Performance Matched Discretionary Accrual Measures

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Abstract

Using discretionary accruals to test for earnings management and market efficiency is commonplace in the literature. We develop a well-specified (rejects the null hypothesis, when it's true, at the test's nominal significance level) and powerful (rejects a false null hypothesis with high probability) measure of discretionary accruals. A key feature of the discretionary accrual measure is that it is adjusted for the accrual performance of a matched firm where matching is on the basis of return on assets and industry. We advocate matching to control for the impact of performance on accruals. Our results suggest that performance matching is crucial to the design of well-specified tests based on discretionary accruals. Researchers will be able to draw more reliable inferences if they use a performance-matched discretionary accrual measure as proposed in this study.

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, Teoh, Welch, and Wong, 1998a and 1998b, and Kothari, 2001). In an influential study examining the specification and power of commonly used discretionary-accrual models, Dechow, Sloan, and Sweeney (1995, p. 193) conclude that "all models reject the null hypothesis of no earnings management at rates exceeding the specified test levels when applied to samples of firms with extreme financial performance." Unfortunately, there has been little research since Dechow et al. (1995) on the properties of discretionary accrual models. Furthermore, and notwithstanding their conclusion above, the discretionary accrual models identified as misspecified continue to be used in research examining non-random samples (i.e., samples that firms self-select into by, for example, changing auditors).

Our objective in this paper is to develop a discretionary-accrual estimation approach that is both well specified and powerful. 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 for the past year and industry membership.

Our results suggest that performance matching is crucial to designing well-specified tests of earnings management. The critical importance of controlling for the effect of past performance in tests of earnings management is not surprising. The simple model of earnings, cash flows, and accruals in Dechow, Kothari, and Watts (1998) 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 mean reversion or momentum (i.e., performance is not a random walk), then forecasted accruals would be non-zero. Firms with high growth opportunities often exhibit persistent growth patterns and accounting conservatism can produce earnings persistence 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 non-random samples of firms might be systematically non-zero.

The correlation between performance and accruals is problematic in tests of earnings management because commonly used discretionary accrual models (e.g., the Jones and modified-Jones models) are severely mis-specified when applied to samples experiencing non-random performance (see Dechow, et al., 1995). Previous research therefore recommends and 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. To do 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 develop a control for prior performance by using a performance-matched firm's discretionary accrual. Using a performance-matched firm's discretionary accrual does not impose any 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 unspecified impact of performance on accruals is identical for the test and matched control samples. Results below suggest that tests using a performance-matched companion portfolio approach to estimate discretionary accruals are better specified than those using a regression-based approach (which imposes a linear functional form) to control for the effect of past performance on future accruals.

We also study discretionary accrual models' properties over multi-year horizons, for a range of sample sizes, and for many types of non-random samples (e.g., large vs. small firms, growth versus value stocks, high vs. low earnings yield stocks, high vs. low past sales growth, etc.) and with and without controlling for potential survivorship biases. These features are designed to mimic characteristics of typical research studies in accounting. Previous research (e.g., Dechow et al., 1995, and Guay, Kothari, and Watts, 1996) does not simulate test conditions like multi-year horizons, different sample sizes, or survivorship biases. Nor does it systematically examine properties of discretionary accruals adjusted for performance-matched firms' discretionary 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), 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).

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 quite well specified. We label these as performance-matched discretionary accruals. Performance matching is on the basis of industry and past year's return on assets.[1] Performance-matched discretionary accruals exhibit only a modest degree of mis-specification in certain non-random samples, but otherwise tests using them perform quite well. We reach this conclusion on the basis of analyzing random as well as non-random samples of firms, one- and multi-year measurement intervals, a wide range of sample sizes, and tests for both positive and negative discretionary accruals. We, however, caution the reader that non-random sample firms might be engaging in earnings management for contracting, political, and capital market reasons. Therefore, the well-specified rejection rate of the performance-matched approach might in fact indicate under-rejection of the null hypothesis (see Guay et al., 1996). Our result that performance-matched measures are well specified is nevertheless 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). Performance-matched 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 non-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 abnormal accruals approximately 50% of the time. The rejection frequency jumps to about 90% if the discretionary accruals are 4% of assets. Our rejection rates are considerably higher than those reported in Dechow et al. (1995). We believe that differences in research design account for the differences in the rejection rates reported in their versus our study. Specifically, Dechow et al. report the

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[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.

percentage of times out of 1,000 samples of *one* firm each that the null hypothesis of no earnings management is rejected when a given level of discretionary accrual is introduced into the data. In comparison, we report rejection frequencies when sample sizes are 100 or more. Our rationale is straightforward. Invariably, researchers examine whether there is evidence of non-zero discretionary accruals, on average, in a sample of firms, not for a single firm.[2]

In contrast to Dechow et al.'s conclusion that all discretionary accrual models are misspecified and thus problematic when applied in actual research, our simulation results provide clear guidance to researchers in selecting an abnormal 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.

To provide some 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. In essence we replicate Teoh et al. (1998a) using measures of discretionary accruals (based on the Jones Model) with and without performance matching. The results clearly demonstrate that the magnitudes of discretionary accruals are substantially attenuated upon performance matching. Moreover, the inferences about the behavior of discretionary accruals around seasoned equity offerings that are drawn by Teoh et al (1998a) are not robust when performance-matched discretionary accruals are used.

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[2] Another difference between Dechow et al. and our study is that they estimate a firm-specific time-series discretionary accrual model, whereas we estimate discretionary accruals using within-industry cross-sectional models. Firm-specific estimation imposes more stringent data requirements and thus biases the sample toward large firms, which means our samples likely consist of a greater proportion of smaller firms than Dechow et al. Since small firms' accruals are more volatile, the power is expected to be lower (see our results in section 5). Therefore, the greater power in this study compared to Dechow et al. is notwithstanding the bias against such a finding due to the difference in sample selection procedures.

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 4% 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 following 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.[3] While the Jones and modified-Jones discretionary accrual models attempt to control for contemporaneous performance on non-discretionary accruals, 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

[3] 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).

(i) sales, S_t, follow a random walk, (ii) cash margin of sales is a constant percentage π, (iii) α fraction of sales are on credit, and (iv) all expenses are cash, Dechow et al. show that

$$CF_t = \pi S_t - \alpha \varepsilon_t \quad (1)$$

$$A_t = \alpha \varepsilon_t, \text{ and} \quad (2)$$

$$X_t = CF_t + \alpha \varepsilon_t = \pi S_t, \quad (3)$$

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,

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

and the forecast of future cash flows is current earnings,

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

The above analysis suggests that as long as the assumption of a random walk for sales, and therefore earnings, is descriptive of a sample of firms, forecasted accruals are zero.[4] Moreover, since a random walk in sales and earnings is a reasonable assumption for a randomly selected sample of firms (see, for example, Ball and Watts, 1972), discretionary accrual models that do not include a good control for firm performance might still be well specified and lead to valid inferences. 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 also non-zero. Forecasted sales and earnings changes can be positive or negative depending on whether the past performance is expected to be mean reverting or expected to exhibit momentum. Extreme one-time increases or

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[4] 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.

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 predictability in future accruals and 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. 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 non-random 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 that are immune to the effects of performance. In this spirit, we augment the Jones (1991) and modified-Jones discretionary models to include past return on assets. Another approach that we investigate is to adjust the Jones and modified-Jones 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.

