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Predicting Operating Income via a Generalized Operating-Leverage Model

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Abstract: We propose a generalized, practitioner-oriented operating-leverage model for predicting operating income using net sales, cost of sales, depreciation, and SG&A. Prior research links operating income directly to these items; hence, our model includes all aggregate revenues and expenses that comprise operating income. Prior research finds that the cost of sales is "much less" sticky than depreciation and SG&A; hence, we use the cost of sales as a proxy for the total variable costs and depreciation and SG&A as proxies for the sticky fixed costs. We introduce a new adjustment to the textbook operating-leverage model so that the ratio of sales to the cost of sales remains constant for the reference and forecast periods. Inspired by prior research, we adjust depreciation and SG&A for cost stickiness. We find that using our generalized operating-leverage model improves the forecast accuracy of next-quarter and next-year operating income predictions compared to predictions made using textbook operating leverage, which is a special case of our model.

Keywords: contribution margin; cost volume profit; fixed costs; operating income; operating leverage; sticky costs; variable costs

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1. Introduction

We propose an earnings forecast model using the Standard and Poor's (S&P) Compustat database items that Casey et al. (2016) show coincide with Compustat OIADP. We denote the names of items reported in financial statements in lowercase and the names of Compustat items in uppercase, for example, cogs in an income statement versus COGS in Compustat. We utilize the SALE (net sales revenue), COGS (cost of goods sold), DP (total depreciation and amortization), and XSGA (selling, general, and administrative expenses) to predict OIADP (operating income after depreciation and amortization). Casey et al. (2016) show that Equation (1) generally holds in Compustat for each company in every year and quarter:

$$\text{OIADP} = \text{SALE} - \text{COGS} - \text{DP} - \text{XSGA} \quad (1)$$

Anderson et al. (2003) (hereafter, "ABJ") found that XSGA is a mixture of fixed and variable costs that, on average, increase more for a 1% increase in the SALE than they decrease for a 1% decrease in the SALE and thereby exhibit "sticky" cost behavior. Shust and Weiss (2014) show that depreciation is also a sticky accrual accounting cost. Chen et al. (2019) find that the COGS is mostly variable, while the DP, like the XSGA, is a sticky, mixed cost. Based on this prior research, we use the Compustat cost items in (1) as proxies for the variable and fixed costs in the traditional cost–volume–profit (CVP) income statement. We also apply such proxies to the calculation of the operating leverage derived from the CVP income statement. Managerial and cost accounting textbooks generally describe the following:

$$\begin{gathered}\text{Operating Leverage} = \text{Contribution Margin}/\text{Operating Income} \\ \text{where Contribution Margin} = \text{Total Sales Revenue} - \text{Total Variable Costs}\end{gathered} \quad (2)$$

Using (2), our unadjusted proxy for the operating leverage is as follows:

$$\text{Operating Leverage} = (\text{SALE} - \text{COGS})/\text{OIADP} \quad (3)$$

We chose the Compustat OIADP for the operating income because S&P computes the OIADP before deducting income taxes and interest. The Compustat OIADP also subsumes the revenues and expenses that firms include in their continuing operations on an accrual accounting basis. Furthermore, the OIADP represents the parsimonious set of aggregate Compustat variables shown in (1).

Managerial accounting textbooks usually state the assumptions that must be true for the operating leverage derived from the CVP to predict the future operating income. For example, Hilton and Platt (2023) say that, within the relevant range, the total fixed expenses must remain constant as activity changes, and the unit variable expense remains unchanged as activity varies. We provide mathematical proof in Appendix A that (1) the ratios of the total sales-to-total variable costs and (2) total fixed costs must each remain constant in the reference and forecast periods for the traditional operating leverage, multiplied by the future period's percent change in sales, to accurately predict a future period's operating income.

SALE-to-COGS will generally vary as companies change product mixes, selling prices, and sales markups, and as the costs of goods and services vary. Hence, we introduce an adjustment so that the SALE-to-COGS remains constant by estimating each company's future-period ratio of SALE-to-COGS and using this estimate to modify the operating leverage model (3) so that the current and future periods' SALE-to-COGS ratios are equal. Additionally, prior research has demonstrated that the XSGA and DP are asymmetrically variable (sticky) with increases and decreases in sales (ABJ; Shust and Weiss 2014). Thus, we follow these prior authors by adjusting the XSGA and DP in model (3) so that, on average, these costs change in a more realistic sticky manner as the SALE changes. These modifications result in a generalized model of the operating leverage for which the textbook operating leverage is a special case with invariant sales-to-total variable costs and fixed costs.

We assess our modified operating-leverage model's predictive power by regressing the change in the OIADP, sized by the total assets, on the change in our model's estimate of the OIADP, sized by the total assets. We also study the error levels of our model's estimates. We evaluate our model for predicting firms' OIADPs in the next quarter and next year.

A primary contribution of this paper is the introduction of a generalized operating-leverage model from the perspective of Equation (1), identified by Casey et al. (2016). Our paper is the first we know to develop a procedure for adjusting operating leverage for a varying sales-to-total-variable-costs ratio. Following prior research on sticky costs, we additionally adjust the DP and XSGA in our model for cost stickiness. We evaluated our Compustat-based operating-leverage model's ability to predict firms' next-quarter and next-year OIADPs via regression analyses and by assessing the prediction errors. Our operating leverage model improves the forecast accuracy of the next-quarter and next-year OIADPs when compared to earlier models that do not account for changes in the ratio of sales to total variable costs or for sticky depreciation, amortization, and SG&A costs. Financial analysts, investors, and other practitioners who use S&P's Compustat data may benefit from using our operating leverage model when forecasting companies' next-quarter and next-year operating incomes.

We proceed with a discussion of prior research on the behavior of accounting costs. Next, we discuss, in more detail, the methodology outlined in the Introduction and then present our detailed findings. We then summarize our findings, discuss future research opportunities, and conclude.

