Evidence on the Management of Earnings Components

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Although recent studies provide convincing evidence that firms manage earnings to achieve certain reporting objectives, there is only limited evidence on what steps firms take to manage their earnings. This paper presents evidence as to which components firms use to manage bottom-line, reported earnings. Specifically, we identify a set of firms believed to be managing earnings upward; plot the empirical distributions of analysts' forecast errors for sales, operating expenses, nonoperating expenses, and depreciation expense; and then examine these distributions for discontinuities around zero. Results suggest that these firms managed earnings upward by managing sales upward and by managing operating expenses downward. There is no evidence to suggest that these firms managed nonoperating expenses or depreciation expense to affect earnings. We then identify firm characteristics (level of current assets, level of current liabilities, and operating margin percentage) that affect the likelihood that these firms used a specific component to manage earnings. Finally, we use a firm's stock recommendation to make predictions about its incentives to manage earnings. Our evidence suggests that firms rated buy (rated sell) manage earnings upward (downward) by managing sales, operating, and nonoperating expenses in predictable directions.

1. Introduction

Although prior research suggests that firms manage earnings to achieve certain reporting objectives, the literature provides limited evidence on which specific components or accruals are used for earnings management. In addition, the few studies that do examine how earnings are managed have generally focused on very narrow...
settings (for example, bank loan loss reserves), or have had to rely on estimation models to separate total accruals into its discretionary and nondiscretionary parts.

In this paper, we use a methodology similar to Burgstahler and Dichev (1997) and Degeorge et al. (1999) to provide evidence on which earnings components firms manage to affect bottom-line earnings. By earnings components, we are referring to items that are specifically reported on the income statement. We first identify a set of firms for which we have strong a priori reasons to expect that they are managing earnings upward. Using analysts’ forecasts of various earnings components (i.e., sales, operating expenses, nonoperating expenses, and depreciation expense), we plot the empirical distributions of analysts’ forecast errors for each of the components. We then examine each forecast error distribution for evidence of discontinuities around zero. Frequencies of forecast errors that are abnormally high or low relative to adjacent regions of the distribution provide evidence that firms are managing earnings upward by managing the particular earnings component. This approach enables us to examine earnings management behavior without relying on an estimation model to decompose earnings into its discretionary and nondiscretionary parts.

For our set of firms that are suspected of managing earnings upward, we find a higher-than-expected frequency of sales forecast errors that are slightly greater than zero, and a lower-than-expected frequency that are slightly less than zero. This pattern suggests that these firms manage earnings upward, in part, by managing sales upward.

For operating expense forecast errors, there is a higher-than-expected frequency of operating expense forecast errors slightly less than zero, and a lower-than-expected frequency slightly greater than zero. This suggests that these firms also manage their earnings upward by managing operating expenses downward. There is no discontinuity around zero in the distributions of forecast errors for nonoperating expenses or depreciation expense, and thus no evidence to suggest that these firms decreased these expenses in an attempt to manage earnings upward.

We then identify firm characteristics that are likely to affect whether firms use a particular component to manage earnings. We find that high levels of beginning-of-year current assets and high operating margin percentages are both associated with an increased likelihood that a firm uses sales to manage earnings upward. We find no evidence to suggest that the level of current liabilities affects the likelihood that a firm uses expenses to manage earnings upward.

Recent evidence suggests that firms with strong investment potential have incentives to manage reported earnings toward analysts’ forecasts, while firms considered poor investments have incentives to manage earnings down and away from analysts’ forecasts (Abarbanell and Lehavy [1999]). For our full sample of firms, we use a firm’s stock recommendation to make predictions about the management of its earnings components. Our evidence suggests that firms rated buy manage earnings upward by increasing sales, and by decreasing operating and nonoperating expenses. Firms rated sell appear to manage earnings downward by decreasing sales, and by increasing operating and nonoperating expenses. There is
no evidence that firms manage depreciation expense in an attempt to manage earnings. Using a firm’s investment potential to make predictions about earnings management enables us to examine the use of earnings components to manage earnings both upward and downward. This provides us with a more complete picture of how earnings components are used to manage earnings.

Our study makes a significant contribution to the earnings management literature by providing evidence on which income-statement items are used to manage earnings. This is important to both standard setters and researchers. Because of concerns over earnings management and its effect on resource allocation, the SEC has formed an earnings management task force and is currently examining new disclosure requirements. Standard setters are therefore very likely to be interested in evidence on which components firms use to manage earnings (Healy and Wahlen [1999]). In addition, it is important to understand how various components are used to manage earnings because of differences in the value-relevance of the different earnings components and their implications for financial statement analysis. Our study is also important because it further demonstrates the efficacy of examining earnings management using a method that does not require accrual estimation models. Last, we provide evidence on firm characteristics that affect the likelihood that a firm will use a specific earnings component to manage earnings.

The remainder of our paper is organized as follows. In the next section, we develop the hypotheses and research design. Section 3 describes our data and sample selection, while Section 4 presents results for firms believed to be managing earnings to meet or beat analysts’ forecasts. This section also presents evidence on conditions likely to affect which earnings components firms use to manage earnings. In Section 5, we use analysts’ stock recommendations to identify firms likely to be managing earnings by managing sales and expenses in predictable directions. Section 6 provides a summary.

2. Hypotheses and Research Design

Empirical studies of earnings management often use discretionary accruals as a proxy for the managed portion of earnings. This requires an estimation model that separates total accruals into its discretionary and nondiscretionary parts. Most models have at least one parameter that must be estimated, typically by using an “estimation period” during which no systematic earnings management is believed to occur. These models are subject to several methodological limitations, including model misspecification, measurement error, and low power (Kang and Sivaramakrishnan [1995]; Dechow et al. [1995]). In addition, some of the variables used to predict unmanaged accruals (for example, revenues) are assumed to be uncontam-


2. Earnings components such as sales, COGS, and operating expenses are part of numerous financial ratios used in fundamental analysis (for example, see Palepu, Bernard, and Healy [1996]).
inated by earnings management, but are most likely subject to earnings management themselves. A number of recent studies examine earnings management by focusing on a specific accrual, which enhances precision but does not capture accrual manipulations in many other accounts.\(^3\)

A number of recent studies use a new approach to test for earnings management (Burgstahler and Dichev [1997, 1998]; Degeorge et al. [1999]). These studies examine the distribution of reported earnings around predicted thresholds to assess whether there is evidence of earnings management. The primary advantage of this approach is that there is no need to rely on a model to decompose earnings into its discretionary and nondiscretionary parts. In addition, this approach captures any effects of earnings management through the firm's management of cash flows. Tests using accrual models will not capture such effects.