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 non-random with respect to prior firm performance, earnings changes are predictable and their 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

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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 are likely to affect the magnitude of nondiscretionary accruals.

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 because 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 either 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 highly 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, the regression approach may be less effective at controlling for non-zero estimated discretionary accruals in non-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.

Does controlling for past performance over-correct for the problem? 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. The concern arises because matched firms in the industry might face similar incentives as the treatment firms and thus might have engaged in similar earnings management activities. While such a concern is not entirely misplaced, controlling for performance-related accruals is nevertheless warranted. In an earnings management event 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 the control firms, then the conclusion would be that the firms experiencing the event do not engage in earnings management 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 engage in earnings management. However, this is not central to the researcher's event study because the event study seeks to discern whether the event contributes to earnings management for reasons beyond other known or observable factors like past performance. Therefore, it behooves to match on performance in ascertaining whether an event influences reported earnings performance.

3. 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 non-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 statistics provide a preliminary assessment of the potential biases in the discretionary accrual models, which contribute to test misspecifications.

3.1 Sample construction

We begin with all 552,251 firm-year observations from the COMPUSTAT Industrial Annual and Research files from 1959 through 1998. From these, we exclude firm-year observations that do not have sufficient data to compute total accruals (described in section 2.2) or where the absolute value of total accruals scaled by total assets is greater than one. This reduces the sample to 172,973 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. Finally, we do not allow simulated event dates past 1993 because in one set of simulations we examine accruals over a five-year horizon (e.g., accruals from 1994-1998 for samples selected in 1993). This reduces the number of usable firm-year observations for event-date simulations to 135,332. In much of our analysis, we match firms on the basis of performance (described below). The final sample size as a result of performance matching is 94,045 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 non-random subsets of the population. The non-random subsets are firms in the lowest and highest quartiles of firms ranked on book-to-market ratio (BM), past sales growth (SG), earnings-to-price ratio (EP), and the market value of equity (Size). To construct these non-random subsets of the population, each year we rank all firm-year observations on the basis of each partitioning characteristic (e.g., BM 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 non-random 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.) 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 begin with total accruals (TA) 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.[6] The Jones model discretionary accrual is estimated cross-sectionally each year using all firm-year observations in the same two-digit SIC code.[7]

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

where TA_{it}, is total accruals as defined above, $\Delta SALES_{it}$ is change in sales scaled by lagged total assets ($ASSETS_{it-1}$), and PPE_{it} is net property, plant and equipment scaled by $ASSETS_{it-1}$.

We use residuals from the annual cross-sectional industry regression model in (6) as the Jones model discretionary accruals. To obtain modified-Jones model discretionary accruals, following Dechow et al., we use the parameters from the Jones model eq. (6), but apply those to a modified sales change variable defined as ($\Delta SALES_{it} - \Delta AR_{it}$), where ΔAR_{it} is the change in accounts receivable. Dechow et al.'s (1995) assume that sales are not managed in the estimation

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

[7] While eq. (6) does not include an intercept, we repeat estimation of all models with an intercept in the regressions. The tenor of the results from the simulation analysis is unaffected.

period, but that the entire change in accounts receivable in the event year represents earnings management. Teoh et al. (1998a) apply the above methodology using cross-sectional data. However, this approach would be misspecified for firms experiencing substantial growth because they would exhibit growth in receivables that is not necessarily earnings management. Thus, firms experiencing real increases in A/R will likely underestimate non-discretionary accruals and over estimate discretionary accruals.

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

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

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.

The fourth discretionary accrual measure is Discretionary Current Accruals (DCA) that used in a number of studies (e.g., Teoh et al., 1998a and 1998b). For this measure, we estimate the following cross-sectional regression by industry and year:

$$TA\_NODEP_{it} = \beta_0/ASSETS_{it-1} + \beta_1\Delta SALES_{it} + \varepsilon_{it} \qquad (8)$$

where TA_NODEP_{it} is total accruals, as defined above, minus depreciation expense.

Rather than use the residual from this model as DCA, Teoh et al. (1998a) adapt the methodology of estimating discretionary accruals using the modified-Jones model. That is, change in accounts receivables is deducted from the sales change, but estimated parameters are from eq. (8). We evaluate the performance of discretionary current accruals measure because of its growing popularity in accounting research.

Performance matching. For each firm-year observation, we calculate performance-matched discretionary accruals by matching based on return on assets for the firm's two-digit SIC code and year, where ROA is net income divided by lagged total assets. For example, if discretionary accruals are being estimated for year t, then return on assets for the purposes of matching is calculated for year t-1 for both treatment and matched firms. 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 return-on-assets in the same industry and year as firm i from the Jones model discretionary accrual of firm i.[8]

In addition to the above discretionary accrual measures, we perform tests based on other discretionary accrual measures. These include a firm's total accruals minus the industry median total accruals, total accruals minus the matched firm's total accruals, the Jones model discretionary accruals minus the industry median discretionary accruals using the Jones and Modified-Jones models. Since these latter measures tend to perform worse than the performance matched measures, we only briefly comment on the results for these measures. These untabulated results are available from authors.

Survival. Our simulation analysis is also designed to assess the effect of survival requirements on tests of earnings management over multi-year periods. Survival bias can exist in studies examining discretionary-accruals because only the accruals of surviving firms are available in a multi-year examination. One means of mitigating the bias is to not require that the matched firm survive the multi-year horizon. That is, we begin with a sample of treatment and matched control firms in year t and then examine the discretionary accruals of the two groups

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[8] We winsorize extreme observations for all discretionary accrual measures by setting the values in the bottom and top one percent of observations to the values of the 1st and 99th percentiles.

composed of surviving firms over a multi-year period from years t+1 to t+5. Thus, both treatment and control firm samples suffer from survivor bias. The assumption underlying performance matching is that the biases in the treatment and control samples cancel each other out. Thus, treatment firms' discretionary accruals adjusted for those of the control firms are expected to be relatively free from the survivor bias. The success of this procedure obviously hinges on the effectiveness of matching.

An alternative to the above procedure (which is commonly employed in the literature) is to require that the matching firm selected at time t survives as long as the treatment firm. This procedure entails a look-ahead bias in selecting matching firms. We repeat our simulations using this approach as well as the one outlined above. To the extent that performance matching is the primary driver in obtaining well-specified estimates of discretionary accruals, we expect both procedures to be effective in addressing survival.

3.3 Test statistics

For each of the 250 randomly selected samples (per event condition), the significance of the mean discretionary accrual is assessed 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 an estimate of the standard error of $\overline{DA}$, and N is the number of firms in the sample. The standard error of the sample mean discretionary accrual is based on the cross-sectional distribution of the individual firm discretionary accruals in the underlying sample.

The foregoing discussion describes test statistic calculation when the event period is one year. When we examine discretionary accruals over multi-year periods of three and five years, the underlying annual discretionary accruals (i.e., the DA_{it}) are summed through time and then the test statistic above is calculated (i.e., the sum of the DA_{it} for three or five years replaces DA_{it} in the above test statistic). The standard error is then calculated from the underlying cross-sectional distribution of three or five-year individual firm discretionary accrual measures.

3.4 Descriptive statistics and serial correlations for discretionary accrual measures

Descriptive statistics. Table 1 reports descriptive statistics for total accruals and several discretionary accrual measures for the aggregate sample of 100,657 firm-year observations (panel A) and for various non-random samples (panel B). Total accruals average –2.78% 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 11.68%, which means the distribution of total accruals is fat-tailed.