2. Literature Review

Usually, a firm's operating leverage is not explicitly known to external users because the generally accepted accounting principles (GAAP) do not require corporations to specify costs as variable or fixed. As a result, users of general-purpose financial statements must estimate corporations' variable and fixed costs and, hence, their operating leverages. For example, Lev (1974, p. 633) used time-series linear regressions to estimate the beta average variable costs for each firm and found a positive relationship between the estimated variable and fixed costs and returns. Prior to ABJ, it was commonly accepted that Selling and Administrative (S&A) were approximately fixed costs: "Most administrative costs are approximately fixed, therefore, a disproportionate (to sales) increase is considered a negative signal suggesting, among other things, a loss of managerial cost control or an unusual sales effort (Bernstein 1988, p. 692)" (Lev and Thiagarajan 1993, p. 196). However, ABJ found that SG&A costs behave with "sticky" variability partly because managers make decisions that change the resources committed to activities. Restuti et al. (2022) provide further evidence of the link between managerial decisions and cost stickiness.

Lipe (1986) showed that six GAAP financial statement components (gross profits, general and administrative expenses, depreciation expense, interest expense, income taxes, and other items) provide information incremental to earnings for predicting future earnings and returns. Lev and Thiagarajan (1993) identified the fundamental signals in GAAP financial statements that security analysts claimed were useful for evaluating corporations' future earnings and returns. The authors found that these fundamentals added approximately 70%, on average, to the explanatory power of the earnings concerning excess returns. Abarbanell and Bushee (1997) found that the fundamental signals identified by Lev and Thiagarajan (1993) were also relevant to predicting future earnings. Ciftci et al. (2016) demonstrated that considering the variability in and stickiness of costs improves analysts' earnings forecasts, especially when sales decline. Grau and Reig (2021) find that the operating leverage impacts profitability in the context of European firms.

Fairfield et al. (1996) used line items from GAAP income statements to classify earnings into operating and non-operating income components to forecast the future Return on Equity (ROE). The study found incremental predictive content for the average firm by disaggregating earnings into operating income and non-operating income, income taxes, special items, extraordinary items, and discontinued operations. Further disaggregation did not improve the forecasts for the one-year-ahead ROE. The study's operating income (OPINC) variable includes five explanatory variables from GAAP income statements: gross margin; selling, general, and administrative expenses; depreciation expense; interest expense; and minority income. The study found that these five components of operating income are reasonably homogeneous with respect to providing information about future profitability. In contrast, the evidence indicated that the information content of non-operating income, income taxes, extraordinary items, and discontinued operations may be relevant to outcomes other than future profitability. Additionally, the OPINC model has a similar accuracy when predicting the ROE and operating income. In a comparable study, Sloan (1996) uses the line items contained in GAAP financial statements to predict the future ROE based on past cash flows and the accrual components of earnings.

Banker and Chen (2006) propose an earnings forecast model that decomposes earnings into components reflecting the variability in the costs with the sales revenue. They further demonstrate that sticky costs respond differently to sales increases and decreases. Their model forecasts earnings more accurately than the Fairfield et al. (1996) model or Sloan (1996) model. However, all three models are less accurate than analysts' consensus forecasts that consider other factors, such as the macroeconomy and industry contexts. Our generalized operating-leverage model differs from the Banker and Chen (2006) approach in the following ways:

1. By using Casey et al. (2016) finding that the Compustat SALE − COGS − DP − XSGA equates to the Compustat OIADP;
2. By predicting the OIADP operating income as opposed to the Return on Equity (ROE);
3. By specifying the Compustat depreciation and amortization (DP) and selling, general, and administrative costs (XSGA) as sticky costs following Shust and Weiss (2014) and Chen et al. (2019);

4. By employing the COGS as a proxy for the total variable costs following Chen et al. (2019);
5. By predicting the future COGS by using the estimated future SALE-to-COGS ratio.

Our generalized operating-leverage model provides practitioners with a parsimonious earnings forecast model that directly estimates the next-quarter and next-year operating incomes (OIADPs) using only the Compustat SALE, COGS, DP, and XSGA items.

Other research has shown that losses have a lower earnings response coefficient (ERC) than the profit liquidation option (Hayn 1995). Banker and Byzalov (2014) review the theory of cost behavior and problems with estimating the traditional variables and fixed costs, demonstrating that costs have asymmetric behavior that can be "sticky" and "anti-sticky", and that the traditional "fixed" and "variable" cost classifications are extreme cases. Ciftci and Zoubi (2019) find more stickiness for small current sales changes than for large current sales changes.

Other research has examined traditional operating leverage versus financial leverage (Mandelker and Rhee 1984; Simintzi et al. 2015). Furthermore, studies in finance have used traditional operating leverage to study stock return properties (Sagi and Seasholes 2007; Gulen et al. 2011; Novy-Marx 2011; Donangelo 2014; Banker et al. 2018) and the cost of equity (e.g., Chen et al. 2011). Mandelker and Rhee (1984) study the joint impact of operating leverage and financial leverage on systematic risk and find a significant correlation between the two types of leverage. Simintzi et al. (2015) find that employment protection increases operating leverage and reduces financial leverage. Novy-Marx (2011) measures the operating leverage as the cost of goods sold plus the selling, general, and administrative expenses divided by the total assets, and shows that companies with higher operating leverages have higher expected returns. Donangelo (2014) shows that firms face greater operating leverage by providing flexibility to mobile workers. Rouxelin et al. (2018) find that changes in aggregate cost stickiness help predict future macroeconomic outcomes, such as the unemployment rate, and thereby provide relevant information for macroeconomic policy. Kanoujiya et al. (2023) find a link between leverage and firm value in the context of Indian firms. Du et al. (2023) demonstrate the importance of correctly specifying predictive variables in a variety of accounting contexts.

3. Methodology

3.1. Data

Our data source is S&P's Compustat database for North American companies. For quarterly data, due to data limitations, we study from the fiscal year 2005 quarter 2 through to the fiscal year 2021 quarter 4. For annual data, we analyze the fiscal years 1984 through 2021. Zhou et al. (2021) find that the usage of quarterly data improves cash flow forecasts relative to annual data.

3.2. Methodology for Predicting Quarterly OIADP

We introduce a modified operating leverage model that seeks to account for the variability in the SALE-to-COGS ratio and the stickiness of the XSGA and DP. Our adjusted operating-leverage model is parsimonious, yet it considers all the aggregated Compustat items that articulate with the OIADP, namely, all the accrual accounting revenues and expenses from continuing operations summarized in the SALE, COGS, XSGA, and DP. We begin with our base operating-leverage model using the Compustat income statement items that articulate with the operating income. Next, we create the intermediate model by modifying the base model to account for changes in the SALE-to-COGS ratio during the forecast period. Finally, we develop the generalized model from the intermediate model by accounting for the stickiness of the XSGA and DP.

