Identifying unexpected accruals: a comparison of current approaches

Jacob Thomas a,*, Xiao-jun Zhang b

a Department of Accounting, Graduate School of Business, Room 620, Uris Hall, Columbia University, 3022 Broadway, New York, NY 10027-7004, USA
b Department of Accounting, University of California, Berkeley, CA, USA

Abstract

While prior research, as noted in our paper, often uses various accrual prediction models to detect earnings management, not much is known about the accuracy, both relative and absolute, associated with these models. Our paper investigates the accuracy of six different accrual prediction models, and offers the following findings. Only the Kang – Sivaramakrishnan (1995) model performs moderately well. The remaining five models provide little ability to predict total accruals: they are less accurate than a naive model which predicts that total accruals equal -5% of the total assets (TA) for all firms and years. Conventional $R^2$ values from a regression of actual accruals on predicted accruals are less than zero for a substantial majority of firms for these five models. These low $R^2$ values in the prediction period contrast sharply with the much higher $R^2$ values that are obtained within the estimation period. Similar performance is observed when predicting current accruals alone. However, the relative rankings of the different models are altered somewhat: the Jones (1991) model is then the only model that exhibits some predictive ability. © 2000 Elsevier Science Ltd. All rights reserved.

1. Introduction

Numerous studies have used a variety of accrual prediction models for different objectives. Typically, these models have been used to detect earnings management. Earnings are hypothesized to have been managed in predictable
ways in response to certain incentives (e.g., Watts and Zimmerman, 1986; Schipper, 1989), and the discretionary accruals used to manage earnings are estimated from these accrual prediction models. Examples include studies of earnings management due to compensation agreements (Healy, 1985; Gaver et al., 1995; Holthausen et al., 1995), proxy contests (DeAngelo, 1988), and lobbying for trade restrictions (Jones, 1991). Usually, realized accruals are compared with forecasts from an accrual prediction model, and the forecast errors are assumed to represent discretionary accruals, or earnings management. In effect, forecast accruals are assumed to represent non-discretionary accruals, the accruals that would be observed absent any incentives to manage earnings.

While these models have been used often, little attention has been paid to the relative or absolute accuracy of different accrual models. Two recent studies that have examined the accuracy of accrual models are Dechow et al. (1995) and Kang and Sivaramakrishnan (1995). Both papers examine the ability of different models to identify type I errors (reject the null hypothesis of no earnings management when it is true) and type II errors (fail to reject the null hypothesis when it is false). They have also offered insights about extant models and innovative ways to improve the ability to detect earnings management.

Our paper continues in the same vein, but is focused on the more general issue of forecasting accruals, rather than detecting earnings management per se. Of course, the two objectives coincide when predictions from a model are assumed to capture non-discretionary accruals, and the model that most accurately predicts accruals would also be the model that detects earnings management with the lowest error. But we relax this assumption and allow for the possibility that the models also capture predictable earnings management. As a result, we view forecast errors as being unexpected or unpredictable accruals, rather than discretionary accruals (Healy, 1996, p. 114). Given this perspective, we do not seed discretionary accruals to compare models based on type II errors.

Our primary motivation is to offer readers a simple description of the absolute and relative ability of extant models to predict accruals. We use an adjusted or pseudo-$R^2$ and firm-specific rankings of the six models to compare

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1 Other contexts in which earnings management has been studied include valuation, corporate control, and financial distress. Examples of such studies include Bartov (1993), DeAngelo (1986), DeAngelo et al. (1994), DeFond and Jiambalvo (1994), Guay et al. (1996), Guenther (1994), Kang and Sivaramakrishnan (1995), Pourciau (1993), Perry and Williams (1994), and Subramanyam (1996). While most studies examine accruals, some have focused on the choice of accounting methods to infer earnings management. Studies in this group include Dhaliwal et al. (1982), and Skinner (1993).
the different models. Although our results are for the most part similar to those in Dechow et al. (1995) and Kang and Sivaramakrishnan (1995), we emphasize more a fundamental finding that is common to all three papers: at an absolute level, the models used in the literature are not very accurate. While the in-sample (or estimation period) explanatory power for some models might create misplaced confidence in the accuracy of that model, because the $R^2$ values appear reasonably high, the out-of-sample performance is generally not strong. In particular, simply assuming that total accruals equal $-5\%$ of the total assets (TA) and current accruals equal $0\%$ of TA for all firms for all years performs as well or better than most models we consider, in terms of out-of-sample forecast errors.\footnote{This estimate of $-5\%$ ($0\%$) of TA was obtained from the distribution of total (current) accruals over a prior period. Examination of the year-by-year distribution of total (current) accruals indicates that the mean of these distributions is approximately $-5\%$ ($0\%$) of TA in each year.} Only the Kang and Sivaramakrishnan (1995) (KS) model slightly outperforms the naïve total accrual model, and the Jones (1991) model (suitably adjusted to predict current accruals) slightly outperforms the naïve current accruals model. Hereafter, the Jones (1991) and Kang and Sivaramakrishnan (1995) models are referred to as the Jones and KS models.

A second motivation to study forecast errors for models that predict accruals, unrelated to any links to earnings management, is to improve our understanding of accruals. What is the cross-sectional and time-series correlation structure among forecast errors? How much of the variation in total accruals is due to each of its components: current and non-current accruals? What is the correlation of forecast errors across models, and how much is gained by combining forecasts from different accrual prediction models? Examination of forecast errors from a variety of accrual prediction models allows us to provide answers to these questions. Given that accruals lie at the core of accounting, additional understanding of the behavior of accruals should be valuable to all aspects of accounting thought.

A more detailed discussion of the similarities and differences between discretionary accruals and unexpected accruals is laid out in Section 2. Section 3 offers a description of the different accrual models considered. In Section 4, we report the primary results based on accrual forecasts for a sample of 1,748 Compustat firms over the 5-year period between 1990 and 1994. In addition to reporting the distribution of forecast errors and a pseudo-$R^2$ for the forecast period, we also provide a simple non-parametric analysis: each model is ranked (first through sixth) in terms of mean squared error for each firm and the distribution of ranks reported across the sample. Section 5 contains the results of extensions to the primary analysis, and Section 6 concludes.
2. Unexpected accruals versus discretionary accruals

Despite our focus on the properties of forecast accruals per se, we consider briefly in this section the relation between forecast errors from accrual prediction models (unexpected accruals) and the ability to detect earnings management (discretionary accruals).

Consider the usual separation of total accruals (\( \text{TOTACC}_{it} \)), for firm \( i \) in year \( t \), into the following two parts: true discretionary (\( \text{DISCACC}_{it} \)) and true non-discretionary accruals (\( \text{NONDISCACC}_{it} \))

\[
\text{TOTACC}_{it} = \text{NONDISCACC}_{it} + \text{DISCACC}_{it}.
\]

Each model then generates a forecast for total accruals (\( \hat{\text{TOTACC}}_{it} \)), which can in turn be viewed as the sum of the forecast values of non-discretionary (\( \hat{\text{NONDISCACC}}_{it} \)) and discretionary accruals (\( \hat{\text{DISCACC}}_{it} \)). Therefore, forecast errors (\( \hat{\text{FE}}_{it} \)) from each model can be viewed as the sum of forecast errors on the two components of total accruals

\[
\hat{\text{FE}}_{it} = \text{TOTACC}_{it} - \hat{\text{TOTACC}}_{it}
\]

\[
= \text{NONDISCACC}_{it} + \hat{\text{NONDISCACC}}_{it} + \hat{\text{DISCACC}}_{it}
- \text{DISCACC}_{it}.
\]

Since the researcher, in general, observes only total accruals, \(^3\) it is hard to draw links between \( \text{FE}_{it} \) and \( \text{DISCACC}_{it} \), without imposing additional structure. The prior literature has assumed that discretionary accruals are negligible during the estimation period, and the model used is in effect derived for non-discretionary accruals alone (e.g., Dechow et al., 1995, p. 195). As a result, any forecast error in the period of suspected earnings management is viewed as a reasonable estimate for discretionary accruals in that period. If, however, discretionary accruals exist even in the estimation period, the models revert to predicting unexpected accruals, since the predictable portion of both non-discretionary and discretionary accruals is captured in the forecast. \(^4\)

There are two important differences between a methodological study such as ours and the typical earnings management study. First, unlike studies that examine accruals around events hypothesized to have caused firms to manage earnings, there is no reason to expect more earnings management in our non-

\(^3\) It has been suggested that discretionary accruals are easier to detect if researchers focus on any one component of accruals, rather than on total accruals (see Beneish, 1998a, pp. 86–87). McNichols and Wilson (1988) and Miller and Skinner (1998) are examples of such studies.

\(^4\) If, for example, revenue changes predicted both non-discretionary accruals as well as some portion of discretionary accruals, then an accrual model which uses revenue changes as an explanatory variable would capture that portion of discretionary accruals in its forecast of non-discretionary accruals.
event forecast period. That is, the estimation and forecast periods are conceptually similar in our study, and are drawn from the same underlying population. Second, when evaluating the relative performance of different models, we are comparing the distribution of forecast errors across models for the same forecast firm-years. In effect, each firm-year serves as its own control, and the level of true discretionary and non-discretionary accruals are held constant across the different models for each firm-year.