With the exception of discretionary current accruals, average discretionary accruals are negative. Performance-matched Jones and modified-Jones model discretionary accruals exhibit smaller means compared to those without performance matching. However, performance matching results in increasing the standard deviation from about 10% for the Jones model discretionary accrual to about 14% for the performance-matched Jones model discretionary accrual. This represents about a 40% 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 potential trade-off of diminished power. However, any adverse impact on power might be minimal at a portfolio level because of diversification across firms.

[Table 1]

Consistent with the claims in previous research, descriptive statistics in panel B indicate discretionary accrual models' inadequacy in generating zero-mean estimates when applied to non-random samples. For example, the average discretionary accrual using the modified-Jones model for value stocks (i.e., the top quartile of stocks ranked on book-to-market ratio at the beginning of each year) is -1.14% of assets and it is -3.06% of assets for the stocks in the lowest quartile of stocks ranked on earnings yield. The benefit from performance matching is readily apparent by comparing the average discretionary accruals estimated using measures with and without performance matching. For example, the low earnings-yield stocks' average discretionary accrual using the performance-matched modified-Jones model is -0.89% compared to -3.06% using the modified-Jones model without performance matching. In general, estimated

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[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.

discretionary accruals using performance-matched measures are closer to zero than those without performance matching. While the bias is not completely eliminated, it is the case that the greater the bias, the more likely it is that the null hypothesis of zero discretionary accrual will be spuriously rejected.

Serial correlations. Well-specified models should generate discretionary accrual estimates that are approximately serially uncorrelated regardless of a firm's past performance.[10] In contrast, if past performance compromises the specification of a discretionary-accrual model, then for non-random samples estimated discretionary accruals are likely to be serially correlated. We estimate serial correlation in various discretionary accrual measures for the entire sample as well as non-random subsamples of firms. We estimate serial correlation from the following Fama-MacBeth (1973) cross-sectional regression 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. A serial correlation estimate from a cross-sectional regression assumes that the serial correlation is identical across the firms in the cross-section used in estimating the regression (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 it does not require data availability for individual firms to estimate a time-series model. 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.

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

Table 2 reports the average of the 15 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 standard error in calculating the t-statistics incorporates the Newey-West (1987) autocorrelation correction for five lags.

[Table 2]

Return on assets is highly positively autocorrelated for the entire sample as well as all the subsamples. The serial correlation is slightly lower for extreme earnings yield portfolios, which is consistent with mean reversion in extreme earnings (e.g., Brooks and Buckmaster, 1976). Serial correlation in total accruals is highly positive for the all-firm sample, but it is small or zero for value stocks, low earnings yield stocks, low past sales growth stocks, and small firms. On balance, the discretionary accrual models are successful in considerably mitigating the serial correlation as seen from the correlation estimates for discretionary accrual estimates. Performance matching further mitigates the serial correlation. For example, serial correlation in the modified-Jones model discretionary accruals is -0.115 for the low earnings yield stocks, which is reduced to -0.036 by performance matching. Corresponding numbers for value stocks are -0.042 and -0.006.

Overall, performance matching appears to be successful in reducing 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 that we address 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 that the null hypotheses of nonnegative 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.[11]

4.1 Rejection rates under the null hypothesis

The numbers in the left half of 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, with and without an adjustment for the industry median, 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 is 22% for value stocks and 32.4% for low sales growth stocks. In contrast, the performance-matched discretionary accrual measures based on the Jones or modified-Jones models appear reasonably well specified.

[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 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

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

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 high book-to-market (from 31.2% to 36.8%), low sales growth (from 49.6% to 58.4%), low EP ratio (from 69.6% to 76.8%), and small firms (from 30.0% to 35.6%). The rejection rate is the highest, 58.4%, using the modified-Jones model for samples of low sales growth firms. This result is somewhat surprising considering that discretionary accruals are initially estimated by regressing total accruals on sales growth. One explanation for this result is that the relation between accruals and sales growth is nonlinear.

Misspecification problems are attenuated but not eliminated when past ROA is included in the accrual regressions. Rejection rates remain high for samples selected from quartiles of high book-to-market (from 22% to 24%), low sales growth (from 32.4% to 35.2%), low EP ratio (39.6% to 40.4%) and small firms (from 22.8% to 24.4%). Another important aspect of the results in table 3 is that discretionary accruals calculated as the Jones or modified-Jones model discretionary accrual minus the industry 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. Furthermore, untabulated results indicate that adjustment by the mean industry accrual leaves the rejection frequencies largely unchanged relative to the median-adjustment results.

Performance matching. Table 3 rejection rates based on performance-matched discretionary accrual measures suggest only a modest degree of misspecification. For example, performance-matched Jones model discretionary accruals indicate negative discretionary accruals close to 5% of the time in all cases except when sampling is restricted to low sales growth and large market capitalization stocks. In the latter two cases the rejection frequencies of

10.8% and 14.8% deviate from the expected rejection rate of 5%. On balance, however, across the event conditions simulated in table 3, the performance matched discretionary accrual measures consistently perform the best.

Jones versus modified-Jones model. The results also show that the differences between the rejection rates of the Jones and modified-Jones models are small (and statistically indistinguishable from zero).[12] For example, for samples from the low sales growth quartiles, the rejection rate using the Jones measure is 53.6% compared to 58.4% using the modified-Jones model. The key is to use one of these models in conjunction with performance matching. Moreover, adjusting the estimated accruals of the basic Jones and Modified Jones models for a performance-matched firm's discretionary accrual tends to control for the misspecification of the basic Jones and modified-Jones models.

Survivor bias implications. While not separately reported in table 3, a comparison of the performance-matched accrual measures with and without the control for survivor bias shows that our refinement of controlling for survivor bias does not improve the test's specification. It appears that performance matching implicitly serves as a control for survivor bias as well as other factors affecting the test's specification. Alternatively, it is possible that non-surviving firms perform neither predominantly poorly or well such that a lack of explicit control for survival does not affect the specification of the test using performance-matched discretionary accrual models.

Rejection rates for the alternative hypothesis of positive discretionary accruals. Simulation results of testing for positive discretionary accruals are reported in the right hand columns of table 3. They indicate that, regardless of the sample firm characteristics, all models of discretionary accruals exhibit low Type I error rates. The Jones and modified-Jones models reject the null hypothesis slightly too often (about 13% to 21% of the time) in high sales growth samples and too infrequently when samples consist of high book-to-market, low earnings-to-price, and small stocks. Inclusion of ROA in the Jones and Modified Jones accrual models does little to improve model specification. Fortunately, performance matching eliminates the specification problems with the Jones and modified-Jones models.

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 occurs when testing for positive discretionary accruals.

4.2 Tests of discretionary accruals over three- and five-year horizons

Panels B and C of table 3 report results similar to those in panel A except that the discretionary accrual measurement horizon is three years in panel B and five years in panel C. We obtain 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.

Results in panels B and C show that the discretionary accrual models' misspecification is muted as the measurement horizon is increased. While the Jones- and modified-Jones models remain misspecified (even when lagged ROA is included in the accrual estimation models), especially when applied to non-random samples, the rejection rates are not as extreme as observed when the horizon is one year, (see panel A). The performance-matched discretionary

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

accrual models (with and without survivor bias) continue to perform very well. Their rejection rates are consistently within the 95% confidence interval for the expected rejection rate of 5%.