These distribution-based studies provide persuasive evidence that firms manage earnings to avoid earnings decreases and losses (Burgstahler and Dichev [1997]), and to meet or beat analysts' earnings forecasts (Degeorge et al. [1999]; Burgstahler and Eames [1998]). However, what is lacking from these studies is evidence of the steps that these firms take to manage their reported earnings (Healy and Wahlen [1999]).\(^4\) In all these instances, firms cannot directly manage the bottom-line, reported earnings number. Rather, firms must manage the various components that generate earnings. For example, firms can increase reported earnings by either increasing sales, decreasing expenses, or a combination of both. Our study contributes to the earnings management literature by examining components that are specifically reported on the income statement, and providing evidence on which of these is used to manage the reported earnings number.

We choose a set of firms for which we have strong a priori reasons to expect that they are managing earnings upward to meet or beat analysts' earnings forecasts, and then examine whether they manage earnings by managing sales upward and/or managing expenses downward. Thus, our primary hypotheses are

\[ H_1: \text{In order to manage earnings upward, firms manage sales upward.} \]

\[ H_2: \text{In order to manage earnings upward, firms manage expenses downward.} \]

Hypotheses 1 and 2 examine whether the earnings-management behavior is attributable to firms managing sales upward and/or expenses downward.\(^5\)

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4. Burgstahler and Dichev (1997) provide evidence that firms use cash flow from operations and changes in working capital to increase earnings and avoid reporting a loss. Our paper differs substantially in that we examine components that firms specifically report on the income statement (i.e., sales and expenses). This enables us to determine where on the income statement the management of bottom-line earnings arises.

5. If firms manage earnings to meet a particular threshold (e.g., analysts' forecasts), then they must be managing either sales and/or expenses, but not necessarily both. In this paper, we provide evidence on which components firms use, on average, to manage earnings, as well as identify conditions for which the management of earnings components is more or less likely. In addition, we examine
We test hypotheses 1 and 2 in a manner similar to Burgstahler and Dichev (1997) and Degeorge et al. (1999). First, we construct empirical histograms of the forecast error distributions. Forecast error is defined as the reported actual value minus the analyst's forecast, scaled by the firm's market value of equity. Managing sales upward (hypothesis 1) will be reflected in a cross-sectional distribution with an unusually small number of sales forecast errors slightly less than zero, and an unusually large number of sales forecast errors slightly greater than zero. Managing expenses downward (hypothesis 2) will be reflected by the opposite pattern: an unusually large number of expense forecast errors slightly less than zero, and an unusually small number of expense forecast errors slightly greater than zero.

We then perform formal tests to examine the significance of any discontinuities of the forecast error distributions around zero. Because the mode of the analysts' forecast errors is likely to be zero, the peak \( P \) of the forecast error distributions will likely occur at the same value as the threshold \( T \) we are examining (i.e., \( P = T = 0 \)). Therefore, we use the test statistic \( \tau \) described by Degeorge et al. (1999) for the special case when the threshold coincides with the peak of the distribution (see their Appendix, Case A2). Earnings management is detected by testing whether the slope of the density function immediately to one side of the threshold is significantly different from the slope (adjusted for sign) immediately to the other side of the threshold. See our Appendix for a detailed discussion of the test statistic.

### 3. Data

This study's sample consists of firms regularly covered by *Value Line Investment Survey*. For the period examined in this study (1971 through 1989), Value Line covers approximately 1,700 firms classified into about 91 industries. Each week, Value Line issues reports for about 130 firms in seven or eight industries on a predetermined schedule. Accordingly, a report for each of the 1,700 firms is issued once every 13 weeks (i.e., quarterly), for a total of four times each year. Within each firm's report, Value Line analysts forecast several different financial measures for the current year (year \( t \)). For each firm in each year, we hand-collected different types of expenses (operating, nonoperating, and depreciation). Our ability to detect the management of earnings components will depend on several factors, including the degree of earnings management, the extent to which firms use a given component to manage earnings, and the power of our empirical tests.

6. To construct the empirical histograms, we use interval widths computed from bin-width rules outlined in Silverman (1986, 43–48) and Scott (1992, 72–80). For all suggested rules-of-thumb, the bin width is positively related to the variability of the data and negatively related to the number of observations. In this paper, we present histograms using a bin width of \( 2(IQR)n^{-1/3} \), where IQR is the sample interquartile range of the forecast error and \( n \) is the number of observations. This is consistent with the rule-of-thumb used by Degeorge et al. (1999). However, the other bin-width formulas outlined in Silverman (1986) and Scott (1992) yield results qualitatively consistent with those presented in this paper.

7. All results reported in the paper are based on the forecast errors scaled by market value of equity. However, we repeat all analyses using forecast errors scaled by book value of equity, number of shares, and sales. We obtain qualitatively similar results as those in the paper.
data from the first Value Line report issued after a firm's annual report for the prior year (year $t-1$) was released. Therefore, we have one observation per firm per year.$^8$\textsuperscript{9}

A firm was included in the sample if it had the following: (1) Value Line forecasts of annual sales, operating earnings, and net earnings for the current year (year $t$); (2) actual annual sales, operating earnings, and net earnings for year $t$, as reported in Value Line; and (3) a timeliness ranking (i.e., stock recommendation) from the same Value Line report as the forecast for year $t$ is collected.$^7$ These restrictions provide a sample of 18,933 firm-year observations over the 19-year period 1971 through 1989. Because earnings forecast errors differ dramatically for firms reporting losses versus profits (Dowen [1996]; Hwang, Jan, and Basu [1996];

8. We use Value Line because they are the only forecasting service that has provided forecasts of earnings components (i.e., sales and expenses) for an extended period of time. Evidence suggests that Value Line is a good source for earnings data and forecasts and that Value Line earnings forecasts reflect market expectations relatively better than other sources. For example, Philbrick and Hicks (1991) conclude that, for quarterly data, Value Line and IBES are comparable in terms of their forecast data, but Value Line provides a higher association between forecast errors and announcement-period excess returns. A disadvantage of Value Line forecasts is that they are issued by a single analyst. To the extent that managers are attempting to meet or beat a consensus forecast, the Value Line earnings forecast will be less relevant than a consensus forecast. Therefore, we examine the sensitivity of our results to using Value Line earnings forecasts, and discuss this analysis in footnote 9.

9. On average, the Value Line forecasts we use are made in the sixth month of a firm’s fiscal year. The possibility exists that the forecasts we use are stale and no longer represent a threshold that management cares about meeting. In addition, we examine annual earnings forecast errors (consistent with Burgstahler and Dichev [1997]). It could be that managers are more concerned with meeting or beating analysts’ quarterly forecasts. However, both these factors (staleness and the use of annual earnings forecasts) would bias against our finding evidence of earnings management.