The links between forecast errors and discretionary accruals that can be forged from our study are a function of the structure imposed on discretionary and non-discretionary accruals in non-event (estimation) periods. If, discretionary accruals are rare, then forecast errors can be used to offer insights about the absolute and relative ability of each model to predict non-discretionary accruals in non-event-periods. These forecast errors also represent the error with which discretionary accruals will be measured in an event period with systematic earnings management when that particular model is used.  

On the other hand, if non-event-periods are associated with substantial earnings management, forecast errors cannot be used to make statements about the absolute level of earnings management in event-periods. Some inferences about the relative ability (across models) to detect earnings management in event-periods are possible, however, given certain assumptions about the relation between forecast errors for discretionary and non-discretionary accruals.

In sum, if forecast errors provide information about the absolute level of discretionary accruals, our study adds to the literature on errors in detecting earnings management. If, however, forecast errors are informative only about the relative ability of different models to detect earnings management, our study helps to rank the performance of these models. Even if no inferences are possible about the absolute or relative ability of the six models to identify earnings management, we believe that accruals are important enough on their own to merit some study of their properties.

3. The accrual prediction models

Before discussing the different accrual prediction models, it is useful to define accruals and describe the measures used in the empirical literature. Total

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5 Since the forecast error associated with non-discretionary accruals in a non-event period remains for event-periods, the error associated with the discretionary accruals in an event period would then be of the same magnitude but of opposite sign.

6 If, for example, the two errors are independent during non-event-periods, the variance of forecast errors should be inversely related to the relative ability of each model to identify discretionary accruals.
accruals are usually defined (e.g., Dechow et al., 1995, p. 203) as the difference between net income ($NI_{it}$) and cash flow from operations ($CFO_{it}$)

$$\text{TOTACC}_{it} = NI_{it} - CFO_{it}. \tag{3}$$

Rather than compute total accruals from net income and cash flow from operations, it is usually represented by approximate measures for the following two components: current accruals ($\text{CURACC}_{it}$), proxied by the change in working capital (excluding cash), and non-current accrual ($\text{NONCURACC}_{it}$), proxied by depreciation, depletion, and amortization (e.g., Dechow et al., 1995, p. 203). In effect, all other accrual items are ignored

$$\text{TOTACC}_{it} = \text{CURACC}_{it} + \text{NONCURACC}_{it}$$

$$= \Delta[(\#4 - \#1) - \#5] - \#125, \tag{4}$$

where $\Delta$ represents the year-to-year change, and the various $\#n$ represent data items from Compustat ($\#4 = \text{current assets}$, $\#1 = \text{cash}$, $\#5 = \text{current liabilities}$, and $\#125 = \text{depreciation, depletion, and amortization from the cash flow statement}$). The KS model is slightly different, and predicts the balance sheet levels of accounts represented in current accruals, rather than changes in those accounts, and includes amortization from the income statement ($\#14$), rather than amortization from the cash flow statement (Kang and Sivaramakrishnan, 1995, p. 358). To allow comparisons across firms, accrual measures in all models are typically scaled by $\text{TA}_{it-1}$, obtained from data item $\#6$ of Compustat.

The different accrual prediction models fall into two broad categories: those that do and those that do not peek ahead. A peek-ahead model (e.g., Jones, 1991, p. 211) uses information from the year being forecasted, whereas the models that do not peek-ahead (e.g., DeAngelo, 1986, p. 409) are limited to information available as of the prior year. Since peek-ahead models access more current information, they might reasonably be expected to perform better than models that do not peek ahead. Depending on the context of the investigation, peek-ahead models may or may not be appropriate. For example, peek-ahead models are appropriate for detecting earnings management, but not for examining investment strategies based on prediction of future unexpected accruals (e.g., Sloan, 1996). For our primary analysis, we consider a total of six models: three non-peek-ahead models and three peek-ahead models.

In extensions to the primary analysis, we consider modifications to these models, and also consider predictions of current accruals alone, rather than total accruals. This last extension is motivated by the presumption that even though the magnitudes of non-current accruals exceed those of current accruals, there is more management of current accruals than there is of
non-current accruals. 7 Brief descriptions of the six models are provided next, and details of the variables used are provided in Appendix A.

3.1. Random walk model

After noting various limitations of the random walk model as a predictor of accruals, DeAngelo (1986, p. 409) proposes it as a convenient first approximation of how non-discretionary accruals behave. To allow comparisons across firms, her model has typically been adapted slightly in prior research (e.g., Dechow et al., 1995, p. 198) and applied to scaled accruals, rather than the unscaled accruals she used. 8 This adapted version of the DeAngelo model can be represented as follows:

\[
\frac{\text{TOTACC}_{it}}{\text{TA}_{it-1}} = \frac{\text{TOTACC}_{it-1}}{\text{TA}_{it-2}} + e_{it},
\]

The random walk model is relatively simple to use: no estimation period is required, unlike other models, and first differences in scaled accruals represent forecast errors.

3.2. Mean-reverting accruals

Accruals, especially the current accrual component, have been shown to vary from a random walk and exhibit mean reversion (e.g., Dechow, 1994, p. 18). Based on this insight, Dechow et al. (1995, p. 197), used the mean of the past five years’ accruals as an expectation for this year’s accrual 9

\[
\frac{\text{TOTACC}_{it}}{\text{TA}_{it-1}} = \frac{1}{5} \left( \sum_{t=-5}^{t-1} \frac{\text{TOTACC}_{it}}{\text{TA}_{it-1}} \right) + e_{it}.
\]

7 Beneish (1998b, p. 211) argues that managing earnings via depreciation is potentially transparent (because changes in estimates that alter depreciation expense are disclosed in footnotes) and economically implausible (because the timing of capital expenditures would need to be divorced partially from the arrival of profitable investment opportunities).

8 DeAngelo (1986, p. 414) also considered scaled accruals for her study, but the results remained fairly similar.

9 Recently, a few papers have labeled this model the Healy model (e.g., Dechow et al., 1995, p. 197; Guay et al., 1996, p. 83). Although Healy (1985, p. 86) expects non-discretionary accruals to equal zero, his tests effectively assume that non-discretionary accruals for each firm equal the mean accrual of all other firm-years in his sample (since his tests are based on comparisons of mean accruals across portfolios of firm-years with different predictions for discretionary accruals). Thus, the mean-reverting model above is slightly different from that used in Healy (1985), because it is based on a time-series firm-specific mean, rather than a cross-sectional mean.
Unlike the random walk model, which is influenced entirely by last year’s accrual, the mean-reverting model gives equal weight to accruals from each of the prior five years. As a result, however, accruals cannot be forecast if missing values of scaled accruals exist for any of the previous five years.

3.3. Components model

The random walk and mean-reverting models described above can be viewed as representing polar opposite processes for total accruals. We speculate that a process that falls in between these two extremes might better represent accruals. That is, total accruals might be better represented by a weighted-average of the random walk and mean-reverting models. Also, given that current accruals exhibit more mean reversion than non-current accruals, predictions should improve if current and non-current accruals are allowed to have separate weights. The specific models we estimate are as follows:

\[
\frac{\text{CURACC}_{it}}{\text{TA}_{it-1}} = (\alpha) \frac{\text{CURACC}^{t-1}_{it}}{\text{TA}_{it-2}} + (1 - \alpha) \left( \frac{1}{5} \sum_{t-5}^{t-1} \frac{\text{CURACC}_{it}}{\text{TA}_{it-1}} \right) + e_{it},
\]

\[
\frac{\text{NONCURACC}_{it}}{\text{TA}_{it-1}} = (\beta) \frac{\text{NONCURACC}^{t-1}_{it}}{\text{TA}_{it-2}} + (1 - \beta) \left( \frac{1}{5} \sum_{t-5}^{t-1} \frac{\text{NONCURACC}_{it}}{\text{TA}_{it-1}} \right) + e_{it}.
\]

The weights, \(\alpha\) and \(\beta\), are estimated over all firm-years with available data in the estimation period 1975–1989, and the requirements for non-missing prior period accruals are similar to those for the mean-reverting model. For firm-years in the prediction period, the weights from the estimation period are used to obtain predictions for current and non-current accruals, which are then summed to yield a predicted total accrual. 10

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10 Note that the weights do not have firm subscripts, which requires that all firms have the same weights for current and non-current accruals. We also examined predictions based on firm-specific weights, but found substantially greater prediction errors. Apparently, the errors in estimating weights from a limited number of time-series observations exceed the errors caused by forcing all firms to fit the same profile.
3.4. Jones model

The Jones model uses changes in revenues (Compustat data item #12) from period $t - 1$ to $t$ and period $t$ gross plant, property, and equipment (Compustat item #7) to predict total accruals, as follows (Jones, 1991, p. 211):

$$
\frac{\text{TOTACC}_{it}}{\text{TA}_{it-1}} = a_i \frac{1}{\text{TA}_{it-1}} + b_{1i} \frac{\Delta \text{REV}_{it}}{\text{TA}_{it-1}} + b_{2i} \frac{\text{PPE}_{it}}{\text{TA}_{it-1}} + e_{it}.
$$

Eq. (9) is fitted over an estimation period for each firm $i$, to provide the three parameter estimates ($a_i$, $b_{1i}$, and $b_{2i}$). These estimates are then used to forecast non-discretionary accruals in prediction periods, using values of the explanatory variables from those periods. That is, the Jones model is a peek-ahead model, unlike the first three models. Also, since the relation is estimated separately for each firm, only firms with sufficient years of non-missing data in the estimation period (10 years) are included in the sample.