The excessive rejection of the null hypothesis for discretionary accruals cumulated over three- or five-year periods suggests that the likelihood of finding significant discretionary accruals in some of the years in a multi-year horizon is much higher than indicated by the rejection rates for the multi-year average. Unless a researcher specifies *ex ante* the year in which a reversal might be observed, our results suggest a spurious rejection of the null hypothesis of no earnings management is quite likely. Fortunately, performance-matched discretionary-accrual measures eliminate the misspecification problem in the random and non-random samples we examine.

4.3 Sensitivity to sample size

We next examine the performance of the various models in sample sizes greater than 100 firm-years. One potential source of misspecification as the sample size is increased stems from potential violation of the cross-sectional independence assumption. As more stocks are sampled and the performance-measurement horizon is increased to three and five years, it is more likely that the selected sample firms share a common time period, which potentially induces cross-correlation in the accrual measures.[13] Previous research shows that tests that ignore cross-sectional dependence reject the null hypothesis too frequently (e.g., Collins and Dent, 1984, Bernard, 1987, and Kothari and Wasley, 1989).

We find that increased sample size does not alter the tenor of the results. Specifically, the Jones and modified-Jones models remain misspecified and performance-matching results in tests that are well specified. Moreover, larger sample size does not change the rejection frequencies by much, suggesting that even with samples of 300 firms and five-year horizon, the cross-

[13] See Brav (2000) for similar arguments and evidence in the context of long-horizon security returns.

sectional dependence in the estimated discretionary accruals does not appear to be a severe problem.

5. The power of performance-matched discretionary accrual measures

Table 4 summarizes the results of comparing the power of the performance-matched discretionary accrual measures based on the Jones and modified-Jones models, with and without a control for survivor bias. We report rejection frequencies for random and non-random samples of 100 firms with plus/minus 1%, 2%, or 4% discretionary accrual added to each firm's estimated discretionary accrual (the percentage discretionary accrual added to the data is accrual as a percentage of the firm's total assets). We do not report on the power of other discretionary accrual measures since earlier analysis finds them to be misspecified under the null hypothesis.

Results in table 4 are very similar across the different models. Power, however, differs among the random and non-random samples. Specifically, the power is lower in high sales growth, low book-to-market ratio and small firm samples compared to other non-random and random samples of firms. The models detect a 1% discretionary accrual about 10% to 25% of the time in various samples. This frequency jumps to about 30% to 50% of the time when the discretionary accrual is plus or minus 2% of assets. Finally, the rejection rate reaches about 75% to 95% with a discretionary accrual of 4%. Rejection rates tend to be somewhat lower for small firms, probably because small firms' economic performance is more volatile than larger stocks. Comparison of the rejection frequencies for models with and without a control for survivor bias reveals (as in case of the specification of the test examined in section 3) that control for survivor bias has little discernible effect on the power of the tests. In addition, use of the Jones versus modified-Jones models makes little difference.

[Table 4]

Results in table 4 suggest that the power of the performance-matched discretionary accrual model is quite high. This is in sharp contrast to Dechow et al.'s (1995, p. 193) conclusion that "the models all generate tests of low power for earnings management of economically plausible magnitudes (e.g., one to five percent of total assets)." Their figure 3 indicates that the power is so low that all models would detect 10% to 20% earnings management (i.e., discretionary accrual) less than 20% of the time. Our results in table 2 suggest that even 4% discretionary accrual would almost certainly be detected in the all-firm and non-random firm samples. As noted earlier, the difference between the two sets of results is due largely because we report results for samples of 100 firms (or more) whereas Dechow et al. report rejection rates for repeated samples of one firm each. We believe our results using samples of 100 to 300 firms each are more informative about the power expected in a typical research study. Most 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, Welch, and Wong, 1998b).

6. Sensitivity analysis

To summarize the results of our sensitivity analysis, figures 1-3 plot the sensitivity of the models' power to different random and non-random samples, sample sizes from 100 to 300, and horizons from one year to three years. Figure 1 shows that a little over 4% average discretionary accrual in an "all-firms" sample of 100 firms will almost certainly be detected using the performance-matched Jones or modified-Jones model. If samples consist of smaller firms, an average discretionary accrual of 7%-8% is needed to ensure almost certain rejection of the null hypothesis of zero discretionary accrual. In other words, the discretionary accrual models are unlikely to conclude earnings management unless the magnitude of discretionary accruals is rather substantial among small firms.

[Figures 1-3]

Figure 2 plots the models' power as a function of sample size for all-firm samples and low and high earnings-to-price ratio samples. As expected, power rises with sample size and the increase in power is quite substantial. For example, for the earnings-to-price ratio samples, power using 200-firm samples is approximately 15-20 percentage points greater than using 100-firm samples over a wide range of discretionary accrual introduced in the data. 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.

Finally, figure 3 shows that there is little noticeable effect of accrual measurement horizon on the power of the tests. Tests of discretionary accrual over one-, three-, and five-year horizons all possess similar power to detect discretionary accrual. Since we sum estimated discretionary accruals over multi-year periods, if discretionary accruals were serially uncorrelated, the variance of the summed discretionary accruals over longer horizons would increase proportionately with the horizon. This would diminish the tests' power to detect a given amount of discretionary accrual as the horizon lengthens. Since we fail to observe an erosion in power, either discretionary accruals are negatively serially correlated or long-horizon discretionary accruals are cross-sectionally positively correlated or both. Negative serial correlation in estimated discretionary accruals is consistent with the time-series properties of total accruals (e.g., Dechow, Kothari, and Watts, 1998). Positive cross-sectional dependence in long-horizon discretionary accruals is possible because at longer horizon it is more likely that sampled firms share a common calendar time. However, as observed earlier, since the performance-matched discretionary accrual is well specified (see table 3), cross-sectional dependence does not appear to be a significant problem under the simulated sampling conditions.

7. Replication using a seasoned-equity-offerings sample

To evaluate the effectiveness of our measure of discretionary accruals, we replicate a study where performance is likely correlated with the treatment variable. This is the context where performance matching mitigates the likelihood of Type I errors. Teoh et al. (1998a) examine discretionary accruals of firms making Seasoned Equity Offerings (SEO's). 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 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. All non-IPO equity issues are obtained 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.[14] This shrinks the sample to

[14] 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 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 offerers 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).

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 where any one of the four discretionary measures cannot be estimated. This forces the sample to be constant across discretionary accrual measures, but reduces the sample to 1,561 firms.

Table 5 reports discretionary accruals from event years -3 to +3. We report discretionary accruals estimated using the Jones model with and without performance matching. We also report discretionary current accruals (DCA) for reasons below. The results 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 discretionary accruals for both Jones model and current accruals in the pre- and post-SEO years, but not the year of the SEO and the effect is marginal in event year +1. Discretionary accruals in event years 0 and +1 are difficult to interpret because the SEO proceeds are likely to 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 will increase accruals, but the discretionary accrual models, with or without performance matching, do not capture such increases. Therefore, they will appear as discretionary accruals. We therefore focus on discretionary accruals in event years –3 to –1 and +2 to +3.

[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 statistically not 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.

Following Teoh et al. (1998a), we also examine discretionary current accruals and the general conclusion remains that performance matching produces muted evidence of opportunistic accrual management. As observed in section 3 and table 1, discretionary current accruals are on average positive for growth firms. In table 1, we report mean discretionary current accruals of 2% of assets for firms experiencing high past sales growth. Therefore, even in the absence of SEO-related incentives to manage earnings, we would expect positive discretionary current accrual for an SEO firm because it is likely to be a growth firm.

