched accrual measures remain the preferred measure of choice in these larger samples.

### 6.2 Multi-year horizon

Since many earnings management studies examine accrual behavior over multi-year horizons (e.g., Teoh et al., 1998a and 1998b), we study specification and power of performance-matched discretionary accrual measures over three- and five-year horizons. We obtain

[15] The increase in power with sample size suggests the cross-sectional independence assumption underlying the t-tests is a reasonable approximation. If data were highly correlated cross-sectionally, then incremental reduction in the cross-sectional variance of discretionary accruals as a function of sample size would be small and we would not expect to observe an appreciable increase in power with increased sample size.

discretionary accruals in each of the three- and five-year periods by re-estimating the Jones- and modified-Jones models cross-sectionally every year. We then aggregate the annual discretionary accruals over multi-year periods and test whether the cumulative average discretionary accrual for each sample is significantly below or above zero using one-tailed tests. We find that the Jones- and modified-Jones models remain misspecified, but the rejection rates are less extreme than when the horizon is one year. The performance-matched discretionary accrual models continue to perform well.

### 6.3 Relaxing the within-industry restriction on Jones model estimation

To relax data availability conditions, we experiment with Jones model cross-sectional estimation using all non-financial firms, instead of within-industry estimation. We repeat the procedure using all financial firms. Simulation results using performance-matched discretionary accrual measures are similar to those using within-industry estimation procedures. Results suggest performance matching is critical, but not within-industry estimation.

### 6.4 Other discretionary accrual measures

We examine properties of numerous other discretionary accrual measures, including: (i) a firm's total accruals minus the industry median total accruals; (ii) total accruals minus the matched firm's total accruals; (iii) the Jones (and modified-Jones) model discretionary accrual minus the industry median discretionary accrual using the Jones (modified-Jones) model. All of these measures tend to perform worse than the performance matched measures.

## 7. Replication using a seasoned-equity-offerings sample

To assess the sensitivity of results in prior research to our measure of discretionary accruals, we replicate a study where performance is likely correlated with the treatment variable. In such contexts performance matching mitigates the likelihood of Type I errors. Teoh et al.

(1998a) examine discretionary accruals of firms making SEOs. They hypothesize and find that firms have incentives to make income-increasing discretionary accruals in the years leading up to an SEO. However, it seems plausible that firms in this nonrandom sample performed strongly (i.e., high ROA) in the years prior to the offering. Therefore, the observed positive discretionary accrual in the year of an SEO and subsequent reversal might be partially indicative of past performance instead of opportunistic earnings management. We replicate Teoh et al. (1998a), using our measure of performance-matched discretionary accruals to control for performance-related accruals.

For the replication, we obtain seasoned equity issues from the SDC database. These are all non-IPO equity issues for the period 1980-1998. We eliminate observations if the offering coincides with a spin off or other corporate transactions, which reduces the sample from 9,101 to 7,848. As in Teoh, et al. (1998a), we exclude SEOs from the sample if firms had additional SEOs in the six-year period surrounding the offering.[16] This shrinks the sample to 4,186. We then exclude firms for inadequate data on Compustat to estimate the Jones model, reducing the sample to 1,955 observations. Finally, we eliminate observations if both discretionary accrual measures cannot be estimated. This makes the sample identical across discretionary accrual measures. The final sample consists of 1,561 firms. Following Teoh et al. (1998a), we match on year -1 performance.

[16] This sample selection criterion might not be innocuous with respect to inferences about earnings management in the firms making seasoned equity offerings. Firms making multiple seasoned equity offerings are likely to have successfully invested the capital they raised previously and are facing additional attractive investment opportunities. That is, these are successful firms. Since multiple equity offerings could not be foreseen at the time of their first seasoned equity offering, conditioning sample selection on multiple offerings imparts a hindsight bias. The exclusion of multiple offerings from the sample of seasoned equity offering firms biases in favor of finding lack of success following equity offerings and thus creates an appearance of accrual reversal (see Kothari, 2001).

Table 5 reports discretionary accruals from event year -3 to +3. We report discretionary accruals estimated using the Jones model with and without performance matching. Because earlier results show that the biases in the modified-Jones model are correlated with sales growth, we do not report results using the modified-Jones model. The results in table 5 highlight that Teoh et al.'s inferences are sensitive to performance matching. Results without performance matching are similar to Teoh et al. (1998a) results. Thus, in spite of some differences in sample construction and time period, we reproduce the Teoh et al. (1998a) results in our data. Performance matching, however, greatly reduces the magnitude of the Jones-model discretionary accruals in the pre- and post-SEO years, but not the year of the SEO and event year +1. Discretionary accruals in event years 0 and +1 are difficult to interpret because the SEO proceeds have a large impact on accruals in these two years. For example, the proceeds may be used to acquire current assets, such as inventory, or pay off current liabilities. These activities increase accruals, but the discretionary accrual models, with or without performance matching, do not capture such increases. Therefore, they will appear discretionary. We therefore focus on discretionary accruals from event years –3 to –1 and +2 to +3. Note, however, even if year +1 were to be considered, the estimated discretionary accruals are positive, not negative, as predicted under the earnings management hypothesis.