We justify our methodology using the research of Chen et al. (2019), who show that the COGS is much less sticky than the XSGA and DP. Hence, we treat the COGS as a proxy for the total variable cost in our CVP and operating-leverage models. Bostwick et al. (2016) found that S&P subtracts the DP from the cogs to derive the COGS when companies' financial statements do not quantify the allocated depreciation and amortization amounts.[1]

In Appendix B, we use our quarterly data and the ABJ methodology to compute 0.484 (0.205) as the factor by which the DP increases (decreases), on average, for a 1% increase (1% decrease) in the SALE. Similarly, we compute 0.377 (0.235) as the factor by which the XSGA increases (decreases), on average, for a 1% increase (1% decrease) in the SALE. These quarterly results using our data corroborate ABJ's and Shust and Weiss's (2014) findings that the XSGA and DP are sticky costs. We use these four factors to adjust for the stickiness of the DP and XSGA in our generalized model (11) for predicting the next-quarter OIADP. Also, we find that the quarterly COGS increases by 0.879 (decreasing 0.717) for a 1% increase (1% decrease) in the SALE. These results corroborate those of Chen et al. (2019) and further support our use of the COGS as a proxy for the total variable costs in our Compustat proxy for the CVP in Figure 1.

$SALE_{i,t-3}$
$\underline{(COGS_{i,t-3})}$
Contribution $Margin_{i,t-3}$
$(DP_{i,t-3})$
$\underline{(XSGA_{i,t-3})}$
$OIADP_{i,t-3}$

Figure 1. Cost–Volume–Profit (CVP) income statement.

We used the Compustat variables that articulate with the operating income (OIADP) for all SEC-reporting companies (i) for the reference quarters t − 3, where t = Current Quarter:

3.3. Restating Operating Leverage for Constant SALE/COGS Ratio for Quarters

When estimating the next-quarter $OIADP_{t+1}$ during quarter t, we adjusted for the seasonality of the quarterly accounting data (Chang et al. 2017; Welch 1984; Griffin 1977; Jones and Utzenberger 1969). Hence, we used quarter t − 3 Compustat data when forecasting the OIADP for t + 1. We used the Compustat variables in (1) to create the CVP income statement proxy shown in Figure 1.

Managerial accounting textbooks define a company's operating leverage for a period as the operating income/contribution margin. Using Figure 1's Compustat version of the CVP income statement, the company i's operating leverage (OL) for quarter t − 3 is as follows:

$$BASE\_QTR\_OL_{i,t-3} = (SALE_{i,t-3} - COGS_{i,t-3})/OIADP_{i,t-3} \tag{4}$$

Managerial accounting textbooks often show the following for the company (i), current period (t), and future period (t + n):

$$\begin{gathered}\text{Future operating income}_{i,t+n} = (1 + \text{operating income}_{i,t}) * \\ (\text{operating leverage}_{i,t} * \text{percent change in sales from period t to period t + n})\end{gathered} \tag{5}$$

With our base model, we assume that the ratio of the SALE-to-COGS remains constant and that the total DP and XSGA costs remain fixed for quarters t − 3 and t + 1. Then, our base quarterly model is as follows:

$$\begin{gathered}BASE\_MODEL\_EST\_QTR\_OIADP_{i,t+1} = \\ (1 + (CHG\_QTR\_SALE_{i,t+1} * BASE\_QTR\_OL_{i,t-3})) * OIADP_{i,t-3}\end{gathered}$$

where

$$\begin{gathered}CHG\_QTR\_SALE_{i,t+1} = \\ (((\text{average of SALE for periods t} - 2 \text{ through t}) - SALE_{i,t-3})/SALE_{i,t-3})\end{gathered} \tag{6}$$

However, the SALE/COGS can vary from period to period, such as when firms change sales markups. Therefore, we develop model (7), in which we estimate the $SALE_{i,t+1}/COGS_{i,t+1}$ based on the prior periods' SALE/COGS history and adjust the $COGS_{i,t-3}$ so that the $SALE_{i,t-3}$/adjusted $COGS_{i,t-3}$ equals the estimated $SALE_{i,t+1}/COGS_{i,t+1}$:

$$\begin{gathered}\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1} = \\ (1 + (((\text{average of SALE-to-COGS for periods } t-2 \text{ through } t) - \\ \text{SALE\_to\_COGS}_{i,t-3})/\text{SALE\_to\_COGS}_{i,t-3})) * \text{SALE\_to\_COGS}_{i,t-3}\end{gathered} \tag{7}$$

We then compute the restated operating leverage for the reference quarter (t − 3) as follows:

$$\begin{gathered}\text{RESTATED\_QTR\_OL}_{i,t-3} = \\ (\text{SALE}_{i,t-3} - (\text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1}))/(\text{SALE}_{i,t-3} - \\ (\text{SALE}_{i,t-3}/(\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1}/\text{COGS}_{i,t+1})) - \text{DP}_{i,t-3} - \text{XSGA}_{i,t-3})\end{gathered} \tag{8}$$

This intermediate model utilizes the $RESTATED\_QTR\_OL_{i,t-3}$ and assumes that the DP and XSGA are fixed costs, and it does not adjust for the sticky DP or XSGA when estimating the next-quarter $OIADP_{i,t+1}$, as follows:

$$\begin{gathered}\text{INTERMEDIATE\_MODEL\_ESTIMATED\_QTR\_OIADP}_{i,t+1} = \\ (1 + (\text{CHG\_QTR\_SALE}_{i,t+1} * \text{RESTATED\_QTR\_OL}_{i,t-3})) * \\ (\text{SALE}_{i,t-3} - (\text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1}) - \text{DP}_{i,t-3} - \text{XSGA}_{i,t-3})\end{gathered} \tag{9}$$