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 disappear. 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 non-random samples of firms (e.g., Dechow et al. 1995 and Guay et al. 1996). Dechow et al. (1995) conclude that all models of discretionary accruals exhibit low power.

We find that the Jones and modified-Jones models reject the null hypothesis excessively in non-random samples and that adjusting the discretionary accruals of these models by the industry mean or median accrual does not improve their performance. On the other hand, tests using performance-matched measures of discretionary accruals are both well specified and quite powerful. We present detailed simulation evidence on the properties of alternative measures of discretionary accruals based on random and non-random samples. We also examine the properties of discretionary accrual models over multi-year horizons and their sensitivity to sample size. Under all circumstances, performance-matched discretionary accrual models are quite well specified and exhibit substantial power. Although a small degree of misspecification using the performance-matched discretionary accrual models in some non-random samples is observed, on balance, performance-matched models are the most reliable from sample-to-sample in terms of Type I error rates and power of the test.

Our study has important implications for future research using measures of discretionary accruals. Adjusting discretionary accruals for the discretionary accruals of another firm matched on the basis of prior performance 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 so long as performance-matched Jones model discretionary accruals are used.

Our study has at least three 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 (2000) 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 balance sheet approach advocated in Collins and Hribar (2000).

Second, while we simulate several event conditions (e.g., multi-year performance, sample size, and various non-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 non-random samples, we cannot be sure that this necessarily indicates that the tests are well specified. Accounting theory suggests non-random sample firms likely engage in earnings management. Therefore, powerful tests should reject the null hypotheses in non-random samples. Performance-matched accrual measures inform whether the extent of discretionary accruals in non-random samples exceeds that in matched samples with similar performance characteristics except the treatment event.

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Table 1

Descriptive statistics for discretionary accrual measures

Panel A reports mean, standard deviation, lower quartile, median and upper quartile values for the entire sample. Panel B reports means and medians for non-random samples formed on the basis of book-to-market ratio, prior year sales growth, earnings-to-price (EP) ratio and firm size (market value of equity). The values reported in Panel B are based the lower and upper quartiles of the variable used to partition the overall sample into the non-random samples which are formed on the basis of select financial characteristics (book/market, past sales growth, etc.). 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 1959 through 1998. 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 and we also eliminate observations after 1993 because we examine accruals over a five-year horizon. 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 100,657.

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

Description	Mean	STD	Q1	Med	Q3
Total Accruals	-2.78	11.68	-8.16	-3.27	2.12
Jones Model	-0.32	10.08	-4.70	-0.08	4.17
Modified Jones Model	-0.24	10.44	-4.79	-0.09	4.31
Jones Model with ROA	-0.36	9.71	-4.73	-0.20	4.01
Modified Jones Model with ROA	-0.27	10.04	-4.80	-0.21	4.12
Discretionary Current Accruals Model	0.04	9.80	-4.11	-0.03	4.04
Performance-Matched Jones Model	-0.17	14.07	-6.74	-0.03	6.46
Performance-Matched Modified Jones Model	-0.18	14.53	-6.92	-0.05	6.61

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

	Book/Market		Past Sales Growth		E/P Ratio		Size	
Description	**Value**	**Growth**	**High**	**Low**	**High**	**Low**	**Large**	**Small**
Total Accruals	-4.16	-1.66	-0.42	-5.58	-1.59	-6.92	-2.99	-4.42
	(-3.89)	(-2.33)	(-1.67)	(-5.07)	(-2.49)	(-6.52)	(-3.56)	(-4.27)
Jones Model	-1.02	-0.04	0.68	-1.81	0.66	-2.86	0.02	-1.48
	(-0.46)	(0.06)	(0.52)	(-1.03)	(0.44)	(-2.11)	(0.10)	(-0.96)
Modified Jones Model	-1.14	0.27	1.12	-2.02	0.72	-3.06	0.11	-1.61
	(-0.54)	(0.23)	(0.73)	(-1.2)	(0.45)	(-2.29)	(0.09)	(-1.05)
Jones Model with ROA	-0.81	0.00	0.42	-1.30	0.14	-1.65	-0.36	-1.02
	(-0.33)	(-0.19)	(0.25)	(-0.73)	(0.15)	(-1.14)	(-0.16)	(-0.68)
Modified Jones Model with ROA	-0.89	0.33	0.83	-1.42	0.13	-1.67	-0.30	-1.07
	(-0.4)	(-0.04)	(0.43)	(-0.86)	(0.09)	(-1.17)	(-0.18)	(-0.8)
Discretionary Current Accruals (DCA)	-0.98	0.73	1.17	-1.43	0.84	-2.21	0.15	-0.99
	(-0.6)	(0.42)	(0.64)	(-0.87)	(0.37)	(-1.65)	(-0.01)	(-0.76)
Performance-Matched Jones Model	-0.39	0.01	0.41	-0.73	0.09	-0.85	-0.37	-0.59
	(-0.13)	(0.07)	(0.36)	(-0.51)	(0.00)	(-0.65)	(-0.08)	(-0.39)
Performance-Matched Modified Jones Model	-0.50	0.15	0.68	-0.90	-0.01	-0.89	-0.43	-0.71
	(-0.24)	(0.13)	(0.51)	(-0.62)	(0.00)	(-0.71)	(-0.11)	(-0.51)

[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 lagged ROA and modified-Jones model including lagged with 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.

Discretionary Current Accruals (DCA) are estimated as in Teoh et al. (1998a) and are based on the following model estimated by industry and year: $TA\_NODEP_{it}=\beta_0/ASSETS_{it-1} + \beta_1\Delta SALES_{it}+e_{it}$, where TA_NODEP_{it} is total accruals excluding depreciation expense. Using the estimated parameters of this model, Nondiscretionary accruals are calculated as: $NDA_{it} = \beta_0/ASSETS_{it-1} + \beta_1(\Delta SALES_{it}-\Delta AR_{it})$. Discretionary Current Accruals are equal to TA_NODEP_{it} - NDA_{it}. To measure performance matched discretionary accruals, we precision match firms in period t-1 based on return-on-assets. To calculate a performance-matched Jones model (Modified-Jones model) discretionary accrual for firm i we subtract the Jones model (Modified-Jones model) discretionary accrual of the firm with the closest return-on-assets in the same industry as firm i.

Table 2

Serial correlation in return on assets (ROA), total accruals and discretionary accrual measures for the entire sample and non-random subsaples of firms from 1959-1993

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 non-random samples based on select financial performance measures (e.g., book-to-market, past sales growth, earnings-to-price ratio and firm size). 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 1959 through 1998. 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 and we also eliminate observations after 1993 because we examine accruals over a five-year horizon. All variables are winsorized at the 1^{st} and 99^{th} percentiles. The final sample size is 100,657.