3.5. Industry model

Dechow et al. (1995, p. 199) suggest that non-discretionary accruals might potentially be explained by accruals made by other firms in the same industry. In other words, each firm has a certain sensitivity to industry accruals defined as follows:

$$
\frac{\text{TOTACC}_{it}}{\text{TA}_{it-1}} = i_{1i} + i_{2i} \left( \text{industry median} \frac{\text{TOTACC}_{it}}{\text{TA}_{it-1}} \right) + e_{it}.
$$

Eq. (10) is fitted over the estimation period for each firm $i$, to provide the two parameter estimates, and these estimates are used to forecast non-discretionary accruals in prediction periods. Firms are grouped into industries based on two-digit SIC codes, and industry medians are computed each year over all firms with non-missing values of scaled accruals. Like the Jones model, the industry model is a peek-ahead model, and the same requirement of 10 years of non-missing data in the estimation period is imposed for sample firms.

3.6. Kang–Sivaramakrishnan (KS) model

Kang and Sivaramakrishnan (1995, p. 358) offer a different peek-ahead approach to identifying discretionary accruals, relative to the two peek-ahead models discussed in Sections 3.4 and 3.5. They predict the level of current assets and liabilities, rather than changes in those accounts, and estimate one set of model parameters for all firms, rather than estimate firm-specific parameters. Firm-specific estimation is difficult because of the data requirements (in
addition to requiring additional variables, they require twice and thrice lagged values of all variables for their instrument set). Their model mitigates the omitted variables problem by including additional variables (cost of goods sold and other operating expenses), and mitigates the simultaneity and errors-in-variable problems by using the instrumental variables (IV) and generalized method of moment (GMM) procedures

\[
\frac{\text{ACCBAL}_t}{\text{TA}_{t-1}} = c_0 + c_1 \frac{\text{REV}_t}{\text{TA}_{t-1}} \left( \frac{\text{ART}_{t-1}}{\text{REV}_{t-1}} \right) + c_2 \frac{\text{EXP}_t}{\text{TA}_{t-1}} \left( \frac{\text{OCAL}_{t-1}}{\text{EXP}_{t-1}} \right) + c_3 \frac{\text{GPPE}_t}{\text{TA}_{t-1}} \left( \frac{\text{DEP}_{t-1}}{\text{GPPE}_{t-1}} \right).
\]

(Appendix A provides details of the variables in Eq. (11). Based on results in Kang (1999, p. 4), which indicate that the IV and GMM procedures provide very similar results, we consider only the IV procedure.

3.7. Other models

We report on results obtained from some of the other models that have been proposed in the literature. Boynton et al. (1992, p. 137) estimate the Jones model using data pooled for each industry, rather than estimate the model separately for each firm. Boynton et al. (1992) only include the five most recent years in the estimation period to minimize problems caused by potential non-stationarity. We consider this modification in Section 5 and confirm that the results are indeed better than the traditional Jones model, in terms of forecast accuracy. Beneish (1997, p. 273) suggests that lagged total accruals and contemporaneous price performance be also included to improve the Jones model. We examine these modifications too but are unable to find much improvement over the Jones model (see discussion in Section 5).

Dechow et al. (1995, p. 199) propose a modification of the Jones model which removes changes in net account receivables from the revenue changes used as an explanatory variable in Eq. (9). Note that this adjustment is only made in the test period, and the standard Jones model is fitted in the estimation period. Dechow et al. (1995, p. 199) argue that earnings management might influence reported revenue numbers and such an adjustment mitigates the effect of earnings management on this explanatory variable. We do not examine this modification of the Jones model, as it applies only to firms that are ex ante likely to undertake earnings management. Examining all firms in the population, many of which are unlikely to have managed earnings, creates the potential of increasing forecast errors by changing the model for such firms between the estimation and forecast periods.
4. Sample selection and results

Financial data were obtained from the 1995 editions of the annual Compustat files (industrial, research, and full-coverage). The first 15 years (1975–1989) of the 20 years available in this database are designated as the estimation period, and are used to estimate model parameters (if necessary) for the different models. Since the prior year’s data is required to compute accruals, only 14 years of data were available in the estimation period. To maintain period-to-period consistency, all firm-years with fiscal year changes or extreme changes in TA (this period’s assets are less than half or more than one and a half times last year’s TA) were deleted. All dependent and independent variables were Winsorized to lie between −100% and +100%, and all forecasts were also Winsorized to lie between those limits.

The last five years (1990–1994) were designated as the prediction period, and were used to compare forecast errors across models. As with the estimation period, accruals were missing for firm-years with fiscal year changes or extreme changes in TA. Forecasts were unavailable for any model if any of the variables input to that model are missing or if model parameters are missing. A firm-year was included in the final prediction sample, only if accrual forecasts were available for all models. Forecasts were available for all models for a total of 7,195 firm-years in the prediction period, representing 1,748 firms. The model parameters estimated over the estimation period (1975–1989) were fixed over the entire prediction period. In Section 5, we show that updating the model to include prior years in the prediction period (e.g., estimating the model over 1975–1993 when forecasting accruals for 1994) does not change the results substantially.

4.1. Descriptive statistics

Table 1, Panel A, contains a description of the distribution of total accruals over the prediction period. The mean and median is approximately −5% (of prior period TA). There is considerable variation across firm-years, as indicated by a standard deviation of approximately 11%, and an interquartile range of about 8%. Analysis of the year-by-year distributions suggests that the distribution is fairly stationary over time, i.e., much of the total variation is caused by across firm variation.

Distributions are also provided in Panel A for the two components of total accruals: current accruals and non-current accruals. The two distributions are quite different. Current accruals, representing the increase in non-cash working capital (scaled by last period assets) are centered on zero (mean and median of −0.02% and 0.13%), whereas non-current accruals have a mean and median close to −5%. The variation in current accruals is, however, much larger than that of non-current accruals, as indicated by the higher interquartile range (75th percentile less 25th percentile) and the higher standard deviation.
Table 1
Summary statistics for total accruals and its components 7,195 firm-years (1,748 firms) over the prediction period (1990–1994)*

<table>
<thead>
<tr>
<th></th>
<th>Mean (%)</th>
<th>Standard deviation (%)</th>
<th>10th percentile (%)</th>
<th>25th percentile (%)</th>
<th>50th percentile (%)</th>
<th>75th percentile (%)</th>
<th>90th percentile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Distributional statistics for accrual components</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current accrual</td>
<td>−0.02</td>
<td>10.50</td>
<td>−7.38</td>
<td>−2.95</td>
<td>0.13</td>
<td>3.26</td>
<td>7.38</td>
</tr>
<tr>
<td>Non-current accrual</td>
<td>−5.37</td>
<td>2.98</td>
<td>−8.91</td>
<td>−6.62</td>
<td>−4.88</td>
<td>−3.51</td>
<td>−2.34</td>
</tr>
<tr>
<td>Total accrual</td>
<td>−5.39</td>
<td>10.90</td>
<td>−13.78</td>
<td>−8.99</td>
<td>−5.24</td>
<td>−1.51</td>
<td>3.11</td>
</tr>
</tbody>
</table>

|                  |          |                        |                     |                     |                     |                     |                     |
| **Panel B: Correlation among accrual components** | Pearson correlation above main diagonal, and Spearman rank correlation below |          |                        |                     |                     |                     |                     |
|                  | Current accrual | Non-current accrual | Total accrual |          |                        |                     |                     |
| Current accrual  | −0.003   | 0.962                  | 0.962             |          |                        |                     |                     |
| Non-current accrual | −0.013  | −0.003                 | 0.270             |          |                        |                     |                     |
| Total accrual    | 0.879    | 0.384                  | −              |          |                        |                     |                     |

*All firm-years between 1990 and 1994 on Compustat with forecasts available for all six accrual prediction models (see Appendix A for details of models) are included in the sample. Total accruals and its two components are measured as follows. 

$\text{TOT ACC}_t = \text{CUR ACC}_t + \text{NON CUR ACC}_t = A([#4 - #1] - #5) - #125,$

where data # are from Compustat. All accruals items are scaled by beginning-of-year total assets (TA), which is data item #6.

*Correlations greater than 0.023 (0.030) are significant at the 5% (1%) level.
Correlations among these three variables are reported in Panel B. A considerable portion of the variation in total accruals is due to that in current accruals (Pearson correlation of 0.962 and Spearman correlation of 0.879). The correlation between non-current and total accruals is much lower, and there is almost no correlation between current and non-current accruals. Overall, current accruals are more variable than non-current accruals, and appear to be responsible for most of the variation in total accruals.

Parameters estimated for the different models are reported in Table 2. No estimates are required for the random walk and mean-reverting models. For the components model (results reported in Panel A), very different weights are estimated for current and non-current accruals. Current accruals are completely mean-reverting, at least for this pooled sample, indicated by a weight on the random walk model that is close to zero (estimated \( \alpha \) equals \(-0.2\%\)). For non-current accruals, however, the weights are more balanced: a weight of 59.9\% (40.1) is assessed on the random walk (mean-reverting) model.