In the generalized quarterly model, we modify (8) and (9) to adjust for the sticky DP and XSGA using the factors in Table A1 in Appendix B and compute the $RESTATED\_QTR\_OL\_WITH\_STICKY\_DP\_AND\_XSGA_{i,t-3}$ as follows:

$$\begin{gathered}\text{If CHG\_QTR\_SALE}_{i,t+1} \geq 0 \\ \text{RESTATED\_QTR\_OL\_WITH\_STICKY\_DP\_AND\_XSGA}_{i,t-3} = \\ (\text{SALE}_{i,t-3} - \text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1})/ \\ (\text{SALE}_{i,t-3} - \text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1} - \text{DP}_{i,t-3} - \text{XSGA}_{i,t-3} - \\ (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.484 * \text{DP}_{i,t-3}) - (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.377 * \text{XSGA}_{i,t-3})) \\ \text{If CHG\_QTR\_SALE}_{i,t-1} < 0 \\ \text{RESTATED\_QTR\_ OL\_WITH\_STICKY\_DP\_AND\_XSGA}_{i,t-3} = \\ (\text{SALE}_{i,t-3} - \text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1})/ \\ (\text{SALE}_{i,t-3} - \text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1} - \text{DP}_{i,t-3} - \text{XSGA}_{i,t-3} - \\ (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.205 * \text{DP}_{i,t-3}) - (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.235 * \text{XSGA}_{i,t-3}))\end{gathered} \tag{10}$$

Then, we estimate the next quarter's $OIADP_{i,t+1}$ using our generalized (full) model as follows:

$$\text{If CHG\_QTR\_SALE}_{i,t+1} \geq 0$$

$$\begin{gathered}\text{FULL\_MODEL\_ESTIMATED\_QTR\_OIADP}_{i,t+1} = (1 + (\text{CHG\_QTR\_SALE}_{i,t+1} * \\ \text{RESTATED\_QTR\_OL\_WITH\_STICKY\_DP\_AND\_XSGA}_{i,t-3})) * \\ (\text{SALE}_{i,t-3} - (\text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1}) - \text{DP}_{i,t-3} - \text{XSGA}_{i,t-3} - \\ (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.484 * \text{DP}_{i,t-3}) - (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.377 * \text{XSGA}_{i,t-3}))\end{gathered}$$

$$\begin{gathered}\text{If CHG\_QTR\_SALE}_{i,t+1} < 0 \\ \text{FULL\_MODEL\_ESTIMATED\_QTR\_OIADP}_{i,t+1} = (1 + (\text{CHG\_QTR\_SALE}_{i,t+1} * \\ \text{RESTATED\_QTR \_OL\_WITH\_STICKY\_DP\_AND\_XSGA}_{i,t-3})) * \\ (\text{SALE}_{i,t-3} - (\text{SALE}_{i,t-3}/\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1}) - \text{DP}_{i,t-3} - \text{XSGA}_{i,t-3} - \\ (\text{CHG\_QTR\_SALE}_{i,t+1} * 0.205 * \text{DP}_{i,t-3}) - (\text{CHG\_SALE}_{i,t+1} * 0.235 * \text{XSGA}_{i,t-3}))\end{gathered}$$

where

$$\text{EST\_QTR\_SALE\_to\_COGS}_{i,t+1} = (1 + (((\text{average of SALE-to-COGS for quarters } t-2 \text{ through } t) - [\text{SALE}_{i,t-3}/\text{COGS}_{i,t-3}])/[\text{SALE}_{i,t-3}/\text{COGS}_{i,t-3}])) * [\text{SALE}_{i,t-3}/\text{COGS}_{i,t-3}] \quad (11)$$

Using linear regression analysis, we regress $\text{CHG\_QTR\_OIADP}_{i,t+1}$ on

$$\text{CHG\_QTR\_EST\_OIADP}_{i,t+1} \text{ sized by total assets } (\text{AT}_{i,t-1})$$

where

$$\text{CHG\_QTR\_OIADP}_{i,t+1} = (\text{OIADP}_{i,t+1} - \text{OIADP}_{i,t-3})/\text{AT}_{i,t-1} \quad (12)$$

and

$$\text{CHG\_QTR\_EST\_OIADP}_{i,t+1} = (\text{ESTIMATED\_QTR\_OIADP}_{i,t+1} - \text{OIADP}_{i,t-1})/\text{AT}_{i,t-1} \quad (13)$$

In addition, we consider the distribution of the absolute value of the error percent for our model estimates of the quarterly $\text{OIADP}_{i,t+1}$ as follows:

$$\text{Absolute Value of Estimate Error} = \text{Absolute Value } ((\text{OIADP}_{i,t+1} - \text{ESTIMATED\_QTR\_OIADP}_{i,t+1})/\text{OIADP}_{i,t+1}) \quad (14)$$

3.4. Methodology for Predicting Annual OIADP

Our models for predicting the next-year OIADP mirror our models for predicting the next-quarter OIADP, except that t denotes the fiscal year, and the reference year is the current year (t) rather than the third prior quarter. Hence, the base (textbook) operating-leverage model (3) for predicting the next-year OIADP is as follows:

$$\text{BASE\_1YR\_OL}_{i,t} = (\text{SALE}_{i,t} - \text{COGS}_{i,t})/\text{OIADP}_{i,t} \quad (15)$$

With our base model, we assume that the ratio of the SALE-to-COGS remains constant, and that the total DP and XSGA costs remain fixed for years t and t + 1. Hence, our base model for predicting the next-year OIADP is as follows:

$$\text{BASE\_MODEL\_EST\_1YR\_OIADP}_{i,t+1} = (1 + (\text{CHG\_1YR\_SALE}_{i,t+1} * \text{BASE\_1YR\_OL}_{i,t})) * \text{OIADP}_{i,t}$$

where

$$\text{CHG\_1YR\_SALE}_{i,t+1} = (\text{SALE}_{i,t} - ((\text{SALE}_{i,t} + \text{SALE}_{i,t-1})/2))/((\text{SALE}_{i,t} + \text{SALE}_{i,t-1})/2) \quad (16)$$

Using annual data and making only our adjustment that enables a constant SALE-to-COGS, the restated operating leverage is as follows:

$$\text{RESTATED\_1YR\_OL}_{i,t} = (\text{SALE}_{i,t} - (\text{SALE}_{i,t}/\text{EST\_1YR\_SALE\_to\_COGS}_{i,t+1}))/(\text{SALE}_{i,t} - (\text{SALE}_{i,t}/\text{EST\_1YR\_SALE\_to\_COGS}_{i,t+1}) - \text{DP}_{i,t} - \text{XSGA}_{i,t}) \quad (17)$$
$$\text{where EST\_1YR\_SALE\_to\_COGS}_{i,t+1} = ((\text{SALE}_{i,t}/\text{COGS}_{i,t}) + (\text{SALE}_{i,t-1}/\text{COGS}_{i,t-1}))/2$$