	All Firms	**Book/Market**		**Past Sales Growth**		**E/P Ratio**		**Size**	
Description[a]		**Value**	**Growth**	**High**	**Low**	**High**	**Low**	**Large**	**Small**
ROA	0.687 **	0.674 **	0.669 **	0.661 **	0.628 **	0.621 **	0.568 **	0.761 **	0.600 **
Total Accruals	0.161 **	0.061 **	0.197 **	0.173 **	-0.010	0.102 **	-0.002	0.279 **	0.077 **
Jones Model Accruals	-0.001	-0.053 **	0.033	0.028	-0.071 *	-0.074 **	-0.115	0.105 **	-0.055 **
Modifed Jones Model Accruals	0.018 *	-0.042 *	0.058 *	0.043 **	-0.052 *	-0.061 **	-0.133	0.121 **	-0.035 *
Performance-Matched Jones	-0.019 **	-0.016	-0.008	-0.006	-0.077 **	-0.056 **	-0.041	0.025	-0.039 *
Perfomance-Matched Modified Jones	-0.012 *	-0.006	0.002	0.000	-0.064 **	-0.046 *	-0.036	0.026	-0.028

[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 precision match in period t-1 based on return-on-assets. 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 non-random samples formed on the basis of financial characteristics [book-to-market ratio, sales growth over the prior year, earnings-to-price (EP) ratio and firm size (market value of equity)]

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. 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 1959 through 1998. 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 and we also eliminate observations after 1993 because we examine accruals over a five-year horizon. All variables are winsorized at the 1st and 99th percentiles. The final sample size is 100,657.

Panel A. Accruals over one year:[a]	**H_A: Accruals < 0**									**H_A: Accruals > 0**								
	All Firms	**Book/ Market**		**Sales Growth**		**EP Ratio**		**Size**		**All Firms**	**Book/ Market**		**Sales Growth**		**EP Ratio**		**Size**	
		Value	**Growth**	**High**	**Low**	**High**	**Low**	**Large**	**Small**		**Value**	**Growth**	**High**	**Low**	**High**	**Low**	**Large**	**Small**
Jones Model:																		
Cross sectional within-industry Jones model	7.2	33.2	6.4	2.0	53.6	0.4	72.8	3.6	34.0	2.4	0.4	5.2	13.2	0.0	21.6	0.0	4.8	0.4
Industry median adjusted discretionary accruals	6.8	31.2	5.2	2.0	49.6	0.8	69.6	4.0	30.0	2.4	0.4	6.4	12.8	0.0	20.8	0.0	4.8	0.4
ROA included in accrual estimation equation	9.6	22.0	8.4	2.4	32.4	4.4	40.4	18.4	24.4	2.0	0.8	7.6	10.8	0.0	7.6	0.0	0.0	0.8
Performance matched discretionary accruals	8.0	6.0	4.0	2.4	10.8	5.2	6.8	12.8	8.8	3.6	4.0	7.6	4.4	0.8	4.0	2.8	3.6	3.6
Modified Jones Model:																		
Cross sectional within-industry Jones model	5.2	36.8	4.0	0.8	58.4	0.0	76.8	2.4	35.6	2.8	0.4	6.8	19.6	0.0	23.2	0.0	6.0	0.4
Industry median adjusted discretionary accruals	4.8	36.0	3.6	0.4	52.8	0.4	72.4	2.8	32.4	4.0	0.4	10.0	21.6	0.0	21.6	0.0	6.0	0.4
ROA included in accrual estimation equation	8.0	24.0	6.0	1.2	35.2	4.4	39.6	15.6	22.8	3.2	0.8	12.0	14.8	0.0	7.6	0.0	0.4	0.8
Performance matched discretionary accruals	8.0	6.8	2.8	1.2	10.8	5.6	6.8	14.8	9.2	3.6	2.8	7.6	7.6	0.8	3.2	3.2	2.4	3.6

Panel B. Accruals over three years:[a]

	H_A: Accruals < 0									H_A: Accruals > 0								
	All	Book/ Market		Sales Growth		EP Ratio		Size		All	Book/ Market		Sales Growth		EP Ratio		Size	
	Firms	Value	Growth	High	Low	High	Low	Large	Small	Firms	Value	Growth	High	Low	High	Low	Large	Small
Jones Model:																		
Cross sectional within-industry Jones model	10.8	9.2	10.0	12.4	21.6	5.2	30.8	10.0	12.4	1.2	2.0	2.4	2.0	1.6	6.8	0.0	2.8	2.8
Industry median adjusted discretionary accruals	10.8	9.2	9.2	11.2	21.2	6.8	27.6	10.4	11.2	1.6	2.0	4.0	2.4	2.0	5.2	0.4	2.8	2.8
ROA included in accrual estimation equation	11.2	9.6	13.6	14.4	14.8	10.0	18.0	26.0	8.4	1.6	2.8	1.2	1.2	2.0	2.0	0.8	0.0	4.0
Performance matched discretionary accruals	5.6	3.2	5.2	4.4	4.4	6.0	6.0	6.0	2.8	6.8	5.6	6.4	4.8	6.8	4.8	3.2	3.2	7.2
Modified-Jones Model:																		
Cross sectional within-industry Jones model	10.8	9.2	8.8	10.4	25.6	5.2	33.6	11.2	11.6	1.6	2.0	3.6	2.0	2.0	6.4	0.0	2.8	1.6
Industry median adjusted discretionary accruals	8.4	9.2	7.6	10.0	24.8	6.0	28.4	10.4	10.4	1.2	2.0	4.0	2.4	2.4	6.0	0.0	3.2	1.6
ROA included in accrual estimation equation	11.2	9.2	11.6	11.2	16.8	9.6	17.6	25.2	7.6	2.8	3.2	1.2	1.2	2.0	2.0	0.8	0.0	4.4
Performance matched discretionary accruals	6.0	3.6	5.2	4.4	6.0	6.0	5.6	7.2	2.8	6.0	6.0	6.4	4.8	5.2	4.0	3.6	2.8	6.4

Panel C. Accruals over five years:[a]

Jones Model:																		
Cross sectional within-industry Jones model	15.2	6.0	16.4	18.8	17.2	11.6	19.6	16.8	13.2	1.6	2.8	2.4	1.6	1.2	1.6	0.4	0.8	0.8
Industry median adjusted discretionary accruals	12.4	6.8	14.4	18.0	13.2	10.0	15.6	14.8	12.4	2.0	3.6	3.2	1.6	1.6	1.6	1.2	0.8	1.6
ROA included in accrual estimation equation	12.4	9.6	21.6	25.2	16.4	10.8	16.4	28.8	11.6	1.2	2.0	0.0	1.2	1.6	2.0	0.8	0.0	0.8
Performance matched discretionary accruals	5.2	3.2	4.8	5.6	8.0	7.6	6.0	6.0	4.0	3.2	4.4	4.8	3.6	2.0	4.4	5.6	2.8	6.4
Modified-Jones Model:																		
Cross sectional within-industry Jones model	15.6	6.4	15.2	16.8	17.6	11.2	20.4	20.4	14.0	1.6	2.0	3.2	1.6	0.8	2.0	0.8	0.4	0.8
Industry median adjusted discretionary accruals	13.6	7.2	12.0	15.2	16.8	8.4	15.2	16.4	12.0	2.4	3.2	4.0	2.0	1.2	1.2	1.6	0.4	1.2
ROA included in accrual estimation equation	10.8	9.6	20.4	20.4	16.0	12.0	12.8	30.8	12.0	1.6	2.0	0.0	2.0	0.8	2.0	0.8	0.0	1.2
Performance matched discretionary accruals	4.8	2.8	4.0	5.6	8.8	8.0	6.4	6.8	4.8	2.8	4.0	5.6	4.4	2.0	4.4	4.4	3.2	6.0

[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 precision match in period t-1 based on return-on-assets. 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 return-on-assets that is in the same industry as firm i. Both the sample and control firm must survive for five subsequent years to be included in the sample.