**[Table 5]**

In event year -1, performance matching reduces the average Jones model discretionary accrual from 1.3% to 0.28% of assets. Thus, evidence of performance boosting through positive discretionary accruals in years leading up to an SEO is weakened to the point that estimated average is statistically indistinguishable from zero. The corresponding reduction in event years +2 and +3 is from –0.42% and –1.04% to 0.17% and -0.61%, both instatistically different from zero. The medians exhibit a similar pattern. Thus, instead of statistically significant reversal of accruals in the post-SEO years, the evidence suggests performance matching eliminates the appearance of the significant reversals.

In summary, our replication of Teoh et al. (1998a) shows that when performance-matched discretionary accruals are used, the pattern of positive discretionary accruals in the years leading up to SEOs reported in their study virtually disappears. Furthermore, the pattern of reversing negative discretionary accruals they report in the post-SEO period is weakened. Such results diminish our confidence in the hypothesis that firms engage in income-increasing accrual management in the years leading up to a seasoned-equity offering.

**8. Summary and implications for future research**

Researchers frequently use measures of discretionary accruals in tests for earnings management and market efficiency. Following the results in Dechow et al. (1995) and others, the Jones and modified-Jones models are the most popular choices for estimating discretionary accruals. However, previous research shows that both the Jones and modified-Jones models are severely misspecified when applied to stratified-random samples of firms (e.g., Dechow et al., 1995 and Guay et al., 1996).

We find that tests using performance-matched Jones model measures of discretionary accruals are reasonably well specified and quite powerful. We present detailed simulation evidence on the properties of alternative measures of discretionary accruals based on random and stratified-random samples. We also examine the properties of discretionary accrual models over multi-year horizons and their sensitivity to sample size. Under most circumstances, performance-matched discretionary accrual models are quite well specified. Although we observe some misspecification using the performance-matched discretionary accrual models in some stratified-random samples, on balance, performance-matched models are the most reliable from sample-to-sample in terms of Type I error rates.

Our study has important implications for future research using measures of discretionary accruals. The use of performance-matched accruals appears essential to mitigate the concern of misspecification, and therefore spurious rejection of (or failure to reject) the null hypothesis. The results also suggest that use of modified-Jones model adds little to the Jones model most of the time, and leads to misspecification in samples of firms experiencing unusually high or low sales growth.

Our study has three potential limitations. First, we ignore the consequences of the error embedded in estimated total accruals (and therefore in discretionary accruals) as a result of using the balance-sheet approach to estimating total accruals. Collins and Hribar (2002) show that the error in estimated accruals using the balance-sheet approach is correlated with firms' economic characteristics. Therefore, the error not only reduces the discretionary accrual models' power to detect earnings management, but also has the potential to generate incorrect inferences about earnings management. An interesting extension of our study would be to measure total accruals using the cash-flow statement approach advocated in Collins and Hribar (2002).

Second, while we simulate several event conditions (e.g., multi-year performance, sample size, and various stratified-random samples), our results may not generalize to research settings that we don't examine. In addition, we have made certain research design choices like cross-sectional within-industry estimation of the Jones and modified-Jones models, and re-estimation of the models each year as we examine a multi-year horizon that may not be appropriate in all accounting research settings.

Finally, while we find that tests using performance-matched measures do not over-reject the null of zero discretionary accruals even in stratified-random samples, we cannot be sure that this necessarily indicates that the tests are well specified. Accounting theory suggests stratified-random sample firms likely engage in earnings management. Therefore, powerful tests should reject the null hypotheses in stratified-random samples. Performance-matched accrual measures inform whether the extent of discretionary accruals in stratified-random samples exceeds that in matched samples with similar performance characteristics except the treatment event.

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## Table 1
## Descriptive statistics for various discretionary accrual measures

Panel A reports the mean, standard deviation, lower quartile, median and upper quartile values for the entire sample. Panel B reports means and medians samples formed on the basis of book-to-market ratio, sales growth, earnings-to-price (EP) ratio, firm size (market value of equity) and operating cash flow. The samples in Panel B are from the lower and upper quartiles of the firms ranked on each variable (e.g., book/market, past sales growth, etc.). The performance-matched discretionary accrual measures are constructed by matching each treatment firm with a control firm based on return on assets in period t or t-1. Firm-year accrual observations are from the COMPUSTAT Industrial Annual and Research files from 1963 through 1999. We exclude observations if they do not have sufficient data to construct the accrual measures or if the absolute value of total accruals scaled by total assets exceeds one. We eliminate observations where there are fewer than ten observations in a two-digit industry code for a given year. All discretionary accrual measures are reported as a percent of total assets and all variables are winsorized at the 1st and 99th percentiles. The final sample size is 122,798.