Assuming that the DP and XSGA are fixed and, hence, do not require adjusting for sticky cost behavior, our intermediate model for estimating the next-year $\text{OIADP}_{i,t+1}$ becomes the following:

$$\text{INTERMEDIATE\_MODEL\_ESTIMATED\_1YR\_OIADP}_{i,t+1} = (1 + (\text{CHG\_1YR\_SALE}_{i,t+1} * \text{RESTATED\_1YR\_OL}_{i,t})) * (\text{SALE}_{i,t} - (\text{SALE}_{i,t}/\text{EST\_1YR\_SALE\_to\_COGS}_{i,t+1}) - \text{DP}_{i,t} - \text{XSGA}_{i,t}) \quad (18)$$

In Appendix C, we use our yearly data and the ABJ methodology to compute 0.647 (0.393) as the factor by which the DP increases (decreases), on average, for each 1% increase (decrease) in the SALE. Similarly, we compute 0.440 (0.309) as the factor by which the XSGA increase (decrease), on average, for a 1% increase (decrease) in the SALE. We use these four factors to adjust for the stickiness of the DP and XSGA in our generalized models (19) and (20) for predicting the next-year OIADP. These results, using our annual data, are in line with those of ABJ and Shust and Weiss (2014), who find that both the XSGA and DP are sticky costs. Also, the Appendix C results show that the COGS increases 0.880 (decreases 0.834) for a 1% increase (decrease) in the annual SALE with an adjusted R-square equal to 0.589. These results confirm Chen et al.'s (2019) findings that the COGS is mostly variable and provide additional support for using the COGS as a proxy for the total variable costs in the CVP for Figure 1.

If we then adjust the DP and XSGA following the prior research previously discussed, we compute the $RESTATED\_1YR\_OL\_WITH\_STICKY\_DP\_AND\_XSGA_{i,t}$ as follows:

$$\begin{gathered}
\text{If } CHG_1YR_SALE_{i,t+1} \geq 0 \\
RESTATED_1YR_OL_WITH_STICKY_DP_AND_XSGA_{i,t} = \\
(SALE_{i,t} - SALE_{i,t}/EST_1YR_SALE_to_COGS_{i,t+1})/ \\
(SALE_{i,t} - SALE_{i,t}/EST_1YR_SALE_to_COGS_{i,t+1} - DP_{i,t} - XSGA_{i,t} - \\
(CHG_1YR_SALE * 0.647 * DP_{i,t}) - (CHG_1YR_SALE * 0.440 * XSGA_{i,t})) \\
\\
\text{If } CHG_1YR_SALE_{i,t+1} < 0 \\
RESTATED_1YR_OL_WITH_STICKY_DP_AND_XSGA_{i,t} = \\
(SALE_{i,t} - SALE_{i,t}/EST_1YR_SALE_to_COGS_{i,t+1})/ \\
(SALE_{i,t} - SALE_{i,t}/EST_1YR_SALE_to_COGS_{i,t+1} - DP_{i,t} - XSGA_{i,t} - \\
(CHG_1YR_SALE * 0.393 * DP_{i,t}) - (CHG_1YR_SALE * 0.309 * XSGA_{i,t}))
\end{gathered} \quad (19)$$

Then, we estimate the next fiscal year's $OIADP_{t+1}$ using our generalized (full) model as follows:

$$\begin{gathered}
\text{If } CHG_1YR_SALE_{i,t+1} \geq 0 \\
ESTIMATED_1YR_OIADP_{i,t+1} = \\
(1 + (CHG_1YR_SALE * RESTATED_1YR_OL_WITH_STICKY_DP_AND_XSGA_{i,t})) * \\
(SALE_{i,t} - (SALE_{i,t}/EST_1YR_SALE_to_COGS_{i,t+1}) - DP_{i,t} - XSGA_{i,t} - \\
(CHG_1YR_SALE * 0.647 * DP_{i,t}) - (CHG_1YR_SALE * 0.440 * XSGA_{i,t})) \\
\\
\text{If } CHG_1YR_SALE_{i,t+1} < 0 \\
ESTIMATED_1YR_OIADP_{i,t+1} = \\
(1 + (CHG_1YR_SALE * RESTATED_1YR_OL_WITH_STICKY_DP_AND_XSGA_{i,t})) * \\
(SALE_{i,t} - (SALE_{i,t}/EST_1YR_SALE_to_COGS_{i,t+1}) - DP_{i,t} - XSGA_{i,t} - \\
(CHG_1YR_SALE_{i,t+1} * 0.393 * DP_{i,t}) - (CHG_1YR_SALE_{i,t+1} * 0.309 * XSGA_{i,t}))
\end{gathered} \quad (20)$$

We regress the annual $CHG\_1YR\_OIADP_{i,t+1}$ on the $CHG\_1YR\_EST\_OIADP_{i,t+1}$ sized by the $AT_{i,t-1}$, where the following apply:

$$CHG\_1YR\_OIADP_{i,t+1} = (OIADP_{i,t+1} - OIADP_{i,t})/AT_{i,t-1} \quad (21)$$

$$CHG\_1YR\_EST\_OIADP_{i,t+1} = (ESTIMATED\_1YR\_OIADP_{i,t+1} - OIADP_{i,t})/AT_{i,t-1} \quad (22)$$

Furthermore, we analyze the strata and percentiles of the absolute values of the errors for our generalized, full-model estimates of the annual $OIADP_{i,t+1}$ as follows:

$$\text{Absolute Value } ((OIADP_{i,t+1} - ESTIMATED\_OIADP_{t+1})/OIADP_{i,t+1}) \quad (23)$$

3.5. Testing the Veracity of the Generalized Operating-Leverage Model

Given (1), perfect knowledge of the future $SALE_{i,t+1}$, $COGS_{i,t+1}$, $DP_{i,t+1}$, and $XSGA_{i,t+1}$ should provide a perfect estimate of the $OIADP_{i,t+1}$. Using this same perfect knowledge, the generalized (full) models (19) and (20) for predicting the next-year OIADP become the following:

$$\begin{gathered}\text{RESTATED\_OL} = \\ (\text{SALE}_{i,t} - (\text{SALE}_{i,t}/(\text{SALE}_{i,t+1}/\text{COGS}_{i,t+1})))/ \\ (\text{SALE}_{i,t} - (\text{SALE}_{i,t}/(\text{SALE}_{i,t+1}/\text{COGS}_{i,t+1})) - \text{DP}_{i,t+1} - \text{XSGA}_{i,t+1})\end{gathered} \quad (24)$$

$$\begin{gathered}\text{NEXT\_YR\_OPERATING\_INCOME}_{i,t+1} = \\ (1 + (((\text{SALE}_{i,t+1} - \text{SALE}_{i,t})/\text{SALE}_{i,t}) * \text{RESTATED\_OL})) * \\ (\text{SALE}_{i,t} - (\text{SALE}_{i,t}/(\text{SALE}_{i,t+1}/\text{COGS}_{i,t+1})) - \text{DP}_{i,t+1} - \text{XSGA}_{i,t+1})\end{gathered} \quad (25)$$