Table 4

A comparison of the power of the discretionary accrual models to detect abnormal accruals when they have been seeded into the data

For each sample the indicated seed level is simply added to the mean discretionary accrual of the sample. 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 of the 250 random samples 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 1959 through 1998. 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 and we also eliminate observations after 1993 because we examine accruals over a five-year horizon. All variables are winsorized at the 1st and 99th percentiles. The final sample size is 100,657.

Panel A. H_A: Accruals < 0:

	Seeded Abnormal Accrual	All Firms	Book/ Market		Sales		EP Ratio		Size	
			Value	Growth	High	Low	High	Low	Large	Small
Jones Model: [a]										
Performance matched discretionary accruals	-1%	21.2	21.2	13.6	10.4	23.2	20.8	16.0	41.2	14.4
	-2%	43.2	44.0	34.8	29.2	45.6	49.6	33.2	76.8	32.4
	-4%	88.0	92.0	78.8	72.0	86.4	91.2	74.8	98.8	74.8
Performance matched discretionary accruals without survivor bias	-1%	18.8	20.4	18.8	12.8	32.0	20.0	18.8	43.6	18.0
	-2%	44.8	50.0	36.0	32.4	52.8	50.8	37.6	78.0	35.6
	-4%	89.2	93.2	85.2	78.4	85.6	96.8	80.4	98.4	80.0
Modified-Jones Model: [a]										
Performance matched discretionary accruals	-1%	22.8	21.6	12.4	9.2	26.4	20.0	18.0	44.4	15.6
	-2%	45.2	43.6	31.2	22.8	45.2	48.0	32.0	77.6	32.8
	-4%	86.0	91.2	76.4	63.6	86.0	92.8	70.8	99.2	74.0
Performance matched discretionary accruals without survivor bias	-1%	18.8	22.8	16.8	9.6	32.8	22.0	20.8	46.8	19.6
	-2%	42.8	50.8	38.0	26.4	53.6	49.2	38.4	77.2	36.4
	-4%	86.8	92.0	82.4	75.2	84.4	96.4	80.4	98.8	76.8

Panel B. H_A: Accruals > 0:										
	Seeded Abnormal Accrual	All Firms	Book/ Market		Sales		EP Ratio		Size	
			High	Low	High	Low	High	Low	Large	Small
Jones Model: [a]										
Performance matched discretionary accruals	1%	16.8	18.8	13.6	21.6	12.8	24.8	11.2	13.2	14.8
	2%	41.6	48.8	27.2	43.2	25.6	51.2	25.2	40.4	32.4
	4%	86.4	91.6	75.2	86.8	71.2	95.6	66.0	93.2	74.8
Performance matched discretionary accruals without survivor bias	1%	15.2	17.6	8.4	16.0	10.4	20.4	9.2	11.6	12.8
	2%	35.6	42.8	23.6	37.6	24.0	51.2	20.4	41.6	27.6
	4%	88.8	92.0	71.2	84.0	62.4	95.2	59.6	93.2	72.0
Modified-Jones Model: [a]										
Performance matched discretionary accruals	1%	16.8	16.8	14.4	26.4	10.4	24.8	12.0	12.0	16.0
	2%	38.4	46.4	28.4	47.2	22.8	48.0	25.6	34.8	30.4
	4%	84.8	89.2	75.6	86.8	66.8	93.2	64.0	91.6	72.4
Performance matched discretionary accruals without survivor bias	1%	16.0	14.4	9.2	20.4	9.6	18.8	8.4	11.2	13.6
	2%	33.2	36.4	22.8	38.0	21.2	48.0	18.4	37.6	28.0
	4%	86.8	90.0	68.8	84.8	58.8	94.8	58.0	89.6	67.2

[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. Both the treatment and control firm must survive for five subsequent years to be included in the sample.

To reduce the effect of survivorship bias resulting from our precision-matching procedure, we use the same precision matching technique described above, but we do not require that the matching firm to survive as long as the treatment firm. These measures are referred to as performance matched discretionary accruals without survivor bias.

Table 5

Discretionary accruals of firms engaging in Seasoned Equity Offerings from 1980-1998

Seasoned Equity Offerings (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 in COMPUSTAT to estimate the Jones model (1955). 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]

	-3	**-2**	**-1**	**0**	**+1**	**+2**	**+3**
Jones Model							
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							
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
Discretionary Current Accruals							
Median	0.48 ###	0.85 ###	1.26 ###	2.14 ###	1.19 ###	0.33 ###	-0.06
Mean	2.00 ***	2.93 ***	3.17 ***	4.60 ***	2.20 ***	0.79 ***	0.06
Standard Error	0.42	0.41	0.38	0.37	0.32	0.28	0.31
Performance Matched discretionary current accruals							
Median	0.00	1.04 ###	0.07	2.19 ###	0.84 ###	0.09	-0.09
Mean	0.63	1.59 ***	0.84 *	3.41 ***	1.44 ***	0.45	-0.28
Standard Error	0.57	0.54	0.51	0.48	0.45	0.44	0.47
N	**928**	**1,141**	**1,519**	**1,561**	**1,392**	**1,211**	**1,043**

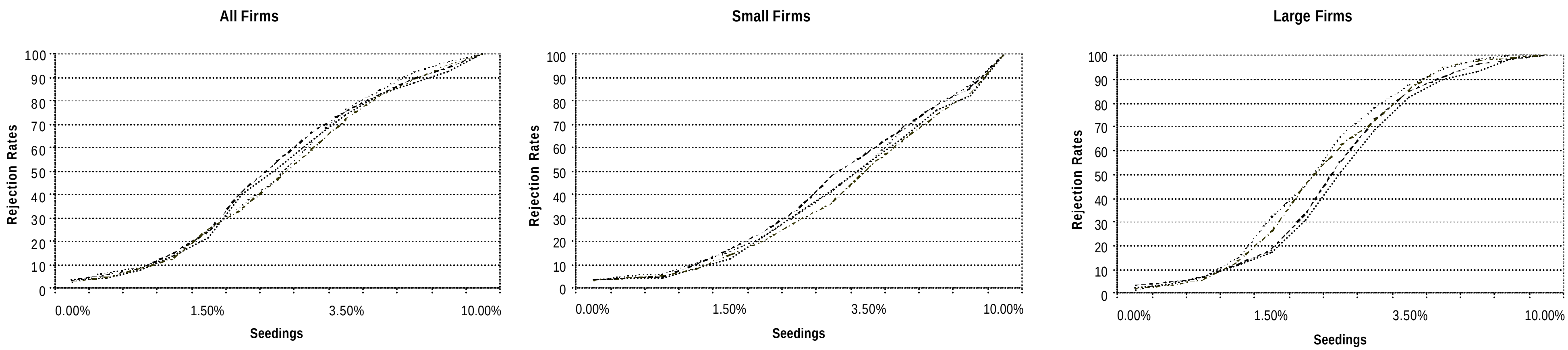
[a] Cross sectional within-industry discretionary accruals are the residuals from the Jones model. Discretionary accruals from the Jones model are estimated for each industry and year as follows: $TA_{i,t}=\alpha_0/ASSETS_{i,t-1} + \alpha_1\Delta SALES_{i,t}+\alpha_2 PPE_{i,t}+\varepsilon_{i,t}$, where 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 $ASSETS_{i,t-1}$.