**Panel A. Descriptive Statistics for Discretionary Accrual Measures:**[a]

| Description | Mean | STD | Q1 | Med | Q3 |
|---|---|---|---|---|---|
| Total Accruals | -3.03 | 11.62 | -8.40 | -3.46 | 1.87 |
| Jones Model | -0.39 | 10.11 | -4.79 | -0.10 | 4.21 |
| Modified Jones Model | -0.33 | 10.45 | -4.89 | -0.13 | 4.30 |
| Jones Model with ROA | -0.51 | 9.78 | -4.96 | -0.31 | 3.95 |
| Modified Jones Model with ROA | -0.49 | 10.05 | -5.08 | -0.37 | 4.00 |
| Performance-Matched Jones Model t-1 | 0.08 | 14.54 | -6.90 | 0.05 | 7.10 |
| Performance-Matched Jones Model t | -0.02 | 15.67 | -7.35 | 0.00 | 7.33 |
| Performance-Matched Modified Jones Model t-1 | 0.09 | 14.97 | -7.10 | 0.04 | 7.30 |
| Performance-Matched Modified Jones Model t | -0.02 | 16.11 | -7.50 | 0.00 | 7.47 |

**Panel B. Means (Medians) of Discretionary Accrual Measures for Stratified-Random Sub-Samples:**[a]

| | **Book/Market** | | **Sales Growth** | | **E/P Ratio** | | **Size** | | **Operating Cash Flow** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Description** | **Value** | **Growth** | **High** | **Low** | **High** | **Low** | **Large** | **Small** | **High** | **Low** |
| Total Accruals | -3.54 | -3.95 | 1.31 | -7.68 | -1.33 | -8.63 | -3.18 | -5.15 | -0.29 | -7.55 |
| | (-3.63) | (-3.9) | (-0.23) | (-6.5) | (-2.33) | (-7.83) | (-3.77) | (-4.7) | (-1.34) | (-7.34) |
| Jones Model | -0.34 | -1.64 | 0.11 | -1.51 | 0.32 | -3.73 | -0.04 | -1.76 | 0.13 | -2.98 |
| | (-0.09) | (-0.92) | (-0.04) | (-0.62) | (0.25) | (-2.76) | (0.05) | (-1.1) | (0.1) | (-2.4) |
| Modified Jones Model | -0.53 | -1.42 | 1.26 | -2.38 | 0.46 | -4.14 | 0.11 | -2.08 | 0.68 | -3.33 |
| | (-0.24) | (-0.81) | (0.75) | (-1.3) | (0.26) | (-3.13) | (0.07) | (-1.41) | (0.39) | (-2.74) |
| Jones Model with ROA | -0.34 | -1.41 | 0.12 | -1.31 | -0.31 | -2.30 | -0.47 | -1.62 | -1.15 | -1.55 |
| | (-0.09) | (-1.06) | (-0.08) | (-0.66) | (-0.13) | (-1.62) | (-0.28) | (-1.09) | (-1.03) | (-1.2) |
| Modified Jones Model with ROA | -0.49 | -1.20 | 1.20 | -2.12 | -0.32 | -2.47 | -0.39 | -1.90 | -0.91 | -1.66 |
| | (-0.22) | (-1.03) | (0.65) | (-1.32) | (-0.21) | (-1.79) | (-0.32) | (-1.34) | (-1.02) | (-1.37) |
| Performance-Matched Jones Model t-1 | 0.46 | -0.72 | 0.70 | -0.51 | 0.14 | -1.62 | -0.27 | -0.34 | -0.83 | -0.80 |
| | (0.29) | (-0.51) | (0.4) | (-0.1) | (0.03) | (-1.24) | (-0.09) | (-0.17) | (-0.53) | (-0.72) |
| Performance-Matched Jones Model t | -0.16 | -0.20 | 0.53 | -0.01 | -0.29 | -0.17 | -0.88 | -0.12 | -1.22 | 1.00 |
| | (0.00) | (-0.12) | (0.22) | (0.15) | (-0.01) | (-0.12) | (-0.31) | (0.01) | (-0.7) | (0.65) |
| Performance-Matched Modified Jones Model t-1 | 0.32 | -0.61 | 1.76 | -1.37 | 0.20 | -1.93 | -0.22 | -0.59 | -0.55 | -1.05 |
| | (0.22) | (-0.41) | (1.22) | (-0.77) | (0.06) | (-1.49) | (-0.06) | (-0.39) | (-0.31) | (-0.97) |
| Performance-Matched Modified Jones Model t | -0.26 | -0.10 | 1.48 | -0.78 | -0.39 | -0.21 | -0.92 | -0.31 | -1.29 | 1.06 |
| | (0.00) | (-0.07) | (1.01) | (-0.37) | (-0.07) | (-0.15) | (-0.33) | (-0.15) | (-0.78) | (0.69) |

[a] Total Accruals ($TA_{it}$) is defined as the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt minus depreciation and amortization [with reference to COMPUSTAT data items, TA = (ΔData4 - ΔData1 - ΔData5 + ΔData34 - Data14)/lagged Data6]. Cross sectional within-industry discretionary accruals are the residuals from the Jones, Modified-Jones model, Jones model including ROA as an additional regressor and Modified-Jones model including ROA, respectively. Discretionary accruals from the Jones model are estimated for each industry and year as follows: $TA_{i,t} = \alpha_0/ASSETS_{i,t-1} + \alpha_1\Delta SALES_{i,t} + \alpha_2 PPE_{i,t} + \varepsilon_{i,t}$ , where $\Delta SALES_{i,t}$ is change in sales scaled by lagged total assets and $PPE_{i,t}$ is net property, plant and equipment scaled by lagged assets. Discretionary accruals from the modified-Jones model are estimated for each industry and year as for the Jones model except that the change in accounts receivable is subtracted from the change in sales. Discretionary accruals from the Jones Model (Modified-Jones Model) with ROA are similar to the Jones Model (Modified-Jones Model) except for the inclusion of lagged ROA as an additional explanatory variable in the model.