Because of concern over the staleness of our earnings forecast and the fact that it is not a consensus forecast, we identify the subset of our firms for which we also have IBES earnings forecasts. We use the last IBES annual earnings consensus forecast issued prior to the firm’s fiscal year end. Of our sample of 17,667 observations, there are 9,930 for which we have IBES earnings forecasts. We define firms for which management is attempting to meet or beat analysts’ earnings forecasts as those observations with IBES forecast errors between zero and $0.01 (one penny) per share. This criterion provides a sample of 1,712 observations for which reported EPS meets or slightly exceeds analysts’ consensus forecast. We then repeat the empirical tests in Sections 4.1 and 4.2 using this sample of 1,712 observations. (We still must use the Value Line data for our forecasts of sales and expenses because these forecasts are not available elsewhere.) The inferences using this alternative sample are qualitatively similar to those reported in Section 4. We find evidence that these firms manage earnings by decreasing nonoperating expenses or depreciation expense.

10. Value Line timeliness ranks are ratings for the stock’s expected performance, relative to the market, over the next 12 months. Stocks ranked 1 (highest) and 2 (above average) are likely to outpace the year-ahead market. Those ranked 4 (below average) and 5 (lowest) are not expected to outperform the market over the next 12 months. Stocks ranked 3 (average) will probably advance or decline with the market in the year ahead. Value Line recommends that investors should try to limit purchases to stocks ranked 1 and 2. Value Line further recommends that once a stock ranked 1 or 2 has been bought, it should be held until its rank drops to 3, 4, or 5. Accordingly, we refer to timeliness ranks of 1 and 2 as “strong buy” and “buy,” respectively. A timeliness rank of 3 is defined as “hold,” while timeliness ranks of 4 and 5 are defined as “sell” and “strong sell,” respectively. Research suggests that analysts’ recommendations tend toward “buys” rather than “sells” (Schultz [1990]; Francis and Soffer [1997]). Value Line is unique in that their stock recommendation procedure forces a predetermined buy-hold-sell distribution on the companies they follow (i.e., approximately 24% buys, 52% holds, and 24% sells).
TABLE 1
Descriptive Statistics for Reported Annual Amounts
(dollars in millions; \( N = 17,667 \))

<table>
<thead>
<tr>
<th></th>
<th>As a percentage of Sales</th>
<th>Mean</th>
<th>Median</th>
<th>Q1</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>100.0</td>
<td>$1,737.6</td>
<td>$454.6</td>
<td>$192.2</td>
<td>$1,357.1</td>
</tr>
<tr>
<td>Operating expenses*</td>
<td>85.9</td>
<td>1,490.2</td>
<td>390.5</td>
<td>161.6</td>
<td>1,171.8</td>
</tr>
<tr>
<td>Operating earnings</td>
<td>13.0</td>
<td>247.4</td>
<td>58.9</td>
<td>23.6</td>
<td>177.4</td>
</tr>
<tr>
<td>Nonoperating expenses</td>
<td>3.2</td>
<td>81.1</td>
<td>14.6</td>
<td>4.8</td>
<td>47.7</td>
</tr>
<tr>
<td>Net earnings before tax</td>
<td>8.6</td>
<td>166.3</td>
<td>39.3</td>
<td>14.7</td>
<td>119.6</td>
</tr>
<tr>
<td>Tax expense</td>
<td>3.9</td>
<td>74.8</td>
<td>17.7</td>
<td>6.6</td>
<td>53.8</td>
</tr>
<tr>
<td>Net earnings after tax</td>
<td>4.8</td>
<td>91.5</td>
<td>21.6</td>
<td>8.1</td>
<td>65.8</td>
</tr>
</tbody>
</table>

*Percentages are calculated using median numbers.
*Operating expenses include both COGS and other operating expenses.

Brown [1999]), we delete the 1,266 observations for which year \( t \)'s reported earnings are negative.\(^{11}\) This results in a final sample of 17,667 observations. For the years 1984 through 1989, we also have 5,112 firm-year observations of forecasted and reported depreciation expense. We use these observations to examine whether firms manage depreciation expense when managing earnings.\(^{12}\)

Unlike many studies that restrict the sample to firms that existed for all years in the sample period, this study does not impose such a restriction and therefore reduces survivorship bias. We also do not limit our sample on the basis of fiscal year-end or exchange-listing status. Including non-December year-end firms results in broader industry representation (Smith and Pourciau [1988]), while including OTC firms increases the proportion of smaller firms in the sample.

Value Line reports both forecasted and actual sales, operating earnings, and after-tax net earnings.\(^{13}\) Table 1 provides descriptive statistics for the reported annual amounts for the full sample. We compute operating expenses as the difference between sales and operating earnings. We compute nonoperating expenses as the difference between operating earnings and after-tax net earnings, less an estimate for the firm's income tax expense. It is important to extract income tax expense from nonoperating expenses. If a firm engages in income-increasing behavior, it

\(^{11}\) Dowen (1996) shows that, in 11 of 12 holding periods, analysts have a relatively greater optimistic bias when firms report losses. Hwang, Jan, and Basu (1996) find that the optimistic bias in analysts' forecasts is 10 times greater when firms report losses. Brown (1999) shows that the well-known optimistic bias for analysts' forecasts pertains only to firms reporting losses.

\(^{12}\) We repeat all analyses using the full set of firm-year observations, including losses, and obtain essentially identical results as those reported in the paper. This is attributable to the fact that only 20 of the 1,266 loss-firm observations have scaled earning forecast errors between 0 and 0.005.

\(^{13}\) Value Line defines operating earnings as earnings before deduction of depreciation, depletion, amortization, interest, and income tax. Value Line defines net earnings as earnings before extraordinary gains or losses.
will necessarily increase income tax expense, thereby increasing nonoperating expenses and biasing against hypothesis 2.\textsuperscript{14}

To test hypothesis 1, we examine the distribution of sales forecast errors using two measures of sales forecast errors. Our first measure is actual sales minus the analyst's sales forecast. Our second measure recognizes that sales are not managed in isolation. That is, when sales are managed upward, related variable costs will also likely increase. Therefore, our second measure is actual sales minus forecasted sales (i.e., the simple sales forecast error), multiplied by the analyst’s forecast of the firm’s operating margin percentage. This provides an estimate of the net effect on earnings (before taxes) of managing sales upward.\textsuperscript{15} For ease of exposition, we refer to the first measure as the sales forecast error and the second measure as the gross margin forecast error.

We test hypothesis 2 by examining the forecast error distribution for operating expenses (other than the variable cost related to sales), nonoperating expenses, and depreciation expense. To compute the operating expense forecast error, we multiply the forecast error for operating margin percentage by actual sales, times negative one. This removes the portion of the operating expense forecast error that is attributable to a forecast error in sales, and provides an estimate of the net effect on earnings (before taxes) of managing operating expenses.