Discretionary Current Accruals (DCA) are estimated as in Teoh et al. (1998a) based on the following regression which is estimated for each industry and year: $TA\_NODEP_{it}=\beta_0/ASSETS_{it-1} + \beta_1\Delta SALES_{it}+e_{it}$, where TA_NODEP_{it} is equal to total accruals excluding depreciation expense. With parameters obtained from the accruals regression, Nondiscretionary accruals are estimated as: $NDA_{it}=\beta_0/ASSETS_{it-1} + \beta_1(\Delta SALES_{it}-\Delta AR_{it})$. Discretionary Current Accruals are equal to $TA\_NODEP_{it}-NDA_{it}$.

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 .01, .05 and .10, respectively.

###, ##, # Based on Wilcoxin test, medians are significant at .01, .05 and .10, respectively.



Jones Model Performance Match

Modified Jones Model Performance Match

Jones Model Performance Match Without Survivor Bias

Jones Model Performance Match Without Survivor Bias

Fig. 1. A comparison of the power of the four performance matched-firm discretionary accrual measures derived from the Jones and Modified Jones Models. Each plot portrays the power function for each discretionary accrual measure where the power function is based on the empirical distribution of the 250 test statistics underlying each event condition. Results in the figure are based on samples of 100 firms and are presented for the full sample (all firms) and for select sub-samples based on firm size (large firms are from the upper quartile and small firms from the lower quartile of the distribution of the market value of equity). Plots based on other sub-samples (E/P, B/M, and Sales Growth) are qualitatively similar and are not presented to save space. In each event condition, the indicated seed level is simply added to the mean discretionary accrual of the sample. Firm-year observations are randomly selected (without replacement) from 1959-1998.

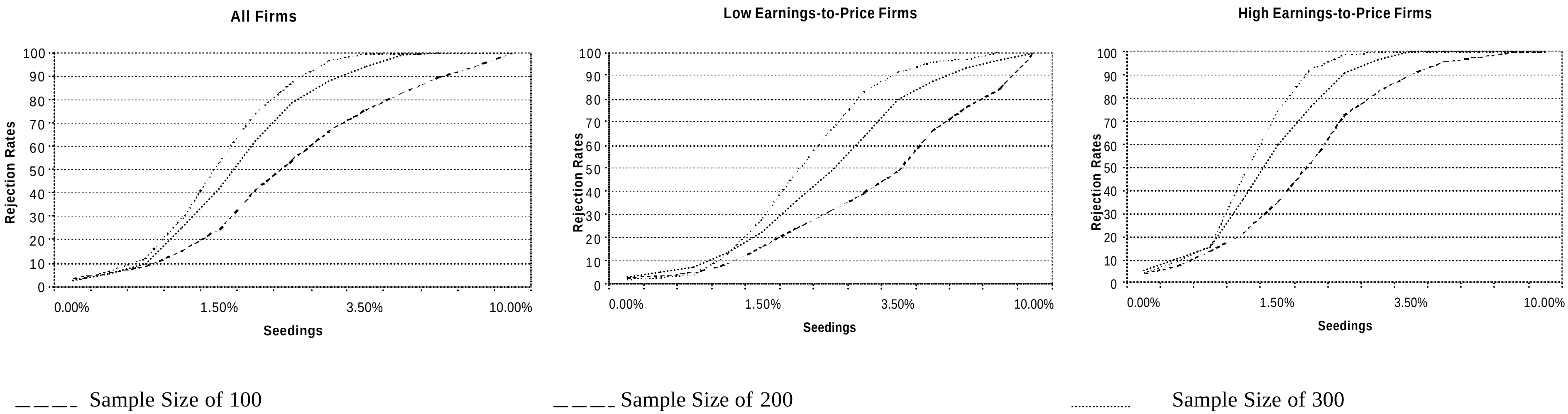
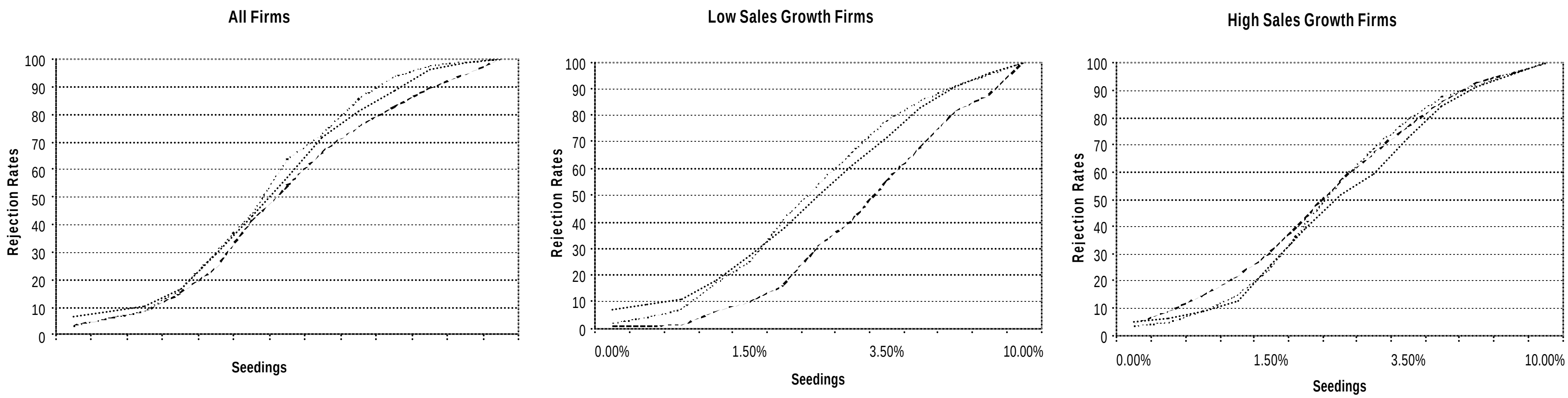


Fig. 2. A comparison of the power to detect discretionary accruals in sample sizes of 100, 200, and 300 firms. Each plot portrays the power function for the performance matched-firm accrual measure derived from the Jones Model (plots using the three other performance matched-firm abnormal accrual measures are qualitatively similar and are not presented to save space). The power function is based on the empirical distribution of the 250 test statistics underlying each event condition. Results in the figure are presented for the full sample (all firms) and for select sub-samples based on E/P ratio (high E/P firms are from the upper quartile and low E/P firms from the lower quartile of the distribution of E-P ratios). Plots based on other sub-samples (Sales Growth, B/M, and Firm Size) are qualitatively similar and are not presented to save space. In each event condition, the indicated seed level is simply added to the mean discretionary accrual of the sample. Firm-year observations are randomly selected (without replacement) from 1959-1998.



Accruals over one year   Accruals over three years   Accruals over five years

Fig. 3. A comparison of the power to detect discretionary accruals over multi-year horizons of one, three, and five years. Each plot portrays the power function for the performance matched-firm accrual measure derived from the Jones Model (plots using the three other performance matched-firm abnormal accrual measures are qualitatively similar and are not presented to save space). The power function is based on the empirical distribution of the 250 test statistics underlying each event condition. Results in the figure are based on sample sizes of 100 firms and are presented for the full sample (all firms) and for select sub-samples based on sales growth (high growth firms are from the upper quartile and low growth firms from the lower quartile of the distribution of sales growth in the prior year). Plots based on other sub-samples (E/P, B/M, and Firm Size) are qualitatively similar and are not presented to save space. In each event condition, the indicated seed level is simply added to the mean discretionary accrual of the sample. Firm-year observations are randomly selected (without replacement) from 1959-1998.