The distributions across firms for estimated parameters for the Jones model are reported in Panel B of Table 2. These results are similar to those reported in prior literature (e.g., Jones, 1991, p. 213). In concept, the coefficient \( b_{1i} \) on the first difference of revenues should be positive (sales increases should cause proportionate increases in current assets and current liabilities), and the coefficient \( b_{2i} \) on gross plant should be negative (depreciation, depletion and amortization should increase with gross plant). Note, however, that there are many firms with coefficients of the wrong sign. For example, a negative 25th percentile value for \( b_{1i} \) indicates that more than 25% of all sample firms had working capital increases (decreases) when sales decreased (increased). The proportion of firms with wrong signs for \( b_{2i} \) is less than that observed for \( b_{1i} \), but yet alarmingly high: as many as 20% of firms had a positive value for \( b_{2i} \), which indicates that depreciation decreased (increased) as gross plant increased (decreased). The relatively high proportion of firms with wrong values for these two coefficients suggests that predictions from this model are likely to contain considerable error.

The distributions for firm-specific coefficients estimated for the industry model are reported in Panel C of Table 2. Although the distribution for \( i_{2} \) is centered on 1, this measure of sensitivity to industry norms varies considerably across firms, with about 20% of firms exhibiting a negative coefficient. While one might in general expect positive values for \( i_{2} \), an argument could be made for why some firms should exhibit a negative correlation with industry median accruals, based on factors such as competitive reactions to initiatives taken by industry leaders. That is, unlike \( b_{1i} \) and \( b_{2i} \), for the Jones model, we are unable to gauge the proportion of firms with estimates of \( i_{2} \) that are of the wrong sign.
Table 2
Parameters estimated for three of the five prediction models estimation period (1976–1989)*

**Panel A: Estimated weights from pooled regressions for components model**

\[
\frac{\text{CURACC}_i}{\text{TA}_{i-1}} = (\alpha) \frac{\text{CURACC}_{i-1}}{\text{TA}_{i-2}} + (1 - \alpha) \left( \frac{1}{5} \sum_{t=1}^{t-1} \frac{\text{CURACC}_{i-t}}{\text{TA}_{i-t-1}} \right) + \epsilon_i
\]  

(7)

\[
\frac{\text{NONCURACC}_i}{\text{TA}_{i-1}} = (\beta) \frac{\text{NONCURACC}_{i-1}}{\text{TA}_{i-2}} + (1 - \beta) \left( \frac{1}{5} \sum_{t=1}^{t-1} \frac{\text{NONCURACC}_{i-t}}{\text{TA}_{i-t-1}} \right) + \epsilon_i
\]  

(8)

\(\alpha = -0.002\) from Eq. (7), and \(\beta = 0.599\) from Eq. (8), based on 19,943 and 20,966 firm-years

**Panel B: Distributional statistics for firm-specific Jones model parameter estimates (2,692 firms with at least 10 years of data)**

<table>
<thead>
<tr>
<th>Coefficient estimate</th>
<th>Mean (%)</th>
<th>Standard deviation (%)</th>
<th>10th percentile (%)</th>
<th>25th percentile (%)</th>
<th>50th percentile (%)</th>
<th>75th percentile (%)</th>
<th>90th percentile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_i)</td>
<td>7.582</td>
<td>151.512</td>
<td>-8.784</td>
<td>-0.907</td>
<td>0.335</td>
<td>4.632</td>
<td>33.814</td>
</tr>
<tr>
<td>(b_{1i})</td>
<td>0.068</td>
<td>0.290</td>
<td>-0.161</td>
<td>-0.026</td>
<td>0.071</td>
<td>0.178</td>
<td>0.312</td>
</tr>
<tr>
<td>(b_{2i})</td>
<td>-0.121</td>
<td>0.649</td>
<td>-0.297</td>
<td>-0.151</td>
<td>-0.084</td>
<td>-0.028</td>
<td>0.064</td>
</tr>
</tbody>
</table>

**Panel C: Distributional statistics for firm-specific Industry model parameter estimates (2,719 firms with at least 10 years of data)**

\[
\frac{\text{TOTACC}_i}{\text{TA}_{i-1}} = a + i \left( \text{industry median} \frac{\text{TOTACC}_i}{\text{TA}_{i-1}} \right) + \epsilon_i
\]  

(9)

\[
\frac{\text{TOTACC}_i}{\text{TA}_{i-1}} = a + \left( \text{industry median} \frac{\text{TOTACC}_i}{\text{TA}_{i-1}} \right) + \epsilon_i
\]  

(10)

\(a_i\) Two of the five models, random walk and mean-reverting accruals, do not require parameter estimates (see Appendix A for details of models). Parameters for the remaining three models are estimated from all firm-years with available data between 1976 and 1989 on Compustat. Total accruals and its two components are measured as follows. \(\text{TOTACC}_i = \text{CURACC}_i + \text{NONCURACC}_i = \Delta[#4 - #1] - #5] - #125\), where data # are from Compustat. All accruals items are scaled by beginning-of-year total assets (TA), which is data item #6.

---

*Two of the five models, random walk and mean-reverting accruals, do not require parameter estimates (see Appendix A for details of models). Parameters for the remaining three models are estimated from all firm-years with available data between 1976 and 1989 on Compustat. Total accruals and its two components are measured as follows. \(\text{TOTACC}_i = \text{CURACC}_i + \text{NONCURACC}_i = \Delta[#4 - #1] - #5] - #125\), where data # are from Compustat. All accruals items are scaled by beginning-of-year total assets (TA), which is data item #6.
4.2. Accrual forecasts and forecast errors

Although we do not focus on the issue of type I and II errors, a brief discussion of prior results is useful. For type I errors, evidence suggests that the probability of finding earnings management when there is none varies across studies as well as on whether one firm is considered or a sample of firms. For example, at the single firm level, Dechow et al. (1995, p. 205) found that the distribution of the \( t \)-statistic is well behaved for a random sample of 1,000 firms for all five accrual models they consider (i.e., the null hypothesis is rejected at the 5% significance level, two-tailed, in approximately 5% of the firms), whereas Choi et al. (1997, Table 7) found that the distribution of the \( t \)-statistic for Jones model forecast errors for the 1985–1988 period for all firms with available data has fatter tails (tends to reject the null hypothesis at the 5% level, two-tailed, for almost 10% of firms). Moving to random samples of 100 firms, Kang and Sivaramakrishnan (1995, p. 361) found that the distribution of the \( t \)-statistic is well behaved for the Jones model, as well as for two other models they propose.

Inferences regarding type II errors also vary across prior research. Dechow et al. (1995, p. 194) found that power is low even for the models with the lowest standard error (the Jones and modified Jones models had the lowest standard errors, with mean standard errors of about 9% of total assets for forecast accruals over their random sample of 1,000 firms). Earnings management would have to exceed 18% of total assets for the average firm (or 1% of TA for each firm in a sample of 300 firms) to generate significant statistics that would reject the null hypothesis of no earnings management. Kang and Sivaramakrishnan (1995, pp. 361) paint a more optimistic picture, because they move from the individual firm level to samples of 100 firms each. When they seeded their firms with a random accrual that averaged 2% of total assets (it actually ranged between 0.064% and 30.469%), their rate of rejection of the null hypothesis at the 5% level increased from 5% (before seeding) to 23% for the Jones model (and 33% and 47% for their IV and GMM models).

In sum, the prior results suggest that type I errors may not be a big problem for most accrual forecast models. However, the statistical power (based on type II errors) is probably quite low for most models, with the possible exception of the two versions of the KS model.

In this paper, we use four simple ways to describe the accuracy of the six models described earlier. First, we report in Panel A of Table 3, the distribution of raw forecast errors for each model during the five-year prediction period. All models exhibit little bias, as indicated by mean and median forecast errors that are close to zero. However, examination of other points in the distributions indicates that forecast accruals contain considerable error, for all models. Standard deviations for the six models, which range between 10% and 15% of total assets, and interquartile ranges which lie between 6% and 10%, are large
Table 3
Forecast accuracy for six accrual prediction models 7,195 firm-years (1,748 firms) over the prediction period (1990–1994) a

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean (%)</th>
<th>Standard deviation (%)</th>
<th>10th percentile (%)</th>
<th>25th percentile (%)</th>
<th>50th percentile (%)</th>
<th>75th percentile (%)</th>
<th>90th percentile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random walk</td>
<td>-0.18</td>
<td>15.17</td>
<td>-11.65</td>
<td>-4.96</td>
<td>-0.30</td>
<td>4.38</td>
<td>11.12</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-0.65</td>
<td>11.82</td>
<td>-9.55</td>
<td>-4.25</td>
<td>-0.50</td>
<td>2.97</td>
<td>7.80</td>
</tr>
<tr>
<td>Components</td>
<td>-0.62</td>
<td>11.83</td>
<td>-9.54</td>
<td>-4.18</td>
<td>-0.44</td>
<td>2.93</td>
<td>7.96</td>
</tr>
<tr>
<td>Jones</td>
<td>0.38</td>
<td>13.65</td>
<td>-9.93</td>
<td>-3.84</td>
<td>0.47</td>
<td>4.64</td>
<td>10.60</td>
</tr>
<tr>
<td>Industry</td>
<td>-0.69</td>
<td>11.36</td>
<td>-9.57</td>
<td>-4.24</td>
<td>-0.48</td>
<td>3.08</td>
<td>7.98</td>
</tr>
<tr>
<td>KS</td>
<td>0.49</td>
<td>10.62</td>
<td>-6.59</td>
<td>-2.30</td>
<td>0.85</td>
<td>3.99</td>
<td>8.17</td>
</tr>
</tbody>
</table>