4. Managing Earnings to Meet or Beat Analysts’ Forecasts

Before testing hypotheses 1 and 2, we first examine whether our sample firms appear to be managing earnings to meet or slightly exceed analysts’ earnings forecasts. Figure 1 plots the empirical distribution of the scaled earnings forecast errors, with histogram interval widths of 0.001 for the range $-0.04$ to $+0.04$. Our results are consistent with Degeorge et al. (1999) (see their Figure 6). Consistent with the idea that earnings are managed to meet or exceed analysts’ earnings forecasts, the distribution of earnings forecast errors drops off sharply below zero. That is, earnings forecast errors slightly less than zero occur less frequently than would be expected, and earnings forecast errors slightly greater than zero occur more fre-

\textsuperscript{14} Specifically, we estimate income tax expense as: after-tax net earnings times $[t/(1 - t)]$, where $t$ is the maximum effective corporate tax rate. Nonoperating expenses are therefore equal to operating earnings, minus after-tax net earnings, minus income tax expense. To examine the sensitivity of the results to our measure of $t$, we repeat all empirical tests using a firm-specific proxy for $t$. For this second measure of $t$, we use Compustat data (i.e., income tax expense and net income after tax) to calculate a firm-specific effective tax rate. All results are essentially identical to those reported in the paper.

\textsuperscript{15} To the extent that some operating expenses are fixed, operating margin percentage will overstate the variable costs related to sales, and our estimate will underestimate the impact on earnings of managing sales upward. A better proxy for the variable costs related to sales would be a firm’s COGS as a percentage of sales. However, Value Line analysts do not forecast COGS. To examine the sensitivity of the results to our proxy for variable costs, we repeat all empirical tests using gross margin forecast error defined as: the simple sales forecast error multiplied by $[1 - (\text{COGS/Sales})]$. We use Compustat for the COGS data. Our inferences are unchanged.
Empirical distribution of earnings forecast errors, defined as reported earnings minus the analyst’s forecast, divided by market value of equity. The distribution interval widths are 0.001, and the location of zero on the horizontal axis is marked by the dashed line. For example, the first interval to the right of zero contains all scaled forecast errors in the interval (0.000, 0.001), the second interval contains 0.001, 0.002, and so on. The vertical axis labeled frequency represents the number of observations in each forecast error interval.

The significance of the irregularity around zero is confirmed by statistical tests. The \( \tau \)-statistic for the interval to the immediate right of zero is equal to 4.38, and \( \nabla P_i \) is greater than the corresponding values for the neighboring intervals.

Testing our hypotheses requires a sample of firm-years for which we have strong a priori reasons to expect firms to manage earnings to meet or exceed analysts’ forecasts. From our full sample, we choose those firms with scaled earnings forecast errors between 0 and 0.005. This criterion provides a sample of 2,655 observations for which reported earnings meet or slightly exceed analysts’ forecasts. We do not examine all firm-year observations because we do not believe that, on average, firms manage each component to meet or beat the component’s forecast. Rather, for a subset of firms expected to manage earnings, we hypothesize that some or all of the components are managed.\(^{16}\)

\(^{16}\) The 2,655 observations represent 15.0 percent of the full sample of 17,667 observations. Of the 5,112 firm-year observations that have depreciation expense forecasts, 822 observations (16.1%) have earnings forecast errors between 0 and 0.005. We examine this subset of firms with small positive forecast errors because there is good reason to believe that they are managing earnings in a predictable direction (i.e., to meet or beat analysts’ forecasts). This does not mean that we believe firms with large earnings forecast errors cannot also manage earnings. However, it is difficult to identify which subset of firms with large earnings forecast errors are managing earnings in a predictable direction.
4.1 Hypothesis 1: Managing Earnings by Increasing Sales

Figure 2, panel A, plots the empirical distribution of the scaled sales forecast errors, with histogram interval widths of 0.01 for the range \(-0.25\) to \(+0.25\). Results support the hypothesis that firms manage earnings by increasing sales. The \(\tau\) statistic for the interval to the immediate right of zero is 2.36, suggesting that sales forecast errors slightly greater than zero occur more frequently than would be expected. This is difficult to discern from visual inspection of the histogram because the distribution is centered on zero, and the discontinuity is not as sizeable as for the earnings distribution.

Panel B of Figure 2 plots the empirical distribution of the gross margin forecast errors (our second measure of sales forecast errors), with histogram interval widths of 0.001 for the range \(-0.025\) to \(+0.025\). Results support the hypothesis that firms manage earnings by increasing sales. Gross margin forecast errors slightly less than zero occur less frequently than would be expected, while gross margin forecast errors slightly greater than zero occur more frequently than would be expected. The \(\tau\) statistic is 3.14, and \(\nabla p_i\) is greater than the corresponding values for the neighboring intervals.

We repeat the preceding analysis using two control samples for which we have no a priori reasons to expect that firms are managing earnings to meet or exceed analysts' forecasts. The two groups are (1) the 15,012 firm-year observations with scaled earnings forecast errors less than zero or greater than 0.005 and (2) the 5,850 firm-year observations with scaled earnings forecast errors greater than 0.005. We examine the scaled sales and gross margin forecast errors for both control samples, and do not find a discontinuity around zero in any instance. All \(\tau\) statistics for the intervals around zero are insignificant (all \(\tau\) statistics are less than 11.601). There is no evidence that these control firms are managing sales. In sum, the evidence in Figure 2 supports hypothesis 1. To report earnings that meet or slightly exceed analysts’ forecasts, firms increase sales.\(^{17,18}\)

17. Degeorge et al. (1999) present an argument for why the distribution of unscaled earnings forecast errors should be used to identify those firms that are likely to be managing earnings to meet or beat a benchmark. (See their discussion on pp. 16–17.) Accordingly, we repeat our analyses in Figures 2 and 3 using the 2,700 observations with the smallest positive earnings per share (EPS) forecast errors and obtain qualitatively similar results to those reported in the paper. We thank the discussant for suggesting this analysis.

18. The approach adopted in this paper, along with Burgstahler and Dichev (1997) and Degeorge et al. (1999), assumes that the discontinuity in the forecast error distribution can only be explained as earnings management. To test the robustness of our results to assumptions about the underlying distributions, we also examine the sales and expense forecast error distributions using the subset of firms with earnings forecast errors between \(-0.0025\) and \(+0.0025\). This centers the earnings forecast error for our subset of firms about zero. There are 2,686 firm-year observations (901 observations for depreciation expense) in this earnings forecast error interval. We repeat all analyses in Figures 2 and 3, and our inferences remain unchanged from those reported in the paper. This helps lessen the concern that our earnings component results are attributable to restricting the sample to observations with earnings forecast errors greater than zero.
Empirical distribution of sales and gross margin forecast errors, defined as the firm's reported numbers minus the analysts' forecasts, divided by market value of equity. For sales, the distribution interval widths are 0.01. For gross margin, the distribution interval widths are 0.001. The location of zero on the horizontal axis is marked by the dashed line. The vertical axis labeled frequency represents the number of observations in each forecast error interval.
4.2 Hypothesis 2: Managing Earnings by Decreasing Expenses

Figure 3 presents the empirical distributions of forecast errors for three different expenses: operating expenses (panel A), nonoperating expenses (panel B), and depreciation expense (panel C). All histograms have interval widths of 0.001 for the range $-0.025$ to $+0.025$.