Using the $\text{NEXT\_YR\_OPERATING\_INCOME}_{i,t+1}$ from (25) in (22), we obtain the following:

$$\begin{gathered}\text{CHG\_1YR\_EST\_OIADP}_{i,t+1} = \\ (\text{NEXT\_YR\_OPERATING\_INCOME}_{i,t+1} - \text{OIADP}_{i,t})/\text{AT}_{i,t-1}\end{gathered}$$

Regressing (21) on (22) produces linear regression results with an adj. R-square = 1.000, a standard error of the estimate = 0.00003584172, and a beta = 1.000 (t-value = 81,965,653). Also, using model (23), the absolute value $(\text{OIADP}_{i,t+1} - \text{NEXT\_YR\_OPERATING\_INCOME}_{i,t+1})/\text{OIADP}_{i,t+1}$ = 0.00000000 for all but 87 of the 189,319 company-years tested for the fiscal years 2005–2021.[2] We obtain similar untabulated results when testing our generalized (full) models (10) and (11) using our quarterly data. These results are consistent with the accuracy of our generalized models' forecasts of the $\text{OIADP}_{i,t+1}$ depending entirely on the accuracy of forecasting the $\text{SALE}_{i,t+1}$, $\text{SALE}_{i,t+1}/\text{COGS}_{i,t+1}$ ratio, and stickiness of the DP_{t+1} and XSGA_{t+1}.

3.6. Consideration of Dow Jones Industrial Average (DJIA) Firms

We consider separately the results for DJIA firms because the 30 DJIA firms are "blue chip" stock companies that are well established, financially sound, and sell generally high-quality, widely accepted products and services (Chen 2023). We expect that our models will have higher explanatory power and lower error rates in predicting the OIADP for this sub-sample.

4. Results and Discussion

4.1. Results for Estimating Next-Quarter OIADP

Table 1 shows the results from using the generalized, full model (11) with the operating leverage restated for constant SALE-to-COGS ratios, as well as the Appendix B factors used for adjusting the sticky XSGA and DP to predict the next-quarter $\text{OIADP}_{i,t+1}$. Analyses include results from regressing the $\text{CHG\_QTR\_OIADP}_{i,t+1}$ (12) on the $\text{CHG\_QTR\_EST\_OIADP}_{i,t+1}$ (13) and distribution information for the absolute value of errors when estimating the next-quarter $\text{OIADP}_{i,t+1}$ (14). The Table 1 regression results show that our generalized operating-leverage model (11) positively and significantly predicted changes in the next-quarter OIADP for the 241,106 firm-quarters studied with a coefficient of 0.523 (t-value 169.009) and a 0.106 adjusted R-square. The median absolute value estimate error was 35.61%.

Table 2 provides information about the relative predictive powers of the base, intermediate, and full models when estimating the next-quarter OIADP. We used the same 241,106 company-years in our analyses of the three models. Regression analysis for the base model (6) without restating the operating leverage or adjusting the DP or XSGA for sticky costs provides a 0.121 coefficient (t-value 61.415) with an adjusted R-square of 0.015. The base model has a 40.40% median absolute value error. Using the intermediate model (9) that restates the operating leverage to achieve a constant SALE-to-COGS but does not adjust for the stickiness of the DP or XSGA improves the adjusted R-square to 0.099 with a coefficient of 0.378 (t-value 162.314) and reduces the median absolute value error to 38.70%. Finally, results for the generalized, full model (11) show that adding adjustments for the DP and

XSGA cost stickiness to the intermediate model improves the adjusted R-square to 0.106 with a coefficient of 0.523 (t-value 169.009) and reduces the median absolute value error to 35.61%. The robustness of the Table 2 results supports our methodological choices for adjusting for variability in the ratio of the sales-to-cost of goods sold and for the stickiness of the depreciation, amortization, and SG&A costs.

Table 1. Predicting next-quarter operating income (OIADP) using the full model (11) for all companies for fiscal quarters (t) from 2005 quarter 2 to 2021 quarter 4.

Strata of Abs. ERRORS	Count of Company-Years	Percent of Total Company-Years	Cumulative Percent of Company-Years	Percentile of Company-Years	Ordered Obs.	Percentile of Abs. ERRORs
0–5%	25,531	10.59%	10.59%	1st Percentile:	2411	0.46%
5–10%	23,020	9.55%	20.14%	5th Percentile:	12,055	2.29%
10–15%	19,239	7.98%	28.12%	10th Percentile:	24,111	4.71%
15–20%	15,962	6.62%	34.74%	25th Percentile:	60,276	12.97%
20–25%	13,663	5.67%	40.40%	Median:	120,553	35.61%
25–50%	45,670	18.94%	59.35%	75th Percentile:	180,829	93.24%
50–100%	41,436	17.19%	76.53%	90th Percentile:	216,995	245.35%
> 100%	56,585	23.47%	100.00%	95th Percentile:	229,050	499.47%
Total:	241,106	100.00%	100.00%	99th Percentile:	238,694	2498.45%
Linear Regression Results						
N		**Adj. R-square**		**Coeff.**	**t-value**	***p*-value**
241,105		0.106		0.523	169.009	0.000

Table 2. Comparative results for the three models of operating leverage.