Panel A: Distributional statistics for forecast errors

Panel B: % of times each rank is obtained, based on rankings by firm

<table>
<thead>
<tr>
<th>Model</th>
<th>First (%)</th>
<th>Second (%)</th>
<th>Third (%)</th>
<th>Fourth (%)</th>
<th>Fifth (%)</th>
<th>Sixth (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random walk</td>
<td>7.27</td>
<td>6.98</td>
<td>7.72</td>
<td>10.07</td>
<td>19.57</td>
<td>48.40</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>7.61</td>
<td>18.42</td>
<td>25.17</td>
<td>26.72</td>
<td>17.62</td>
<td>4.46</td>
</tr>
<tr>
<td>Components</td>
<td>9.27</td>
<td>18.65</td>
<td>25.74</td>
<td>26.54</td>
<td>16.08</td>
<td>3.72</td>
</tr>
<tr>
<td>Jones</td>
<td>17.56</td>
<td>18.14</td>
<td>11.67</td>
<td>10.18</td>
<td>16.36</td>
<td>26.09</td>
</tr>
<tr>
<td>Industry</td>
<td>21.17</td>
<td>17.91</td>
<td>17.33</td>
<td>14.36</td>
<td>18.19</td>
<td>11.04</td>
</tr>
</tbody>
</table>

Panel C: Distribution of firm-specific explained variation ($R^2 = 1 – ESS/TSS$, where $ESS = \sum (actual – forecast)^2$ and $TSS = \sum (actual – \mu)^2$, where $\mu = mean of five actual accruals$)

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean (%)</th>
<th>Standard deviation (%)</th>
<th>10th percentile (%)</th>
<th>25th percentile (%)</th>
<th>50th percentile (%)</th>
<th>75th percentile (%)</th>
<th>90th percentile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random walk</td>
<td>-19.013</td>
<td>404.55</td>
<td>-4.875</td>
<td>-2.595</td>
<td>-1.751</td>
<td>-1.056</td>
<td>-0.523</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-47.181</td>
<td>1352.41</td>
<td>-2.823</td>
<td>-1.133</td>
<td>-0.529</td>
<td>-0.273</td>
<td>-0.142</td>
</tr>
<tr>
<td>Components</td>
<td>-46.114</td>
<td>1315.77</td>
<td>-2.850</td>
<td>-1.120</td>
<td>-0.495</td>
<td>-0.262</td>
<td>-0.111</td>
</tr>
<tr>
<td>Jones</td>
<td>-28.489</td>
<td>461.54</td>
<td>-11.604</td>
<td>-3.257</td>
<td>-0.730</td>
<td>-0.107</td>
<td>0.156</td>
</tr>
<tr>
<td>Industry</td>
<td>-10.115</td>
<td>226.69</td>
<td>-4.330</td>
<td>-1.622</td>
<td>-0.476</td>
<td>-0.080</td>
<td>0.058</td>
</tr>
<tr>
<td>KS</td>
<td>-28.692</td>
<td>798.39</td>
<td>-2.845</td>
<td>-1.016</td>
<td>-0.246</td>
<td>0.074</td>
<td>0.297</td>
</tr>
<tr>
<td>Model</td>
<td>Mean (%)</td>
<td>Standard deviation (%)</td>
<td>10th percentile (%)</td>
<td>25th percentile (%)</td>
<td>50th percentile (%)</td>
<td>75th percentile (%)</td>
<td>90th percentile (%)</td>
</tr>
<tr>
<td>------------</td>
<td>----------</td>
<td>------------------------</td>
<td>---------------------</td>
<td>---------------------</td>
<td>---------------------</td>
<td>--------------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>Random walk</td>
<td>-451.676</td>
<td>15,209.68</td>
<td>-3.020</td>
<td>-1.728</td>
<td>-0.811</td>
<td>0.019</td>
<td>0.578</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-20.623</td>
<td>507.71</td>
<td>-1.204</td>
<td>-0.447</td>
<td>-0.114</td>
<td>0.290</td>
<td>0.683</td>
</tr>
<tr>
<td>Components</td>
<td>-20.616</td>
<td>507.33</td>
<td>-1.223</td>
<td>-0.435</td>
<td>-0.118</td>
<td>0.307</td>
<td>0.707</td>
</tr>
<tr>
<td>Jones</td>
<td>-332.446</td>
<td>12,822.12</td>
<td>-4.227</td>
<td>-1.133</td>
<td>-0.107</td>
<td>0.292</td>
<td>0.622</td>
</tr>
<tr>
<td>Industry</td>
<td>-23.632</td>
<td>814.70</td>
<td>-1.696</td>
<td>-0.508</td>
<td>-0.025</td>
<td>0.316</td>
<td>0.673</td>
</tr>
<tr>
<td>KS</td>
<td>-412.063</td>
<td>16,734.17</td>
<td>-0.959</td>
<td>-0.204</td>
<td>0.135</td>
<td>0.459</td>
<td>0.751</td>
</tr>
</tbody>
</table>

Panel D: Distribution of firm-specific explained variation, relative to a naive model of forecast accrual = -5% \( R^2_a = 1 - \frac{\text{ESS}}{\text{TSS}} \), where \( \text{ESS} = \sum (\text{actual} - \text{forecast})^2 \) and \( \text{TSS} = \sum (\text{actual} - (-5\%))^2 \)

*a All firm-years between 1990 and 1994 on Compustat with forecasts available for all six accrual prediction models (see Appendix A for details of models) are included in the sample. Total accruals and its two components are measured as follows. \( \text{TOTACC}_t = \text{CURACC}_t + \text{NONCURACC}_t = \Delta(\#4 - \#1) - \#5 - \#125 \), where data \# are from Compustat. All accruals items are scaled by beginning-of-year total assets (TA), which is data item \#6.*
relative to (a) the magnitude of accruals associated with firms managing earnings in prior studies (Kang and Sivaramakrishnan, 1995, p. 360, report a range between 1.5% to more than 5% in different studies), as well as (b) the magnitude of operating income commonly observed (the median across all NYSE + AMEX firms has been approximately 8% of TA in each of the last 30 years).

Comparison across models, based on measures of dispersion, indicates that the random walk model is the least accurate and the KS model is the most accurate. The random walk (KS) model has the highest (lowest) standard deviation, interquartile range, and spread between the 90th and 10th percentiles. The Jones model is better than the random walk model but is outperformed by the other models on all three dimensions (standard deviation, interquartile range, and spread between the 90th and 10th percentiles). The components model mean-reverting model, and industry models are fairly similar on the same three dimensions. Apparently, allowing for a weighted-average of the random walk and mean-reverting models and allowing separate weights for current and non-current accruals provides little improvements in forecast accuracy over that of the mean-reverting model which requires that total accruals follow a mean-reverting process. 11

The results of a second evaluation of accuracy based on firm-specific rankings are reported in Panel B. For each firm, models are ranked from first to sixth based on the sum of squared forecast error for all years with forecasts in the prediction period. Since this second approach uses within-firm ranks it offers a different perspective than that taken in Panel A: it ignores magnitudes of differences. In other words, this evaluation potentially favors models that perform well for most firms, perhaps by a small margin, and not perform well occasionally (even if by a large margin). The KS model is again better than all other models (first almost 40% of the time), and the random walk model is the least accurate (sixth almost 50% of the time). The other two peek-ahead models, the Jones and Industry models, are first about 20% of the time each. Yet, the Jones model is also sixth about 26% of the time. As suggested by the results in Panel A, this model performs better than average often and yet does not perform well in many cases. The performances for the components and mean-reverting models appear to be similar.

The third measure of accuracy we compute is a pseudo-$R^2$ for the prediction period (see Fig. 1 for a summary and illustration of the approach). It is equivalent to an $R^2$ obtained from regressing actual accruals on forecast accruals in the prediction period, for each firm separately, in the presence of two

11 This result is explained by combining two of our earlier findings. First, current accruals provide most of the variation in total accruals (Table 1, Panel A). Second, current accruals follow a mean-reverting model (Table 2, Panel A).
restrictions: that the slope be one and the intercept be zero. A positive value of $R^2$ is obtained if the sum of squared forecast errors (ESS) is less than the sum of squared deviations from the mean actual accrual (TSS). On the other hand, a negative value of $R^2$ suggests that simply using the mean actual accrual as a forecast for all years for that firm outperforms the accruals from that prediction model.