Panel A of Figure 3 plots the empirical distribution of the forecast errors for operating expenses (as defined earlier). There is strong evidence that firms manage earnings by decreasing operating expenses. This is evidenced by the pileup of operating expense forecast errors slightly less than zero, and a sharp drop-off of errors slightly greater than zero. The significance of the irregularity around zero is confirmed by the $\tau$ statistic of $-4.46$ for the interval to the immediate left of zero. We also plot and examine the empirical distributions of the operating expense forecast errors for the two control samples described. There is no evidence of any discontinuity around zero for either control sample, and the $\tau$ statistics for the intervals around zero are not significant at conventional levels.

Panel B of Figure 3 plots the distribution of the forecast errors for nonoperating expenses (excluding income tax expense). There is no evidence that firms manage earnings by decreasing nonoperating expenses. The histogram is relatively smooth, with no visual irregularities around zero. The $\tau$ statistic for the interval to the immediate left of zero is 0.98 and is insignificant. We repeat this analysis using the two control samples, and find similar results; that is, there is no evidence of irregularities around zero, and no $\tau$ statistics are significant (all $\tau$ statistics are less than 11.001).

Figure 3, panel C, plots the empirical distribution of the depreciation expense forecast errors. Although there is a spike in the number of observations immediately to the left of zero, the density function’s slope immediately to the left side of the threshold is not significantly different from the slope immediately to the right side of the threshold ($\tau$ statistic of $-0.37$). There is no evidence that firms manage earnings by decreasing depreciation expense. As before, we repeat the analysis using the two control samples, and find a similar pattern for these firm-year observations. There is no evidence of discontinuities around zero, and all $\tau$ statistics are less than 11.001.\(^{19}\)

In sum, the evidence in Figure 3 suggests that firms decrease operating expenses in order to report earnings that meet or slightly exceed analysts’ forecasts (consistent with hypothesis 2). There is no evidence to suggest that firms decrease nonoperating expenses or depreciation expense in an attempt to meet or beat analysts’ forecasts (inconsistent with hypothesis 2).

\(^{19}\) It would most likely be extremely difficult for managers to use depreciation expense to manage earnings in any meaningful amount. Nonetheless, managers do have a fair amount of discretion over the parameters used to calculate depreciation expense each year. The extent to which they use this discretion to manage earnings is an empirical issue.
Empirical distribution of expense forecast errors, defined as the firm’s reported numbers minus the analysts’ forecasts, divided by market value of equity. The distribution interval widths are 0.001, and the location of zero on the horizontal axis is marked by the dashed line. The vertical axis labeled frequency represents the number of observations in each forecast error interval.
4.3 Conditions Likely to Affect the Earnings Components Firms Use to Manage Earnings

This section identifies firm characteristics that are likely to affect the degree to which a firm uses sales and/or expenses to manage earnings. Using the sample of firms believed to be managing earnings upward to meet or beat analysts' forecasts, we examine three factors that are likely to affect the earnings components used to manage earnings: level of current assets, level of current liabilities, and operating margin percentage. For each characteristic, we partition the sample into three groups (high/medium/low), and compare the median forecast errors for the top one-third and bottom one-third of the sample (i.e., the high and low groups). If the median forecast error for a particular earnings component differs between the groups, this would be consistent with one group of firms using that component to a greater extent than the other group.

4.3.1 LEVEL OF CURRENT ASSETS

Burgstahler and Dichev (1997) argue that firms with high levels of current assets and current liabilities before earnings management are likely to find it relatively less costly to manage earnings through changes in working capital than firms with low levels of current assets and liabilities. For example, they argue that a firm with a high level of receivables is likely to find it less costly to manage earnings through changes in accounts receivable. This would be the case if such earnings management was less noticeable because the percentage change in a given current asset or current liability account was smaller. In addition, high levels of current liabilities could indicate that a firm has more flexibility in the current period to decrease its expense accruals, thereby increasing earnings. Burgstahler and Dichev (1997) examine a sample of firms expected of managing earnings upward (to avoid a loss), and find that these firms appear to have a higher level of beginning-of-year current assets and current liabilities than might otherwise be expected.

Consistent with Burgstahler and Dichev (1997), we use a firm's level of current assets and current liabilities, both scaled by market value of equity, as a proxy for the cost of managing earnings. Firms with high levels of current assets are likely to find it less costly to use sales to manage earnings upward, and are thus more likely to manage earnings by increasing sales. This would result in the sales forecast

20. Of the 2,655 observations, 2,596 have the data necessary to compute current assets, and 1,955 have the data necessary to compute current liabilities. Operating margin percentage is available for all the observations.

21. Burgstahler and Dichev's (1997) current asset and current liability results are consistent with, but not necessarily indicative of, earnings management via changes in working capital.

22. Current assets is defined as the sum of accounts receivable (Compustat item 2), inventory (item 3), and other current assets (item 68). Current liabilities is defined as the sum of accounts payable (item 70), taxes payable (item 71), and other current liabilities (item 72).
### MANAGEMENT OF EARNINGS COMPONENTS

#### TABLE 2

**Conditions Likely to Affect the Management of Earnings Components:**
**Median Forecast Errors Across Different Portfolios**