For performance matched discretionary accruals, we match firms on ROA in period t and on t-1. To obtain a performance-matched Jones model discretionary accrual for firm i we subtract the Jones model discretionary accrual of the firm with the closest ROA that is in the same industry as firm i. A similar approach is used for the modified Jones model.

**Table 2**

**Serial correlation in return on assets (ROA), total accruals and various discretionary accrual measures for the entire sample and select subsamples. Sample period is 1963-1999**

The table reports the mean value of the slope coefficient of the following annual regression: $X_{it} = \alpha + \beta X_{it-1} + \varepsilon_{it}$, where $X_{it}$ ($X_{it-1}$) is the value (lagged value) of the particular variable of interest. $X_{it}$ is ROA, Total Accruals, Jones Model Discretionary Accruals, Modified-Jones Model Discretionary Accruals, Performance-Matched Jones Model Accruals or Performance-Matched Modified-Jones Model Accruals. Results are reported for the full sample (All Firms) and select subsamples based on several financial performance measures (e.g., book-to-market, sales growth, earnings-to-price ratio, firm size and operating cash flow). The performance-matched discretionary accrual measures are constructed by precision matching each treatment firm to a control firm based on return on assets in period t or t-1. Firm-year accrual observations are constructed from the COMPUSTAT Industrial Annual and Research files from 1963 through 1999. We exclude observations if they do not have sufficient data to construct the accrual measures described below or if the absolute value of total accruals scaled by total assets is greater than one. We eliminate observations where there are fewer than ten observations in a two-digit industry code for a given year. All variables are winsorized at the 1st and 99th percentiles. The final sample size is 122,798.

| | All Firms | Book/Market | | Sales Growth | | E/P Ratio | | Size | | Cash Flows | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Description**[a] | | **Value** | **Growth** | **High** | **Low** | **High** | **Low** | **Large** | **Small** | **High** | **Low** |
| ROA | 0.738 ** | 0.549 ** | 0.779 ** | 0.687 ** | 0.664 ** | 0.411 ** | 0.428 ** | 0.763 ** | 0.661 ** | 0.361 ** | 0.402 ** |
| Total Accruals | 0.189 ** | 0.055 ** | 0.244 ** | 0.275 ** | 0.029 | 0.116 ** | 0.020 | 0.353 ** | 0.097 ** | 0.292 ** | 0.019 |
| Jones Model Accruals | 0.009 | -0.053 ** | 0.050 | -0.038 | -0.105 ** | -0.058 ** | -0.077 ** | 0.138 ** | -0.087 ** | 0.072 ** | -0.093 ** |
| Modifed Jones Model Accruals | 0.023 ** | -0.047 ** | 0.072 * | -0.133 | -0.115 * | -0.049 ** | -0.064 ** | 0.149 ** | -0.074 * | 0.086 ** | -0.080 ** |
| Performance-Matched Jones t-1 | -0.019 ** | -0.037 ** | -0.029 | 0.017 | -0.057 ** | -0.050 ** | -0.083 ** | 0.034 ** | -0.029 | 0.006 | -0.090 ** |
| Performance-Matched Jones t | -0.004 | -0.041 * | -0.002 | 0.000 | -0.053 ** | -0.035 * | -0.060 ** | 0.085 * | -0.045 ** | 0.029 | -0.040 ** |
| Performance-Matched Modified Jones t-1 | -0.016 ** | -0.037 ** | -0.023 | 0.008 | -0.066 ** | -0.050 ** | -0.079 ** | 0.038 ** | -0.026 | 0.011 | -0.084 ** |
| Performance-Matched Modified Jones t | 0.000 | -0.039 * | 0.010 | 0.008 | -0.049 ** | -0.029 * | -0.058 ** | 0.083 * | -0.042 ** | 0.035 * | -0.042 ** |

[a] Return on Assets (ROA) is net income (COMPUSTAT data item 18) scaled by lagged total assets. Total accruals is defined as the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt minus depreciation and amortization [with reference to COMPUSTAT data items, TA = (ΔData4 - ΔData1 - ΔData5 + ΔData34 - Data14)/lagged Data6].