Model	Linear Regression Results					Median Abs. Value Error
	N	Adj. R-Square	Coeff.	t-Value	*p*-Value	
BASE MODEL: No adjustment for constant SALE-to-COGS or sticky DP or XSGA (6).	241,106	0.015	0.121	61.415	0.000	40.40%
INTERMEDIATE MODEL: restated SALE-to-COGS but no adjustment for sticky DP or XSGA (9).	241,106	0.099	0.378	162.314	0.000	38.70%
FULL MODEL: adjustment for SALE-to-COGS and adjusting for sticky DP and XSGA, as shown in Table 1 (11).	241,106	0.106	0.523	169.009	0.000	35.61%

Hayn (1995) found that the information content of losses affects the earnings relevance of accounting information. Table 3 summarizes the results from performing the same analyses on the data used in Table 1, except we select only those firm-quarters in which the current-quarter operating income ($OIADP_{i,t}$) and third-quarter prior operating income ($OIADP_{i,t-3}$) are positive. The regression estimation for the positive operating income firm-quarters reported in Table 3 has a 0.147 adjusted R-square and 23.28% median absolute value error compared to the 0.106 adjusted R-square and 35.61% median absolute value error recorded in Table 1 for all the firm-quarters studied.

Table 3. Predicting next-quarter operating income (OIADP) using the full model (11) for 2005 quarter 2 through 2021 quarter 4, where $OIADP_{i,t} > 0$ and $OIADP_{i,t-3} > 0$.

Strata of Abs. Value Errors	Count of Company-Years	Percent of Total Company-Years	Cumulative Percent of Company-Years	Percentile of Company-Years	Ordered Obs.	Percentile of Abs. Value Errors
0–5%	22,456	14.19%	14.19%	1st Percentile:	1582	0.33%
5–10%	19,889	12.57%	26.76%	5th Percentile:	7912	1.70%
10–15%	16,322	10.31%	37.08%	10th Percentile:	15,824	3.46%
15–20%	13,136	8.30%	45.38%	25th Percentile:	39,559	9.23%
20–25%	10,729	6.78%	52.16%	Median:	79,119	23.28%
25–50%	32,233	20.37%	72.53%	75th Percentile:	118,678	55.27%
50–100%	21,288	13.45%	85.98%	90th Percentile:	142,413	143.86%
>100%	22,185	14.02%	100.00%	95th Percentile:	150,325	295.20%
Total:	158,238	100.00%	100.00%	99th Percentile:	156,655	1527.25%
Linear Regression Results						
N		**Adj. R-square**		**Coeff.**	**t-value**	***p*-value**
158,237		0.147		0.453	165.018	0.000

Table 4 displays the results from using the generalized operating-leverage model (11) to predict the next-quarter operating incomes for only the DJIA companies. We use the same average factors specified in Table A1 in Appendix B to adjust for the sticky DP and XSGA. We also use the same Compustat data analyzed for Table 1, but only for the DJIA members. The predictive power of our full model (11) in predicting the quarterly OIADPs for just the 30 DJIA companies increased to a 0.338 adjusted R-square, with the median absolute value error reduced to 13.84%. These results are consistent with our expectation that our model (11), which relies entirely on extrapolations using current and prior Compustat data, performs better when used to estimate the next-quarter OIADPs for more stable companies, such as those in the DJIA.

Table 4. Dow Jones Industrial Average (DJIA). Predicting next-quarter operating income (OIADP) using the full model (11) for companies for fiscal quarters (t) from 2005 quarter 2 to 2021 quarter 4.

Strata of Abs. Value Errors	Count of Company-Years	Percent of Total Company-Years	Cumulative Percent of Company-Years	Percentile of Company-Years	Ordered Obs.	Percentile of Abs. Value Errors
0–5%	380	20.42%	20.42%	1st Percentile:	19	0.24%
5–10%	341	18.32%	38.74%	5th Percentile:	93	1.32%
10–15%	276	14.83%	53.57%	10th Percentile:	186	2.46%
15–20%	184	9.89%	63.46%	25th Percentile:	465	6.15%
20–25%	145	7.79%	71.25%	Median:	930	13.84%
25–50%	319	17.14%	88.39%	75th Percentile:	1395	27.60%
50–100%	107	5.75%	94.14%	90th Percentile:	1674	55.22%
>100%	109	5.86%	100.00%	95th Percentile:	1767	110.55%
Total:	1861	100.00%	100.00%	99th Percentile:	1841	686.40%
Linear Regression Results						
N		**Adj. R-square**		**Beta**	**t-value**	***p*-value**
1860		0.338		0.750	165.018	0.000

4.2. Results for Estimating Next-Year Annual OIADP

Table 5 shows the results of using the generalized, full operating-leverage models (19) and (20), and the Appendix C factors for the annual sticky DP and XSGA. Analyses include results from regressing the $CHG\_1YR\_OIADP_{i,t+1}$ (21) on the $CHG\_1YR\_EST\_OIADP_{i,t+1}$ (22) for the annual data and distribution details for the absolute value errors estimating the next-year OIADP (23). Table 5's results show that our generalized, full models (19) and (20) predicted the next-year OIADPs for the 188,777 company-years studied, with a coefficient of 0.259 (t-value 113.678), a 0.064 adjusted R-square, and 36.15% median accuracy.

Table 5. All company-years predicting next-year operating income using the full model (18) for fiscal years 2005 through 2021.

Strata of Abs. Value Errors	Count of Company-Years	Percent of Total Company-Years	Cumulative Percent of Company-Years	Percentile of Company-Years	Ordered Obs.	Percentile of Abs. Value Errors
0–5%	19,400	10.28%	10.28%	1st Percentile:	1888	0.48%
5–10%	17,613	9.33%	19.61%	5th Percentile:	9439	2.45%
10–15%	15,155	8.03%	27.63%	10th Percentile:	18,878	4.87%
15–20%	12,899	6.83%	34.47%	25th Percentile:	47,194	13.24%
20–25%	10,770	5.71%	40.17%	Median:	94,389	36.15%
25–50%	34,904	18.49%	58.66%	75th Percentile:	141,583	97.33%
50–100%	32,026	16.97%	75.63%	90th Percentile:	169,899	264.52%
>100%	46,010	24.37%	100.00%	95th Percentile:	179,338	536.49%
Total:	188,777	100.00%	100.00%	99th Percentile:	186,889	2760.82%
Linear Regression Results						
N		**Adj. R-square**		**Beta**	**t-value**	***p*-value**
188,776		0.064		0.259	113.678	0.000

Table 6 displays the results from predicting the next-year operating income ($OIADP_{i,t+1}$) using the same generalized, full operating-leverage models (19) and (20) as seen in Table 5 but for the subset of DJIA companies. In comparing the results of Table 4 for the DJIA quarters to the results of Table 6, the regression results are comparable, with adjusted R-squares of 0.338 for quarters and 0.354 for years. The median error of 13.84% for the DJIA quarters in Table 4 is slightly higher than the median error of 11.00% for the annual DJIA.