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A:</strong> Level of current assets ($N = 2,596$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High level</td>
<td>865</td>
<td>0.9514</td>
<td>0.0021</td>
<td>0.0132</td>
<td>0.0020</td>
<td>0.0000</td>
<td>−0.0026</td>
</tr>
<tr>
<td>Low level</td>
<td>866</td>
<td>0.1372</td>
<td>0.0018</td>
<td>0.0088</td>
<td>0.0004</td>
<td>−0.0010</td>
<td>−0.0005</td>
</tr>
<tr>
<td>$z$ score of differences</td>
<td>(p-value)$^a$</td>
<td>36.02</td>
<td>0.36</td>
<td>2.14</td>
<td>1.91</td>
<td>1.46</td>
<td>−1.53</td>
</tr>
<tr>
<td>(0.0001)</td>
<td>(0.721)</td>
<td>(0.033)</td>
<td>(0.056)</td>
<td>(0.144)</td>
<td>(0.126)</td>
<td>(0.251)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B:</strong> Level of current liabilities ($N = 1,955$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High level</td>
<td>651</td>
<td>0.4393</td>
<td>0.0020</td>
<td>0.0041</td>
<td>0.0019</td>
<td>0.0000</td>
<td>−0.0022</td>
</tr>
<tr>
<td>Low level</td>
<td>652</td>
<td>0.0726</td>
<td>0.0018</td>
<td>0.0096</td>
<td>0.0014</td>
<td>−0.0008</td>
<td>−0.0005</td>
</tr>
<tr>
<td>$z$ score of differences</td>
<td>(p-value)$^a$</td>
<td>31.36</td>
<td>0.02</td>
<td>−0.82</td>
<td>1.23</td>
<td>0.04</td>
<td>−0.96</td>
</tr>
<tr>
<td>(0.0001)</td>
<td>(0.983)</td>
<td>(0.411)</td>
<td>(0.217)</td>
<td>(0.968)</td>
<td>(0.337)</td>
<td>(0.389)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel C:</strong> Operating margin percentage ($N = 2,655$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High percentage</td>
<td>884</td>
<td>0.2330</td>
<td>0.0019</td>
<td>0.0097</td>
<td>0.0027</td>
<td>−0.0004</td>
<td>−0.0004</td>
</tr>
<tr>
<td>Low percentage</td>
<td>885</td>
<td>0.0890</td>
<td>0.0019</td>
<td>0.0080</td>
<td>0.0007</td>
<td>0.0000</td>
<td>−0.0022</td>
</tr>
<tr>
<td>$z$ score of differences</td>
<td>(p-value)$^a$</td>
<td>36.41</td>
<td>1.50</td>
<td>1.67</td>
<td>3.49</td>
<td>−0.65</td>
<td>2.23</td>
</tr>
<tr>
<td>(0.0001)</td>
<td>(0.135)</td>
<td>(0.095)</td>
<td>(0.001)</td>
<td>(0.518)</td>
<td>(0.026)</td>
<td>(0.484)</td>
<td></td>
</tr>
</tbody>
</table>

$^a$The level of current assets and current liabilities are measured at the beginning of the year, and both are deflated by market value of equity.

Operating margin is based on the prior year’s results, and is equal to operating earnings as a percentage of sales.

Forecast error = (reported amount − analysts’ forecast)/market value of equity.

The $z$ score is computed using a Wilcoxon rank-sum test for two independent samples.

errors being greater (i.e., more positive) for firms with high current asset levels than for firms with low current asset levels.

Table 2, panel A, presents the median forecast errors for the high- and low-level groups based on beginning-of-year current assets, scaled by market value of equity. The median earnings forecast errors (as a percentage of market value of equity) for firms with high and low levels of current assets are 0.21 percent and 0.18 percent, respectively, and are not significantly different from one another (Wilcoxon $z$ statistic of 0.36). The sales and gross margin forecast errors are both significantly greater for firms with high levels of current assets than for firms with...
low levels of current assets. This is consistent with high-level current asset firms being more likely to use sales to manage earnings upward. The sales forecast error for the high-level current asset group is 1.32 percent, and for the low-level current asset group, it is 0.88 percent (significantly different at \( p = 0.033 \)). The gross margin forecast errors for the high- and low-level current asset groups are 0.20 percent and 0.04 percent, respectively (significantly different at \( p = 0.056 \)).

Although we make no predictions regarding the level of current assets and the likelihood that firms will use expenses to manage earnings upward, we present the median forecast errors for expenses in the last three columns of panel A. None of the median expense forecast errors are significantly different between the two groups. Overall, the results in panel A of Table 2 suggest that firms with high levels of current assets are more likely than firms with low levels of current assets to use sales to manage earnings upward.\(^{23}\)

### 4.3.2 LEVEL OF CURRENT LIABILITIES

We next partition the sample on the level of beginning-of-year current liabilities, scaled by market value of equity. If firms with high levels of current liabilities find it less costly to manage earnings upward by decreasing expenses, then the median expense forecast errors for these firms would be more negative than for firms with low levels of current liabilities. Results are reported in Table 2, panel B. The earnings forecast error for the high-level current liability group (0.20%) is not significantly different from the earnings forecast error for the low-level current liability group (0.18%) (\( z \) statistic of 0.02). For all three expense types, none of the median forecast errors differ between the two groups (all \( p \) values are greater than 0.30). There is no evidence to suggest that firms with high levels of current liabilities are more likely than firms with low levels of current liabilities to manage earnings by managing operating, nonoperating, or depreciation expenses downward. We make no predictions regarding a firm’s level of current liabilities and its propensity to use sales to manage earnings, and the evidence suggests no differences between the two groups.

### 4.3.3 OPERATING MARGIN PERCENTAGE

We next examine whether a firm’s operating margin percentage affects the likelihood that it uses sales to manage earnings upward, where operating margin percentage is defined as operating earnings as a percentage of sales. We hypothesize that firms with a high operating margin percentage are more likely than firms with a low operating margin percentage to use sales to manage earnings upward because each dollar of sales will have a greater effect on bottom-line earnings for high-margin firms. In effect, managing earnings upward by increasing sales is likely to

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23. The results are qualitatively similar when we rank firms on levels of accounts receivable.
TABLE 3
Median Forecast Errors by Stock Recommendation Portfolio* ($N = 17,667$)

<table>
<thead>
<tr>
<th>Stock Rec. Portfolio</th>
<th>$N$</th>
<th>Percentage of Sample</th>
<th>Earnings$^b$</th>
<th>Sales$^b$</th>
<th>Gross Margin$^b$</th>
<th>Operating Expenses$^b$</th>
<th>Non-operating Expenses$^b$</th>
<th>Depreciation Expense$^b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong buy</td>
<td>1,412</td>
<td>8.0</td>
<td>0.0043</td>
<td>0.0154</td>
<td>0.0028</td>
<td>-0.0020</td>
<td>-0.0016</td>
<td>0.0004</td>
</tr>
<tr>
<td>Buy</td>
<td>3,929</td>
<td>22.2</td>
<td>0.0015</td>
<td>0.0098</td>
<td>0.0018</td>
<td>0.0000</td>
<td>-0.0009</td>
<td>0.0006</td>
</tr>
<tr>
<td>Hold</td>
<td>8,492</td>
<td>48.1</td>
<td>-0.0017</td>
<td>-0.0053</td>
<td>-0.0008</td>
<td>0.0048</td>
<td>-0.0007</td>
<td>0.0000</td>
</tr>
<tr>
<td>Sell</td>
<td>2,992</td>
<td>16.9</td>
<td>-0.0073</td>
<td>-0.0221</td>
<td>-0.0033</td>
<td>0.0116</td>
<td>0.0001</td>
<td>0.0004</td>
</tr>
<tr>
<td>Strong sell</td>
<td>842</td>
<td>4.8</td>
<td>-0.0154</td>
<td>-0.0348</td>
<td>-0.0043</td>
<td>0.0194</td>
<td>0.0020</td>
<td>0.0011</td>
</tr>
<tr>
<td>Full sample</td>
<td>17,667</td>
<td>100</td>
<td>-0.0008</td>
<td>-0.0019</td>
<td>-0.0003</td>
<td>0.0039</td>
<td>-0.0007</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

$^a$Forecast error = (reported amount - analysts' forecast)/market value of equity.
$^b$Differences across stock recommendation portfolios are significant at $\alpha < 0.001$ by the Jonckheere test of ordered alternatives (Hollander and Wolfe [1973]).
$^c$Differences across stock recommendation portfolios are not significant at conventional levels using the Jonckheere test of ordered alternatives (Hollander and Wolfe [1973]).

be more efficient for high-margin firms relative to low-margin firms. If high-margin firms are more likely to manage earnings by increasing sales, this would result in the median sales forecast errors being greater (i.e., more positive) for high-margin firms relative to low-margin firms.