Fig. 1. Prediction period $R^2$ and pseudo-$R^2$ ($R^2_a$) Note: For each sample firm and prediction model, data from the estimation period (1975–1989) are used to estimate the parameters that are needed to make forecasts for the five-year prediction period (1990–1994). Actual accruals in those five years are then plotted against forecast accruals (the five points marked as $x$). Forecast accuracy is measured by the sum of squared forecast errors, $\sum (A – F)^2$. To convert this measure of accuracy to a conventional $R^2$ value, we examine the fit of the five data points against the 45° line on the plot, or the regression line which represents actual accruals = forecast accruals, i.e., the regression line with a slope equal to one and an intercept equal to zero. The forecast errors can thus be represented by the residuals from this regression line, and the sum of squared forecast errors is equal to the conventional error sum of squares (ESS). This error sum of squares is normally compared to the total variation in actual accruals, or total sum of squares (TSS), which is measured by the sum of the squared deviations of the five actual accrual numbers from their mean ($\mu$). The conventional $R^2$ is then equal to 1 – ESS/TSS. An $R^2$ value equal to zero suggests that the forecast values perform as well as a naïve constant forecast equal to the mean accrual for all years. Since this mean accrual is not known, we offer a second comparison which results in a pseudo or adjusted $R^2$ ($R^2_a$). Compare the forecasts against a naïve constant forecast equal to $–5\%$ for all firms for all years. This value represents the grand mean for all firms for all years. In other words, compare the ESS against an alternative TSS$_a$, which is the sum of squared deviations of the five actual accrual numbers from $–5\%$.

$$R^2 = 1 - \frac{\text{ESS}}{\text{TSS}} = 1 - \frac{\sum (A – F)^2}{\sum (A – \mu)^2}$$ and $$R^2_a = 1 - \frac{\text{ESS}}{\text{TSS}_a} = 1 - \frac{\sum (A – F)^2}{\sum (A – (–5\%))^2}.$$
The distribution of $R^2$ reported in Panel C of Table 3 indicates less than satisfactory performance for all models. Note that in Panel C (and in Panel D), measures of distributional dispersion (reported standard deviations and interquartile ranges) are not used as indicators of forecast accuracy, unlike the results in Panel A. We examine instead the fraction of firms with positive $R^2$. Less than 10% of firms have positive $R^2$ values for all three no-peek-ahead models (since the 90th percentile is negative for the first three rows). Even for the three peek-ahead models, positive $R^2$ values are observed for less than 25% of all sample firms for the Jones and Industry models, as indicated by the point where $R^2$ is zero. Only the KS model exhibits some predictive ability: slightly over 25% of the firms are associated with a positive $R^2$.

These $R^2$ values observed for the prediction period appear to be unreasonably low compared to estimation period $R^2$ values noted for some models in prior research. For example, the estimation period $R^2$ values reported for the Jones model in Boynton et al. (1992, Table 1) and Jones (1991, Table 4) range between 20% and 30%. Those $R^2$ values are, however, not comparable to the $R^2$ values reported here, because most statistical software packages redefine the $R^2$ when the intercept is suppressed (as in the Jones model). The total sum of squares (TSS), which is normally defined as the sum of the squared deviations of actual accruals from the mean accrual, $\sum (A - \bar{A})^2$, is redefined as the sum of the squared accruals $\sum A^2$. In the normal definition, $R^2$ equals 0 when the forecast performance is the same as a naïve forecast equal to the mean of all accruals ($\mu$). For the $R^2$ definition used when the intercept is suppressed, $R^2$ equals 0 for the case when the forecast performance is the same as a naïve forecast equal to zero. In effect, the explained variation is overstated by the redefined $R^2$, since predictive accuracy is being compared with a base model (predicted accruals = 0) that is clearly inappropriate for predicting total accruals. It is important that researchers not be lulled into a misplaced sense of security by the high $R^2$ values reported by standard statistical packages.

We re-estimated the estimation period $R^2$ for the Jones and Industry models, using the correction mentioned above, and find that the corrected $R^2$ values are indeed lower than corresponding values of $R^2$ reported in the prior literature. However, those corrected estimation period $R^2$ values (results not reported) are still considerably larger than the prediction period $R^2$ values reported in Table 3, Panel C. For example, the 75th percentile points of the estimation period $R^2$ distributions are 18% and 7% for the Jones and Industry models. Again, care should be taken that researchers focus on the prediction period $R^2$, not the estimation period $R^2$, since the latter could simply be due to overfitting.

It might be argued that requiring models to achieve a positive $R^2$ value in the prediction period is an unfair hurdle. Recall that a positive $R^2$ implies that the model outperforms a naïve model which predicts that accruals equal the mean.
accrual for each firm over the five-year prediction period. Of course, the mean accrual for each firm is not known until the last year’s accrual is reported. Therefore, this benchmark might be unreasonably high, especially for models that do not peek-ahead. A less demanding test is to compare accuracy against a naïve benchmark that forecasts total accruals equal to $-5\%$ of last period’s assets for all firms for all years. This value of $-5\%$ was obtained from the pooled distribution of total accruals during the estimation period (see Table 1, Panel A).

Note that the $-5\%$ benchmark is an average across all firms, and is determined primarily by the mean level of non-current accruals (depreciation, depletion and amortization). It is probably the case that a more accurate firm-specific prediction of non-current accruals could be obtained by using the mean level of non-current accruals from an estimation period. But our objective is not to find the best naïve forecast of total accruals. Rather, we simply want to illustrate that the extant accrual models are in general unable to beat even the simplest naïve prediction.

The results of this examination, representing our fourth measure of forecast accuracy, are reported in Panel D. Again, the six models do not perform well. Recall that a negative (positive) $R^2$ in Panel D indicates that the naïve $-5\%$ model performs better (worse) than that accrual prediction model for that firm. The median $R^2$ is negative for all models except the KS model, indicating that the naïve $-5\%$ model is better than each of the remaining five models for at least half the sample firms.

The large standard deviations reported in Panels C and D of Table 3 suggest that the two sets of $R^2$ values reported in these panels are skewed by very large negative values for a few firms. To mitigate the effect of these few outlier values, we generated a new set of results for those two panels, after Winsorizing the $R^2$ values $\pm 100\%$. All numbers that are lower than $-1$ in Panels C and D are moved up to $-1$. While the standard deviations and other measures of dispersion are reduced considerably by this process, the overall tenor of the results reported in Table 3 remains unchanged. In particular, the KS model still performs better than the naïve $-5\%$ model for slightly over 50% of the firms, and the remaining models are outperformed by the naïve $-5\%$ model for more than 50% of the firms. 12

Overall, the results reported so far indicate that even though the different models considered use substantial amounts of relevant information to predict accruals, they exhibit little ability to predict accruals out of sample. A simple forecast model that predicts that all firms will have accruals equal to $-5\%$ of

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12 Recall that in Panels C and D of Table 3, unlike forecast error distributions reported in Panel A, we focus on the fraction of firms with positive $R^2$, not on the measures of dispersion.
last year’s TA outperforms most models, all but the KS model. This low ability to predict accruals suggests that researchers should continue their search for better accrual prediction models.

If accruals are so hard to predict, one would expect a fairly high degree of correlation among forecast errors from different models, since most of the variation in total accruals would appear in the forecast errors of all models. To confirm this conjecture, we examined the correlation among forecast errors, and the results of this analysis are reported in Table 4. As conjectured, there is a very high correlation among forecast errors, especially within the three models that do not peek-ahead. This high degree of correlation suggests that consensus models based on forecasts from all models are unlikely to perform better than any of the individual models. We examined this possibility and the results confirm that performance is not improved by simple aggregation of forecasts from different models (results not reported).

We also examined the serial correlation in forecast errors for each model. That is, conditional on the forecast error being very positive or negative in one period, can we predict the direction and magnitude of forecast error in the following period for that model? The presence of a predictable serial correlation suggests that additional improvements in forecast accuracy are possible by incorporating prior period forecast errors for that model. The correlations between current and lagged forecast errors for all firm-years are reported in Table 5. Serial correlations are close to zero for all but two of the models. The random walk model exhibits severe negative serial correlation, which is consistent with the well-established view that accruals show a tendency to mean revert. The Jones model exhibits a fair degree of positive serial correlation. This

---

Table 4
Correlation among forecast errors from six accrual prediction models 7,195 firm-years (1,748 firms) over the prediction period (1990–1994) *

<table>
<thead>
<tr>
<th>Model</th>
<th>Random walk</th>
<th>Mean-reverting</th>
<th>Components</th>
<th>Jones</th>
<th>Industry</th>
<th>KS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Spearman)</td>
<td>correlation above (below) main diagonal*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random walk</td>
<td>–</td>
<td>0.811</td>
<td>0.812</td>
<td>0.609</td>
<td>0.733</td>
<td>0.614</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>0.728</td>
<td>–</td>
<td>0.998</td>
<td>0.756</td>
<td>0.903</td>
<td>0.731</td>
</tr>
<tr>
<td>Components</td>
<td>0.733</td>
<td>0.994</td>
<td>–</td>
<td>0.755</td>
<td>0.899</td>
<td>0.732</td>
</tr>
<tr>
<td>Jones</td>
<td>0.525</td>
<td>0.705</td>
<td>0.699</td>
<td>–</td>
<td>0.751</td>
<td>0.641</td>
</tr>
<tr>
<td>Industry</td>
<td>0.598</td>
<td>0.802</td>
<td>0.793</td>
<td>0.677</td>
<td>–</td>
<td>0.761</td>
</tr>
<tr>
<td>KS</td>
<td>0.626</td>
<td>0.746</td>
<td>0.752</td>
<td>0.640</td>
<td>0.701</td>
<td>–</td>
</tr>
</tbody>
</table>

* All firm-years between 1990 and 1994 on Compustat with forecasts available for all six accrual prediction models (see Appendix A for details of models) are included in the sample. Total accruals and its two components are measured as follows:

\[ \text{TOTACC}_t = \text{CURACC}_t + \text{NONCURACC}_t = \Delta \left( \text{#4} - \text{#1} \right) - \text{#125}, \]

where data # are from Compustat. All accruals items are scaled by beginning-of-year total assets (TA), which is data item #6.