Cross sectional within-industry discretionary accruals are the residuals from the Jones and Modified Jones models, respectively. Discretionary accruals from the Jones model are estimated for each industry and year as follows: $TA_{i,t} = \alpha_0/ASSETS_{i,t-1} + \alpha_1 \Delta SALES_{i,t} + \alpha_2 PPE_{i,t} + \varepsilon_{i,t}$ , where $TA_{it}$ (Total Accruals) is as defined above, $\Delta SALES_{i,t}$ is change in sales scaled by lagged total assets ($ASSETS_{i,t-1}$), and $PPE_{i,t}$ is net property, plant and equipment scaled by $ASSETS_{i,t-1}$. Discretionary accruals from the Modified-Jones model are estimated for each industry and year as for the Jones model except that the change in accounts receivable is subtracted from the change in sales. For performance matched discretionary accruals, we match firms on ROA in period t and on t-1. To obtain a performance-matched Jones model discretionary accrual for firm i we subtract the Jones model discretionary accrual of the firm with the closest ROA that is in the same industry as firm i. A similar approach is used for the modified Jones model.

**, * denotes that t-statitics are significant at .01 and .05, respectively. t-tests are adjusted for autocorrelation using the Newey-West (1987) correction with 5 lags.

**Table 3**

**Type I error rates of discretionary accrual measures for the full sample and upper and lower quartiles of subsamples formed on the basis of select financial characteristics (book-to-market ratio, sales growth, earnings-to-price (EP) ratio, firm size and operating cash flow)**

The table reports the percentage of 250 samples of 100 firms each where the null hypothesis of zero discretionary accruals is rejected at the 5% level (upper and lower one-tailed tests). The significance of the mean discretionary accrual in each of the 250 random samples is based on a cross-sectional t-test. For comparison purposes, we report performance-matched discretionary accrual measures that are constructed by matching each treatment firm with a control firm based on return on assets in period t or t-1. Firm-year accrual observations are constructed from the COMPUSTAT Industrial Annual and Research files from 1963 through 1999. We exclude observations if they do not have sufficient data to construct the accrual measures described below or if the absolute value of total accruals scaled by total assets is greater than one. We eliminate observations where there are fewer than ten observations in a two-digit industry code for a given year. All variables are winsorized at the 1st and 99th percentiles. The final sample size is 122,798.

**Panel A. $H_A$: Accruals < 0[a]**

| | All Firms | Book-to-Market | | Sales Growth | | EP Ratio | | Size | | Op. Cash Flow | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Value | Growth | High | Low | High | Low | Large | Small | High | Low |
| **Jones Model** | | | | | | | | | | | |
| Cross sectional within-industry | 7.6 | 10.4 | 29.2 | 1.6 | 33.6 | 2.8 | 84.8 | 4.8 | 34.4 | 4.8 | 61.6 |
| ROA included as a regressor | 6.0 | 7.6 | 21.2 | 1.2 | 28.0 | 3.2 | 59.2 | 14.4 | 24.4 | 16.4 | 37.6 |
| Performance matched on ROA at t-1 | 3.6 | 1.2 | 13.6 | 1.2 | 8.8 | 4.0 | 18.4 | 10.0 | 9.6 | 12.4 | 10.0 |
| Performance matched on ROA at t | 7.6 | 5.2 | 6.0 | 2.8 | 3.6 | 6.8 | 7.2 | 16.8 | 5.2 | 20.0 | 0.4 |
| **Modified Jones Model** | | | | | | | | | | | |
| Cross sectional within-industry | 8.4 | 16.4 | 24.0 | 0.0 | 70.4 | 1.2 | 88.4 | 3.2 | 44.4 | 1.2 | 68.0 |
| ROA included as a regressor | 6.0 | 10.8 | 16.8 | 0.0 | 60.8 | 2.8 | 66.0 | 9.2 | 27.2 | 8.0 | 40.8 |
| Performance matched on ROA at t-1 | 3.6 | 2.0 | 12.4 | 0.0 | 21.2 | 2.8 | 21.6 | 8.4 | 12.0 | 10.8 | 11.6 |
| Performance matched on ROA at t | 6.0 | 6.4 | 4.8 | 0.8 | 9.2 | 8.0 | 7.2 | 16.0 | 6.8 | 19.6 | 1.6 |

| Panel B. $H_A$: Accruals > 0[a] | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Book-to-Market | | Sales Growth | | EP Ratio | | Size | | Op. Cash Flow | |
| | All Firms | Value | Growth | High | Low | High | Low | Large | Small | High | Low |
| **Jones Model rejection frequencies** | | | | | | | | | | | |
| Cross sectional within-industry | 4.8 | 2.4 | 0.4 | 6.8 | 0.4 | 10.4 | 0.0 | 3.6 | 0.0 | 9.6 | 0.0 |
| ROA included as a regressor | 5.2 | 4.0 | 0.8 | 7.6 | 0.4 | 6.0 | 0.0 | 0.8 | 0.8 | 0.8 | 0.0 |
| Performance matched on ROA at t-1 | 7.2 | 6.8 | 0.8 | 9.2 | 2.8 | 5.6 | 0.0 | 3.2 | 3.6 | 1.6 | 2.0 |
| Performance matched on ROA at t | 5.2 | 5.2 | 3.6 | 9.2 | 5.6 | 2.8 | 3.6 | 0.4 | 4.8 | 0.4 | 7.6 |
| **Modified Jones Model rejection frequencies** | | | | | | | | | | | |
| Cross sectional within-industry | 5.2 | 1.6 | 0.4 | 24.8 | 0.0 | 12.4 | 0.0 | 4.8 | 0.0 | 22.0 | 0.0 |
| ROA included as a regressor | 6.0 | 3.6 | 0.8 | 32.4 | 0.0 | 7.6 | 0.0 | 1.6 | 0.4 | 3.2 | 0.0 |
| Performance matched on ROA at t-1 | 7.2 | 6.4 | 1.6 | 23.2 | 1.6 | 5.6 | 0.0 | 2.8 | 2.0 | 2.8 | 1.2 |
| Performance matched on ROA at t | 5.6 | 4.4 | 5.2 | 16.4 | 2.8 | 2.4 | 3.6 | 0.4 | 3.2 | 0.0 | 8.4 |