Table 2, panel C, presents the median forecast errors for firms with high and low operating margin percentages. The median earnings forecast error is the same for both groups (0.19%). Consistent with expectations, the median sales forecast error for firms with a high operating margin percentage is greater than that for firms with a low percentage, 0.97 percent and 0.80 percent, respectively (significantly different at $p = 0.095$). In addition, the high-percentage firms have a larger gross margin forecast error than the low-percentage firms (0.27% and 0.07%, significantly different at $p = 0.001$). Relative to firms with a low operating margin, firms with a high operating margin appear to be more likely to use sales to manage earnings upward. The last three columns of Table 2 present the median expense forecast errors for the two groups. There is no significant difference between the median forecast errors for operating expenses or for depreciation expense. However, the median forecast error for nonoperating expenses is negative for both groups, and is smaller (i.e., more negative) for low-margin firms than for high-margin firms. The median forecast errors for the high- and low-margin groups are $-0.04$ percent and $-0.22$ percent, respectively (significantly different at $p = 0.026$). This suggests that firms with a low operating margin may be more likely to manage nonoperating expenses downward in an attempt to manage earnings upward. One potential explanation is that low-margin firms face relatively greater fixed operating expenses and have more flexibility in managing nonoperating expenses.
5. Managing Earnings in Response to Perceived Investment Potential

In this section, we test hypotheses 1 and 2 using a set of firms believed to be managing earnings in response to investor opinions about a stock’s attractiveness as an investment. Recent evidence suggests that the market’s perception of a firm’s investment potential affects the firm’s incentives to manage reported earnings (Abarbanell and Lehavy [1999]). When a firm is regarded as a good investment, the firm has an incentive to manage reported earnings toward analysts’ forecasts to ratify the market’s confidence in the firm. This earnings management behavior will result in a high incidence of reported earnings that meet or slightly exceed analysts’ forecasts. In contrast, when a firm is regarded as a poor investment, it has little to gain from managing earnings to meet analysts’ forecasts and has little to lose if it reports earnings below analysts’ forecasts (i.e., the firm is already regarded as a poor investment). These poor-investment firms have incentives to decrease current reported earnings and create accounting slack for the future. If these firms manage earnings downward and away from analysts’ forecasts, this will result in reported earnings that fall short of analysts’ forecasts.24

Abarbanell and Lehavy (1999) use analysts’ stock recommendations to proxy for a firm’s perceived investment potential and examine the forecast errors for firms rated buy and sell. Their results are consistent with their hypotheses. Firms rated buy have small good-news earnings forecast errors, while firms rated sell have extreme bad-news earnings forecast errors.

We use Value Line’s stock recommendation as a measure of a firm’s investment potential. Firms rated buy are classified as firms with incentives to manage earnings upward. Firms rated sell are classified as firms with incentives to manage earnings downward. Because we are now examining firms that have incentives to both increase and decrease reported earnings, hypotheses 1 and 2 must be expanded to include earnings management upward and downward, specifically:

\[ H'1: \text{In order to manage earnings upward (downward), firms manage sales upward (downward)}. \]

\[ H'2: \text{In order to manage earnings upward (downward), firms manage expenses downward (upward)}. \]

We test the expanded versions of hypotheses 1 and 2 by partitioning our original sample of 17,667 observations into groups based on stock recommendation and computing the median forecast errors for each group. Managing sales upward (downward) will be reflected in positive (negative) forecast errors for sales. Man-

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24. The more accounting slack a firm attempts to create (i.e., the more extreme the earnings bath), the greater the difference between reported earnings and the forecasted amount.
There are at least two advantages to using a firm's investment potential to make predictions about its incentives to manage earnings. First, we are able to examine the use of earnings components to manage earnings both upward and downward. This provides us with a more complete picture of how earnings components are used to manage earnings. Second, in contrast to earnings forecast errors which are not known until earnings are actually announced, a firm's investment potential can be determined at the beginning of the accounting period. (It is an ex ante measure of earnings management.) This enables us to examine a larger set of firms and explore the pervasiveness of earnings management.

To ensure that Abarbanell and Lehavy's (1999) results for earnings forecast errors hold for our sample, we first examine the pattern of earnings forecast errors across firms' stock recommendations. These results are reported in the fourth column of Table 3. Consistent with Abarbanell and Lehavy (1999), we find that the median earnings forecast error monotonically decreases as the stock recommendation moves from "strong buy" to "strong sell" (significant at $p < 0.001$ using the Jonckheere test of ordered alternatives [Hollander and Wolfe (1973)]). The median earnings forecast error for buy firms is positive, indicating that reported earnings exceed analysts' forecasts. For sell firms, the median earnings forecast error is negative, indicating that reporting earnings are less than analysts' forecasts.

The results in Table 3 for earnings forecast errors are consistent with Abarbanell and Lehavy's (1999) hypothesis that (1) firms rated buy engage in earnings management to meet or beat analysts' forecasts, thereby resulting in small positive earnings surprises, and (2) firms rated sell engage in earnings management to deflate earnings, thereby resulting in more extreme, negative earnings surprises.

### 5.1 Hypothesis 1: Managing Earnings by Managing Sales

Given that Abarbanell and Lehavy's results hold for our sample, we now move on to testing our expanded versions of hypotheses 1 and 2. The fifth and sixth columns of Table 3 present the median forecast errors for sales and gross margin.

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25. In this section, we do not test hypotheses 1 and 2 using empirical histograms of the forecast error distributions because it is not clear at what values we would expect to see a discontinuity (i.e., what our threshold value should be).

26. We replicate the analysis in this section after scaling forecast errors by book value of equity, number of shares, and sales. All results are consistent with those reported in Table 3.

27. Note that Abarbanell and Lehavy (1999) compute the earnings forecast error as the analyst's forecast minus the reported amount, while we compute the forecast error as the reported amount minus the analyst's forecast.