* Correlations greater than 0.023 (0.030) are significant at the 5% (1%) level.
suggests that when the parameter estimates are biased, the effect of such bias persists in adjacent years in the prediction period. Research using the Jones model should be able to improve predictive accuracy by incorporating prior period prediction errors.

5. Extensions

We consider next a series of modifications, primarily to the Jones model, that have been suggested in prior research. Our objective is to determine if the performance documented so far can be improved by those modifications.

Beneish (1997, p. 273) suggests that the Jones model should be expanded to include at least two additional explanatory variables: lagged total accruals and that year’s market performance (size-adjusted returns). We estimated firm-specific regressions similar to Eq. (9) for the expanded Jones model with the two additional regressors, and examined all four measures of forecast accuracy considered in Table 3, Panels A–D, for the five-year prediction period. In general, while the in-sample or prediction period $R^2$ values are substantially higher for the expanded Jones model, the forecast are less accurate. For brevity, we only report (in Panel A of Table 6) comparisons based on the fourth measure of accuracy ($R^2$ relative to a naïve forecast of $-5\%$). All the $R^2$ values for the expanded Jones model in Table 6, Panel A, representing the different percentile points are lower than the corresponding points for the Jones model in Table 3, Panel D. We also provide statistics for the $R^2$ distributions for the other five models for comparison. Note that the results for the other models differ slightly from those in Table 3, Panel D, because the final samples are different in the two panels (because of the data requirements of the expanded Jones model, fewer observations remain in Table 6).
<table>
<thead>
<tr>
<th>Model</th>
<th>Mean (%)</th>
<th>Standard deviation (%)</th>
<th>10th percentile (%)</th>
<th>25th percentile (%)</th>
<th>50th percentile (%)</th>
<th>75th percentile (%)</th>
<th>90th percentile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Consider expanded Jones model that incorporates prior period accruals and current period size-adjusted returns to the Jones model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random walk</td>
<td>-300.201</td>
<td>7,191.52</td>
<td>-2.606</td>
<td>-1.698</td>
<td>-0.918</td>
<td>-0.107</td>
<td>0.477</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-28.833</td>
<td>677.56</td>
<td>-0.977</td>
<td>-0.449</td>
<td>-0.141</td>
<td>0.232</td>
<td>0.616</td>
</tr>
<tr>
<td>Components</td>
<td>-27.899</td>
<td>656.63</td>
<td>-0.984</td>
<td>-0.429</td>
<td>-0.129</td>
<td>0.254</td>
<td>0.625</td>
</tr>
<tr>
<td>Expanded Jones</td>
<td>-12.016</td>
<td>150.16</td>
<td>-6.564</td>
<td>-2.162</td>
<td>-0.423</td>
<td>0.176</td>
<td>0.538</td>
</tr>
<tr>
<td>Industry</td>
<td>-11.697</td>
<td>256.06</td>
<td>-1.279</td>
<td>-0.430</td>
<td>-0.024</td>
<td>0.281</td>
<td>0.638</td>
</tr>
<tr>
<td>KS</td>
<td>-32.019</td>
<td>765.75</td>
<td>-0.810</td>
<td>-0.175</td>
<td>0.121</td>
<td>0.399</td>
<td>0.670</td>
</tr>
<tr>
<td><strong>Panel B: Consider updated models that update the parameters using prior years from the prediction period</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random walk</td>
<td>-388.533</td>
<td>13,954.84</td>
<td>-3.639</td>
<td>-1.765</td>
<td>-0.789</td>
<td>0.076</td>
<td>0.651</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-21.274</td>
<td>476.32</td>
<td>-1.448</td>
<td>-0.482</td>
<td>-0.104</td>
<td>0.329</td>
<td>0.706</td>
</tr>
<tr>
<td>Updated components</td>
<td>-24.755</td>
<td>586.38</td>
<td>-1.456</td>
<td>-0.480</td>
<td>-0.095</td>
<td>0.340</td>
<td>0.723</td>
</tr>
<tr>
<td>Updated Jones</td>
<td>-32.994</td>
<td>905.44</td>
<td>-4.391</td>
<td>-1.017</td>
<td>-0.169</td>
<td>0.303</td>
<td>0.665</td>
</tr>
<tr>
<td>Updated industry</td>
<td>-5.888</td>
<td>147.04</td>
<td>-1.761</td>
<td>-0.485</td>
<td>-0.066</td>
<td>0.323</td>
<td>0.697</td>
</tr>
<tr>
<td>Updated KS</td>
<td>-363.992</td>
<td>16,015.66</td>
<td>-1.307</td>
<td>-0.236</td>
<td>0.145</td>
<td>0.497</td>
<td>0.781</td>
</tr>
<tr>
<td><strong>Panel C: Consider industry Jones model that estimates the Jones model over the prior 5 years separately for each two-digit SIC industry</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random walk</td>
<td>-388.350</td>
<td>13,951.48</td>
<td>-3.657</td>
<td>-1.767</td>
<td>-0.794</td>
<td>0.073</td>
<td>0.650</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-21.264</td>
<td>476.21</td>
<td>-1.448</td>
<td>-0.482</td>
<td>-0.103</td>
<td>0.327</td>
<td>0.706</td>
</tr>
<tr>
<td>Components</td>
<td>-24.743</td>
<td>586.24</td>
<td>-1.456</td>
<td>-0.480</td>
<td>-0.095</td>
<td>0.339</td>
<td>0.723</td>
</tr>
<tr>
<td>Industry Jones</td>
<td>-100.707</td>
<td>4,234.91</td>
<td>-2.317</td>
<td>-0.522</td>
<td>0.004</td>
<td>0.345</td>
<td>0.635</td>
</tr>
<tr>
<td>Industry</td>
<td>-5.887</td>
<td>147.00</td>
<td>-1.767</td>
<td>-0.485</td>
<td>-0.068</td>
<td>0.322</td>
<td>0.696</td>
</tr>
<tr>
<td>Industry KS</td>
<td>-748.389</td>
<td>33,291.58</td>
<td>-3.902</td>
<td>-0.804</td>
<td>0.022</td>
<td>0.411</td>
<td>0.732</td>
</tr>
<tr>
<td><strong>Panel D: Use the six standard models to predict current accruals, rather than total accruals. The naive forecast is current accruals = 0% for all firm-years</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random walk</td>
<td>-11.954</td>
<td>246.08</td>
<td>-3.575</td>
<td>-2.011</td>
<td>-1.262</td>
<td>-0.443</td>
<td>0.174</td>
</tr>
<tr>
<td>Mean-reverting</td>
<td>-14.599</td>
<td>566.05</td>
<td>-1.379</td>
<td>-0.550</td>
<td>-0.238</td>
<td>-0.007</td>
<td>0.250</td>
</tr>
<tr>
<td>Components</td>
<td>-14.631</td>
<td>567.39</td>
<td>-1.404</td>
<td>-0.549</td>
<td>-0.237</td>
<td>-0.007</td>
<td>0.251</td>
</tr>
<tr>
<td>Jones</td>
<td>-4.609</td>
<td>86.81</td>
<td>-1.327</td>
<td>-0.300</td>
<td>-0.002</td>
<td>0.186</td>
<td>0.548</td>
</tr>
<tr>
<td>Industry</td>
<td>-11.794</td>
<td>400.24</td>
<td>-1.817</td>
<td>-0.546</td>
<td>-0.095</td>
<td>0.097</td>
<td>0.369</td>
</tr>
<tr>
<td>KS</td>
<td>-6.481</td>
<td>126.07</td>
<td>-1.743</td>
<td>-0.529</td>
<td>-0.045</td>
<td>0.231</td>
<td>0.514</td>
</tr>
</tbody>
</table>

\( a \) Distribution of firm-specific explained variation, relative to a naive model of forecast accruals = 0% (\( R^2_a = 1 - \text{ESS}_a / \text{TSS}_a \), where \( \text{ESS}_a = \sum (\text{actual} - \text{forecast})^2 \) and \( \text{TSS}_a = \sum (\text{actual} - (\text{naive}))^2 \)).
The second extension we consider is the impact of updating the model parameters as we progress through the prediction period. In other words, while the 1975–1989 estimation period is used for the 1990 forecast, the estimation period is expanded to include 1990 for the 1991 forecast, and so on. Note that this updating procedure has no effect on the random walk and mean-reverting models. Again, while all four sets of accuracy measures were examined, only the fourth measure is reported in Panel B of Table 6. The results remain essentially unchanged. Adding additional years does not appear to change the parameter estimates or forecasts substantially, and there are only slight differences in accuracy, in terms of the percentile points in Table 6, Panel B relative to those in Table 3, Panel D. Recall that observing a higher $R^2$ value in Table 6 implies that updating improves forecast accuracy.