[a] Cross-sectional within-industry discretionary accruals are the residuals from the Jones and modified Jones models, respectively. Discretionary accruals from the Jones model are estimated for each industry and year as follows: $TA_{i,t} = \alpha_0/ASSETS_{i,t-1} + \alpha_1\Delta SALES_{i,t} + \alpha_2 PPE_{i,t} + \varepsilon_{i,t}$, where $TA_{it}$ (Total Accruals) is defined as the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt minus depreciation and amortization [with reference to COMPUSTAT data items, TA = (ΔData4 - ΔData1 -ΔData5 + ΔData34 - Data14)/lagged Data6], $\Delta SALES_{i,t}$ is change in sales scaled by lagged total assets ($ASSETS_{i,t-1}$), and $PPE_{i,t}$ is net property, plant and equipment scaled by $ASSETS_{i,t-1}$. Discretionary accruals from the modified-Jones model are estimated for each industry and year as for the Jones model except that the change in accounts receivable is subtracted from the change in sales. Discretionary accruals from the Jones Model (Modified-Jones Model) with ROA are estimated similar to the Jones Model (Modified-Jones Model) except for the inclusion of lagged ROA as an additional explanatory variable in the accruals regression.

For performance matched discretionary accruals, we match firms on ROA in period t and on t-1. To obtain a performance-matched Jones model discretionary accrual for firm i we subtract the Jones model discretionary accrual of the firm with the closest ROA that is in the same industry as firm i. A similar approach is used for the modified Jones model. .

**Table 4**

**A comparison of the power of alternative discretionary accrual models**

For each sample the indicated seed level is added to total accruals before estimating the respective discretionary accrual models. We assume that half of the abnormal accrual arises from credit sales and also add half of the seed to the change in sales and change in accounts receivable before estimating the discretionary accrual models. The table reports the percentage of 250 samples of 100 firms each where the null hypothesis of zero discretionary accruals is rejected at the 5% level (upper and lower one-tailed tests). The significance of the mean discretionary accrual of each sample is based on a cross-sectional t-test. The performance-matched discretionary accrual measures are constructed by precision matching each treatment firm with a control firm based on return on assets in period t-1. Firm-year accrual observations are constructed from the COMPUSTAT Industrial Annual and Research files from 1963 through 1999. We exclude observations if they do not have sufficient data to construct the accrual measures or if the absolute value of total accruals scaled by total assets is greater than one. We eliminate observations where there are fewer than ten observations in a two-digit industry code for a given year. All variables are winsorized at the 1st and 99th percentiles. The final sample size is 122,798.

**Panel A: $H_A$: Accruals < 0**

| Seeded Abnormal Accrual | All Firms | Book-to-Market | | Sales Growth | | EP Ratio | | Size | | Operating Cash Flow | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Value | Growth | High | Low | High | Low | Large | Small | High | Low |
| **Performance-Matched Jones Model Accrual** | | | | | | | | | | | |
| 0% | 3.6 | 1.2 | 13.6 | 1.2 | 8.8 | 4.0 | 18.4 | 10.0 | 9.6 | 12.4 | 10.0 |
| -1% | 12.0 | 10.4 | 17.2 | 4.4 | 21.6 | 13.6 | 34.8 | 24.8 | 15.2 | 24.0 | 18.8 |
| -2% | 33.6 | 32.0 | 27.6 | 17.6 | 41.2 | 34.8 | 55.6 | 60.4 | 31.6 | 47.6 | 27.6 |
| -4% | 68.4 | 80.0 | 66.0 | 34.4 | 72.4 | 80.4 | 79.6 | 91.2 | 65.2 | 87.2 | 61.6 |
| -10% | 100.0 | 100.0 | 98.4 | 98.8 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 98.0 |
| **Jones Model Accrual** | | | | | | | | | | | |
| 0% | 7.6 | 10.4 | 29.2 | 1.6 | 33.6 | 2.8 | 84.8 | 4.8 | 34.4 | 4.8 | 61.6 |
| -1% | 27.6 | 36.8 | 50.4 | 12.4 | 64.8 | 14.4 | 90.0 | 37.6 | 58.0 | 14.0 | 73.2 |
| -2% | 65.2 | 78.4 | 62.0 | 24.4 | 83.6 | 46.0 | 99.2 | 80.4 | 79.6 | 38.4 | 90.4 |
| -4% | 94.0 | 99.6 | 92.4 | 59.6 | 97.2 | 92.8 | 100.0 | 99.6 | 95.6 | 85.6 | 97.6 |
| -10% | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| **Performance-Matched Modifed-Jones Model Accrual** | | | | | | | | | | | |
| 0% | 3.6 | 2.0 | 12.4 | 0.0 | 21.2 | 2.8 | 21.6 | 8.4 | 12.0 | 10.8 | 11.6 |
| -1% | 13.6 | 12.0 | 14.8 | 2.4 | 37.6 | 12.0 | 38.8 | 24.0 | 18.0 | 20.0 | 22.0 |
| -2% | 34.0 | 35.2 | 24.8 | 4.4 | 58.4 | 34.0 | 60.4 | 56.4 | 36.0 | 43.6 | 32.4 |
| -4% | 70.0 | 83.6 | 63.2 | 17.6 | 88.8 | 80.4 | 84.8 | 91.2 | 70.8 | 81.6 | 68.8 |
| -10% | 100.0 | 100.0 | 98.4 | 96.8 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 98.0 |
| **Modifed-Jones Model Accrual** | | | | | | | | | | | |
| 0% | 8.4 | 16.4 | 24.0 | 0.0 | 70.4 | 1.2 | 88.4 | 3.2 | 44.4 | 1.2 | 68.0 |
| -1% | 27.2 | 42.4 | 43.6 | 2.4 | 84.0 | 12.0 | 93.2 | 28.0 | 64.0 | 6.0 | 77.2 |
| -2% | 62.0 | 87.2 | 56.4 | 9.2 | 96.0 | 40.8 | 99.6 | 72.8 | 84.0 | 22.8 | 93.2 |
| -4% | 93.6 | 100.0 | 90.4 | 37.6 | 98.8 | 91.2 | 100.0 | 99.2 | 98.0 | 75.2 | 98.0 |
| -10% | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