28. In addition, the magnitude of the earnings forecast error (in absolute value terms) is greater for sell firms than for buy firms. For sell and strong sell firms, the median forecast errors (as a percentage of a firm's market value) are $-0.73$ percent and $-1.54$ percent, respectively. For buy and strong buy firms, the median earnings forecast errors are $0.15$ percent and $0.43$ percent, respectively.
The results support our expanded hypothesis 1. The median sales and gross margin forecast errors both decrease monotonically as the stock recommendation moves from “strong buy” to “strong sell” (significant at $p < 0.001$ using the Jonckheere test). The median sales and gross margin forecast errors for buy firms are both positive, while the median errors for sell firms are both negative. These results suggest that buy firms manage earnings upward by managing sales upward, and that sell firms manage earnings downward by managing sales downward.

5.2 Hypothesis 2: Managing Earnings by Managing Expenses

The last three columns of Table 3 present the median forecast errors for operating, nonoperating, and depreciation expenses, respectively. For operating and nonoperating expenses, the results support our expanded hypothesis 2. The median forecast errors for both operating and nonoperating expenses increase monotonically as the stock recommendation moves from “strong buy” to “strong sell” (significant at $p < 0.001$ using the Jonckheere test). The median operating and nonoperating forecast errors for buy firms are negative (i.e., actual expenses are less than forecasted), while the median errors for sell firms are positive (i.e., actual expenses are greater than forecasted). These results are consistent with buy firms managing operating and nonoperating expenses downward (to increase earnings), and with sell firms managing operating and nonoperating expenses upward (to decrease earnings).

For depreciation expense (last column of Table 3), there is no evidence to support hypothesis 2. The median depreciation expense forecast errors are positive for both buy and sell firms, and there is no discernible pattern of the median forecast errors across stock recommendation groups. There is no evidence to support the hypothesis that depreciation expense is used by firms rated buy to manage earnings upward or by firms rated sell to manage earnings downward.

Overall, the results in Table 3 are consistent with our expanded versions of hypotheses 1 and 2. To manage earnings upward, buy firms increase sales and decrease operating and nonoperating expenses. To manage earnings downward, sell firms decrease sales and increase operating and nonoperating expenses.²⁹

6. Summary

Prior research suggests that firms manage earnings to achieve certain reporting objectives. However, there is little evidence on how firms accomplish earnings management. This paper provides evidence as to which income-statement compo-

²⁹. On average, the Value Line stock recommendation (i.e., timeliness rank) we collect is made in the sixth month of a firm’s fiscal year. Accordingly, there is the possibility that the stock recommendation at year-end has changed. To address this concern, we identify those firm-year observations for which the timeliness ranks made in years $t$ and $t + 1$ are within one ranking of each other and repeat our analysis. Results are consistent with those reported in Table 3.
ments firms use to affect bottom-line earnings. We hypothesize that, to manage earnings upward, firms can manage sales upward and/or manage expenses downward. To manage earnings downward, firms can manage sales downward and/or manage expenses upward.

We first identify a set of firms for which we have strong a priori reasons to expect that they are managing earnings upward to meet or slightly exceed analysts' forecasts. We plot the empirical distributions of forecast errors for sales, operating expenses, nonoperating expenses, and depreciation expense, and then examine the various forecast error distributions for discontinuities around zero. Our evidence suggests that these firms manage earnings upward by managing sales upward and by managing operating expenses downward. There is no evidence to suggest that these firms used their nonoperating or depreciation expenses to manage earnings. We also identify firm characteristics that affect the likelihood that a firm will use a particular component to manage its earnings. We find that high levels of beginning-of-year current assets and high operating margin percentages are both associated with an increased likelihood that a firm uses sales to manage earnings upward. We find no evidence to suggest that the level of current liabilities affects the likelihood that a firm uses expenses to manage earnings upward.

We then test our hypotheses using a sample of firms believed to be managing earnings in response to investor sentiments about the firm as an investment. Firms rated buy are classified as firms with incentives to manage earnings upward. Firms rated sell are classified as firms with incentives to manage earnings downward. Evidence is consistent with firms increasing (decreasing) sales and decreasing (increasing) operating expenses and nonoperating expenses to manage earnings upward (downward).

Our study contributes to the earnings management literature by providing evidence on which components firms use to manage earnings. Such information is useful to both researchers and accounting standard setters in understanding earnings management behavior. Our study could be extended by examining which earnings components firms use to manage earnings under alternative earnings management scenarios, identifying situations that limit a firm's ability to use a particular earnings component to manage earnings, or identifying additional firm characteristics that are associated with the likelihood that a firm uses a particular component to manage its earnings.

APPENDIX

This appendix describes the test statistic we use to test for discontinuity in the forecast error distribution. Because the mode of the analysts' forecast errors is likely to be zero, the peak \( P \) of the forecast error distributions will likely occur at the same value as the threshold \( T \) we are examining (i.e., \( P = T = 0 \)). Therefore, we use the test statistic \( \tau \) described by Degeorge et al. (1999) for the special case when the threshold coincides with the peak of the distribution (see their Appendix, Case A2). Earnings management is detected by testing whether the slope of the density function immediately to one side of the threshold is sig-
Significantly different from the slope (adjusted for sign) immediately to the other side of the threshold, after allowing for any general local skew in the distribution.

Let \( x \) be the analyst's forecast error. Compute the proportion of the observations that lie in intervals covering \([x_0, x_1), [x_1, x_2), \ldots, [x_n + x_{n+1})\). These proportions are denoted \( p(x) \), and provide estimates of \( f(x) \), where \( f(x) \) is the probability density function of \( x \). The slope at any given point is \( f'(x) \), computed as \( \Delta p(x) = p(x_0) - p(x_{n-1}) \).

To test whether the density function's slope immediately to one side of the threshold \( T \) is significantly different from the slope (adjusted for sign) immediately to the other side of \( T \), we define \( \nabla p \) as

\[
\Delta p(x_{T^-}) - [-1 \times \Delta p(x_{T^+})].
\]

We then test whether \( \nabla p \) is unusual. We use the observations \( \nabla p \) from a small neighborhood \( R (j > 1) \), to compute an estimate of the mean and standard deviation of \( \nabla p \). To test the "unusualness" of \( \nabla p \), we use the \( t \)-like test statistic, \( \tau \), where

\[
\tau_i = \frac{\nabla p_i - \text{mean} \{ \nabla p \}}{\text{std. dev.} \{ \nabla p \}},
\]

where \( i \in R \) and \( i \neq n \).

Consistent with Degeorge et al. (1999), we interpret values of \( \tau \) greater than 2.0 as suggestive of a discontinuity at \( T \). However, because we do not know the distribution of \( \tau \), we also compare \( \nabla p \) to the corresponding values at nearby \( j \)'s and find that, when \( \tau_{T^-} \) is greater than 2.0, \( \nabla p \) is always the largest value in the neighborhood.

Also consistent with Degeorge et al. (1999), we use the log transformation of the estimated density function to help improve the homogeneity of variance across neighborhoods of \( R \). Accordingly, all the tests that we report in the paper are based on \( \Delta \log \{ p(x) \} \) rather than \( \Delta p(x) \).

REFERENCES


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