Boynton et al. (1992, p. 137) estimate the Jones model using pooled data for each industry, rather than estimating the model separately for each firm. Comparison of the distribution of their estimates (reported in an earlier 1991 (Boynton et al., 1991) version of their published paper) with those in our Table 2, Panel B suggests a fair degree of similarity. We proceeded, however, to examine the effect on forecast accuracy. Our results, reported in Panel C of Table 6, suggest that the industry estimation procedure proposed by Boynton et al. (1992) improves forecast accuracy. Comparing the percentile $R^2$ points for the Industry Jones model in Panel C with those for the Jones model in panel D of Table 3 illustrates the extent of improvement. As indicated by the positive median $R^2$ value for the Industry Jones model, this model outperforms the naïve $-5\%$ forecast for more than 50% of the sample. Interestingly, no improvement is observed when the KS model is estimated separately for each industry, as indicated by the lower $R^2$ percentile points for the Industry KS model in Panel C of Table 6, relative to the KS model in Panel D of Table 3.

Our final extension relates to the prediction of current accruals, rather than total accruals. As mentioned earlier, this analysis is motivated by the assumption that earnings management is more likely to occur for current accruals, i.e., firms are less likely to change depreciation methods and estimates, for book purposes, compared to other ways to manage earnings (e.g., Beneish, 1998b, p. 211). We dropped non-current accruals from the dependent variable for all models and adapted the Jones and KS model by dropping the explanatory variable related to fixed assets. The naïve forecast used for comparison purposes is that current accruals equals 0% of TA for all firm-years. While the performance of all other models appears to decline, relative to that reported for total accruals in Table 3, Panel D, the performance of the Jones model increases. The median adjusted $R^2$ is close to zero, which suggests that the

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13 Our Industry Jones model is simpler than the Boynton et al. (1992, p. 137) model, as we do not estimate separate coefficients for the very small and very large firms.
Jones model performed better than the naïve model for almost half the sample firms.

Overall, the results in this section suggest that two of the many modifications considered improve accuracy: (a) estimating the Jones model at the industry level (e.g., Boynton et al., 1992, p. 137), rather than the firm level, and (b) estimating the Jones model for current accruals alone, rather than total accruals. Despite these improvements, however, the absolute performance is still not strong, since the naïve models still perform as well or better.

6. Conclusion

Our paper provides some description of accruals and the ability of extant models to forecast accruals. The following is a brief overview of our findings. Accruals equal about $-5\%$ of last period’s total assets, on average. This mean effect is explained primarily by non-current accruals (depreciation, depletion and amortization), and current accruals (changes in non-cash working capital) have a zero mean. Most of the variance in total accruals, however, is explained by variation in current accruals, with non-current accruals exhibiting much lower variation. We consider the forecasting ability of three models that peek-ahead and use contemporaneous data to identify unexpected accruals: the Jones, the KS, and Industry models. We also consider three models that do not peek-ahead and use only prior year data: the random walk model, the mean-reverting model, and a combination model that separates current accruals from non-current accruals and allows each component to follow a different weighted-average of the random walk and mean-reverting models. Our results indicate low forecasting ability, in general, for all models.

Despite the many items of information that are input into these models, the performance of those models is surprising. Researchers seeking to detect earnings management are in effect using tools that are less accurate than they appear. Simply assuming that total accruals equal $-5\%$ of TA outperforms most models. Similarly, assuming that current accruals equal $0\%$ of TA, also outperforms all models when they are adjusted to predict current accruals alone. There are some bright spots, however, we find that the Jones model estimated separately over different industries and the KS model exhibit some ability to outperform these naïve expectation models by a small margin.

Also, some of these models tend to overfit within the estimation period, and this overfitting creates a misplaced sense of security that the models are able to explain some of the variation in accruals. Ultimately, it is only the explanatory power of the model in out-of-sample or prediction periods that matters.
Acknowledgements

We received helpful comments from Dan Beneish, Paul Healy, and Steve Loeb and workshop participants at CUNY-Baruch College, University of Florida, and M.I.T.

Appendix A. Summary of accrual prediction models

1. Random walk model

\[
\frac{\text{TOTACC}_t}{\text{TA}_{t-1}} = \frac{\text{TOTACC}_{t-1}}{\text{TA}_{t-2}} + e_t. \tag{A.1}
\]

2. Mean-reverting accruals model

\[
\frac{\text{TOTACC}_t}{\text{TA}_{t-1}} = \frac{1}{5} \left( \sum_{t=5}^{t-1} \frac{\text{TOTACC}_{t-\tau}}{\text{TA}_{t-\tau}} \right) + e_t. \tag{A.2}
\]

3. Components model

\[
\begin{align*}
\frac{\text{CURACC}_t}{\text{TA}_{t-1}} &= (\alpha) \frac{\text{CURACC}_{t-1}}{\text{TA}_{t-2}} \\
&\quad + (1 - \alpha) \left( \frac{1}{5} \sum_{\tau=5}^{t-1} \frac{\text{CURACC}_{t-\tau}}{\text{TA}_{t-\tau}} \right) + e_t, \\
\frac{\text{NONCURACC}_t}{\text{TA}_{t-1}} &= (\beta) \frac{\text{NONCURACC}_{t-1}}{\text{TA}_{t-2}} \\
&\quad + (1 - \beta) \left( \frac{1}{5} \sum_{\tau=5}^{t-1} \frac{\text{NONCURACC}_{t-\tau}}{\text{TA}_{t-\tau}} \right) + e_t. \tag{A.3}
\end{align*}
\]

4. Jones model

\[
\frac{\text{TOTACC}_t}{\text{TA}_{t-1}} = a_i + b_1 \frac{\Delta \text{REV}_t}{\text{TA}_{t-1}} + b_2 \frac{\text{PPE}_t}{\text{TA}_{t-1}} + e_t. \tag{A.5}
\]

5. Industry model

\[
\frac{\text{TOTACC}_t}{\text{TA}_{t-1}} = i_{1i} + i_{2i} \left( \text{industry median} \frac{\text{TOTACC}_t}{\text{TA}_{t-1}} \right) + e_t, \tag{A.6}
\]

which is estimated over two-digit SIC industry groups.

---

6. KS model

\[
\frac{\text{ACCBAL}_t}{\text{TA}_{t-1}} = c_0 + c_1 \frac{\text{REV}_t}{\text{TA}_{t-1}} \left( \frac{\text{ART}_{t-1}}{\text{REV}_{t-1}} \right) + c_2 \frac{\text{EXP}_t}{\text{TA}_{t-1}} \left( \frac{\text{OCAL}_{t-1}}{\text{EXP}_{t-1}} \right) + c_3 \frac{\text{GPPE}_t}{\text{TA}_{t-1}} \left( \frac{\text{DEP}_{t-1}}{\text{GPPE}_{t-1}} \right)
\]

and lagged values of the three independent variables are included as instrumental variables.

The variables are defined as follows (#n refers to Compustat Annual data item #):

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOTACC</td>
<td>total accruals (= CURACC + NONCURACC) (current + non-current accruals) = ( \Delta (#4 - #1 - #5 - #125) )</td>
</tr>
<tr>
<td>ACCBAL</td>
<td>non-cash current assets and liabilities (excluding tax receivables and payables) less depreciation (= ( #4 - #1 - #161 - (#5 - #71) - #14 ))</td>
</tr>
<tr>
<td>ART</td>
<td>accounts receivable less tax receivables (= #2 - #161)</td>
</tr>
<tr>
<td>EXP</td>
<td>expenses (= #12 - #13)</td>
</tr>
<tr>
<td>DEP</td>
<td>depreciation from income statement (= #14)</td>
</tr>
<tr>
<td>OCAL</td>
<td>other current assets and liabilities (= ( #4 - #1 - #161 - (#5 - #71) ))</td>
</tr>
<tr>
<td>GPPE</td>
<td>gross plant, property and equipment (= #7)</td>
</tr>
<tr>
<td>TA</td>
<td>total assets (= #6),</td>
</tr>
<tr>
<td>REV</td>
<td>revenues (= #12),</td>
</tr>
<tr>
<td>PPE</td>
<td>plant, property and equipment (= #7)</td>
</tr>
<tr>
<td>#4</td>
<td>current assets,</td>
</tr>
<tr>
<td>#1</td>
<td>cash</td>
</tr>
<tr>
<td>#2</td>
<td>accounts receivables</td>
</tr>
<tr>
<td>#5</td>
<td>current liabilities</td>
</tr>
<tr>
<td>#12</td>
<td>sales</td>
</tr>
<tr>
<td>#13</td>
<td>operating income before depreciation</td>
</tr>
<tr>
<td>#71</td>
<td>income taxes payable</td>
</tr>
<tr>
<td>#125</td>
<td>depreciation, depletion, and amortization from the cash flow statement</td>
</tr>
<tr>
<td>#161</td>
<td>income tax refund</td>
</tr>
</tbody>
</table>
References

Beneish, M.D., 1998b. Discussion of “Are accruals during initial public offerings opportunistic”. Review of Accounting Studies 3 (1,2), 209–221.