| Panel B: $H_A$: Accruals > 0 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Seeded Abnormal Accrual | All Firms | Book-to-Market | | Sales Growth | | EP Ratio | | Size | | Operating Cash Flow | |
| | | Value | Growth | High | Low | High | Low | Large | Small | High | Low |
| **Performance-Matched Jones Model Accrual** | | | | | | | | | | | |
| 0% | 7.2 | 6.8 | 0.8 | 9.2 | 2.8 | 5.6 | 0.0 | 3.2 | 3.6 | 1.6 | 2.0 |
| 1% | 17.2 | 25.2 | 2.4 | 16.4 | 6.0 | 20.4 | 3.2 | 12.8 | 8.8 | 7.2 | 7.6 |
| 2% | 34.0 | 48.8 | 11.6 | 30.0 | 18.8 | 48.0 | 5.6 | 36.8 | 16.4 | 12.4 | 10.8 |
| 4% | 72.4 | 90.0 | 37.6 | 63.2 | 55.2 | 89.6 | 24.0 | 85.2 | 45.2 | 52.4 | 38.0 |
| 10% | 100 | 100 | 96.8 | 100 | 99.6 | 100 | 96.8 | 100 | 99.6 | 99.2 | 98.0 |
| **Jones Model Accrual** | | | | | | | | | | | |
| 0% | 4.8 | 2.4 | 0.4 | 6.8 | 0.4 | 10.4 | 0.0 | 3.6 | 0.0 | 9.6 | 0.0 |
| 1% | 15.6 | 16.4 | 1.6 | 14.4 | 1.6 | 40.0 | 0.0 | 26.8 | 0.8 | 27.6 | 0.0 |
| 2% | 38.0 | 45.6 | 5.6 | 33.6 | 8.0 | 76.4 | 0.0 | 76.4 | 5.6 | 49.2 | 1.6 |
| 4% | 80.8 | 94.0 | 30.8 | 69.6 | 52.8 | 99.2 | 4.8 | 99.6 | 31.6 | 92.8 | 11.6 |
| 10% | 100 | 100 | 99.6 | 100 | 100 | 100 | 95.2 | 100 | 99.6 | 100 | 97.6 |
| **Performance-Matched Modifed-Jones Model Accrual** | | | | | | | | | | | |
| 0% | 7.2 | 6.4 | 1.6 | 23.2 | 1.6 | 5.6 | 0.0 | 2.8 | 2.0 | 2.8 | 1.2 |
| 1% | 17.2 | 21.2 | 4.0 | 32.4 | 2.8 | 19.6 | 2.8 | 12.8 | 6.8 | 10.4 | 6.4 |
| 2% | 33.6 | 45.2 | 12.0 | 46.0 | 7.6 | 51.6 | 5.6 | 40.0 | 13.6 | 16.4 | 10.0 |
| 4% | 74.0 | 89.2 | 40.4 | 77.6 | 36.4 | 90.8 | 19.6 | 85.6 | 40.0 | 58.0 | 32.8 |
| 10% | 100 | 100 | 97.2 | 100 | 99.6 | 100 | 96.4 | 100 | 99.2 | 100 | 97.2 |
| **Modifed-Jones Model Accrual** | | | | | | | | | | | |
| 0% | 5.2 | 1.6 | 0.4 | 24.8 | 0.0 | 12.4 | 0.0 | 4.8 | 0.0 | 22.0 | 0.0 |
| 1% | 13.2 | 12.0 | 2.0 | 38.4 | 0.0 | 44.8 | 0.0 | 34.8 | 0.0 | 46.4 | 0.0 |
| 2% | 37.6 | 40.4 | 8.4 | 60.4 | 2.0 | 81.2 | 0.0 | 81.2 | 4.0 | 64.8 | 0.8 |
| 4% | 82.4 | 92.4 | 35.6 | 87.6 | 28.4 | 100 | 3.6 | 99.6 | 24.8 | 96.0 | 8.8 |
| 10% | 5.2 | 1.6 | 0.4 | 24.8 | 0.0 | 12.4 | 0.0 | 4.8 | 0.0 | 22.0 | 0.0 |

[a] Discretionary accruals from the Jones model are estimated for each industry and year as follows: $TA_{i,t} = \alpha_0/ASSETS_{i,t-1} + \alpha_1\Delta SALES_{i,t} + \alpha_2 PPE_{i,t} + \varepsilon_{i,t}$, where $TA_{it}$ is defined as the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt minus depreciation and amortization [with reference to COMPUSTAT data items, TA = (ΔData4 - ΔData1 - ΔData5 + ΔData34 - Data14)/lagged Data6]. $\Delta SALES_{i,t}$ is change in sales scaled by lagged total assets ($ASSETS_{i,t-1}$), and $PPE_{i,t}$ is net property, plant and equipment scaled by $ASSETS_{i,t-1}$. Discretionary accruals from the modified-Jones model are estimated for each industry and year as for the Jones model except that the change in accounts receivable is subtracted from the change in sales. To calculate a performance-matched Jones model discretionary accrual for firm i we subtract the Jones-model discretionary accrual of the firm with the closest return-on-assets in the same industry as firm i. Matching is based on return-on-assets in year t-1.

## Table 5

### Discretionary Accruals in Event Time for Firms Making Seasoned Equity Offers from 1980-1998

Seasoned Equity Offers (SEOs) are identified from the Securities Data Corporation (SDC) database. All non-IPO equity issues are obtained for the period 1980-1998. Observations are eliminated if the offering coincides with a spin off or another financing transaction. This reduces the sample from 9,101 to 7,848. SEOs are also excluded from the sample if firms had additional SEOs in the six-year period surrounding the offering (4,186) or if there is inadequate data on COMPUSTAT to estimate the Jones model. We also eliminate observations where any one of the four discretionary measures used below cannot be estimated. The resulting sample is 1,561 SEO firms. All variables are winsorized at the 1st and 99th percentiles and are reported as a percent of total assets.[a]

| Event year | -3 | | -2 | | -1 | | 0 | | +1 | | +2 | | +3 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Jones model discretionary accruals in % of assets** | | | | | | | | | | | | | | |
| Median | 0.24 | | 0.32 | ## | 0.48 | ### | 1.32 | ### | 0.73 | ### | -0.26 | | -0.45 | ### |
| Mean | 0.68 | * | 1.31 | *** | 1.30 | *** | 2.69 | *** | 0.81 | *** | -0.42 | | -1.04 | *** |
| Standard Error | 0.39 | | 0.37 | | 0.36 | | 0.35 | | 0.31 | | 0.28 | | 0.31 | |
| **Performance matched Jones model discretionary accruals in % of assets** | | | | | | | | | | | | | | |
| Median | 0.00 | | 0.43 | # | -0.19 | | 1.91 | ### | 0.53 | ## | -0.18 | | -0.05 | |
| Mean | 0.55 | | 1.05 | ** | 0.28 | | 2.62 | *** | 0.98 | ** | 0.17 | | -0.61 | |
| Standard Error | 0.54 | | 0.52 | | 0.49 | | 0.47 | | 0.44 | | 0.43 | | 0.47 | |
| **N** | **928** | | **1,141** | | **1,519** | | **1,561** | | **1,392** | | **1,211** | | **1,043** | |

[a] Cross sectional within-industry discretionary accruals are the residuals from the Jones model. Discretionary accruals from the Jones model are estimated for each industry and year as follows: $TA_{i,t} = \alpha_0/ASSETS_{i,t-1} + \alpha_1 \Delta SALES_{i,t} + \alpha_2 PPE_{i,t} + \varepsilon_{i,t}$, where $TA_{it}$ is defined as the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt minus depreciation and amortization [with reference to COMPUSTAT data items, TA = (ΔData4 - ΔData1 - ΔData5 + ΔData34 - Data14)/lagged Data6], $\Delta SALES_{i,t}$ is change in sales scaled by lagged total assets ($ASSETS_{i,t-1}$), and $PPE_{i,t}$ is net property, plant and equipment scaled by $ASSETS_{i,t-1}$. To calculate the performance-matched Jones model discretionary accrual for firm i we subtract the Jones-model discretionary accrual of the firm with the closest return-on-assets that is in the same industry as firm i. Matching is based on return-on-assets in year t-1.

***, **, * Based on a t-test, means are significant at the 0.01, 0.05 and 0.10 level.

###, ##, # Based on Wilcoxon test, medians are significant at the 0.01, 0.05 and 0.10 level.