Table 6. DJIA company-years only. Predicting next-year OIADP using the full model (18) for fiscal years 2005 through 2021.

Strata of Abs. ERRORS	Count of Firm-Years	Percent of Total Firm-Years	Cumulative Percent of Firm-Years	Percentile of Firm-Years	Ordered Obs.	Percentiles of Abs. Values of Estimate Errors
0–5%	211	24.25%	24.25%	1st Percentile:	9	0.30%
5–10%	199	22.87%	47.13%	5th Percentile:	44	1.05%
10–15%	112	12.87%	60.00%	10th Percentile:	87	1.88%
15–20%	71	8.16%	68.16%	25th Percentile:	218	5.20%
20–25%	54	6.21%	74.37%	Median:	435	11.00%
25–50%	119	13.68%	88.05%	75th Percentile:	653	26.09%
50–100%	55	6.32%	94.37%	90th Percentile:	783	58.06%
>100%	49	5.63%	100.00%	95th Percentile:	827	112.23%
Total:	870	100.00%	100.00%	99th Percentile:	861	475.18%
Linear Regression Results						
N		**Adj. R-square**		**Beta**	**t-value**	***p*-value**
869		0.354		0.936	21.846	<0.001

4.3. Results for Estimating Three-Year-Ahead OIADP

Table 7 displays the results from predicting the three-year-ahead operating income ($OIADP_{i,t+3}$) using essentially the same generalized, full operating-leverage models (19) and (20) used for predicting the next-year OIADP, except using the estimated three-year-ahead sales and sales-to-cogs ratios. Comparing Table 7 to Table 5, the regression results show that the predictive power of the model for forecasting the three-year-ahead OIADP is lower than that for predicting the next-year operating income, with an adjusted R-square of 0.017 for the three-year-ahead OIADP as compared to an adjusted R-square of 0.064 for estimating the next-year OIADP. The median error of 84.92% for predicting the three-year-ahead OIADP in Table 7 is substantially higher than the median error of 11.00% for forecasting the next-year OIADP in Table 5.

Table 7. All company-years predicting three-year-ahead annual operating income using the full model (18) modified to predict the three-year-ahead SALE and SALE-to-COGS ratio for fiscal years 2005 through 2021.

Strata of Abs. Errors	Count of Firm-Years	Percent of Total Firm-Years	Cumulative Percent of Firm-Years	Percentile of Firm-Years	Ordered Obs.	Percentile of Abs. Values of Estimate Errors
0–5%	4821	4.26%	10.40%	1st Percentile:	1131	1.18%
5–10%	4750	4.20%	21.93%	5th Percentile:	5656	5.85%
10–15%	4629	4.09%	29.82%	10th Percentile:	11,313	11.88%
15–20%	4446	3.93%	36.59%	25th Percentile:	28,282	31.64%
20–25%	4276	3.78%	43.86%	Median:	56,564	84.92%
25–50%	17758	15.70%	66.17%	75th Percentile:	84,846	323.61%
50–100%	19555	17.29%	83.21%	90th Percentile:	101,815	1133.40%
>100%	52893	46.76%	100.00%	95th Percentile:	107,472	2721.74%
Total:	113128	100.00%	100.00%	99th Percentile:	111,997	11201800.00%
Linear Regression Results						
N		**Adj. R-square**		**Beta**	**t-value**	***p*-value**
11,3127		0.017		0.068	44.867	0.001

4.4. Results for Estimating Next-Quarter OIADP within Industry Context

Table 8 shows the results from using the full model (11), with the operating leverage restated for constant SALE-to-COGS ratios, and the Appendix B factors used for adjusting the sticky XSGA and DP to predict the next-quarter $OIADP_{i,t+1}$. The results are controlled via one-digit Standard Industry Codes (SICs). These results indicate that the predictive power of the full model in estimating the next-quarter operating income varies significantly amongst industries. We find similar untabulated results for first-digit SICs when predicting the next-year and three-year-ahead operating incomes.

Table 8. Prediction of next-quarter annual operating income using the full model (11) within the context of single-digit Standard Industry Codes (SICs) for all company-quarters for fiscal years 2005 through 2021.

SIC 1-Digit Code	Adj. R-Square	N	Beta	t-Value	*p*-Value
SIC 1	0.189	23,964	0.766	74.857	<0.000
SIC 2	0.121	45,264	0.577	78.762	<0.000
SIC 3	0.123	70,319	0.613	99.135	<0.000
SIC 4	0.116	31,756	0.484	64.536	<0.000
SIC 5	0.058	24,620	0.271	39.007	<0.000

Table 8. *Cont.*

SIC 1-Digit Code	Adj. R-Square	N	Beta	t-Value	*p*-Value
SIC 6	0.155	69,199	0.596	112.75	<0.000
SIC 7	0.067	40,437	0.444	54.043	<0.000
SIC 8	0.107	11,182	0.54	36.586	<0.000
SIC 9	0.087	1299	0.542	11.168	<0.000

SIC 1—Mining, Extraction (Metals, Coal, Oil), and Heavy Construction; SIC 2—Manufacturing—Food, Textiles, Wood, Furniture, Paper, Printing, Petroleum Refining; SIC 3—Manufacturing—Rubber, Plastics, Leather, Glass, Concrete, Metal Products, Machinery, Computers, Electronics, Electrical Equipment, Transportation Equipment, Instruments; SIC 4—Transportation, Communications, Electric, Gas, and Sanitary Services; SIC 5—Wholesale and Retail; SIC 6—Finance, Insurance, and Real Estate; SIC 7—Services: Lodging, Personal, Business, Repair, Amusement and Recreation; SIC 8—Services: Health, Legal, Educational, Social, Museums, Art Galleries, Engineering, Accounting, Research, and Management; SIC 9—Public Administration: Government, Justice, Public Order, Taxation, Human Resources, Environmental, Housing, Quality and Housing Programs, National Security, International Affairs.

5. Conclusions, Summary, and Future Research

We introduce a generalized operating-leverage model that predicts the next-quarter and next-year operating incomes (OIADPs) using a parsimonious set of the disaggregated Compustat items SALE, COGS, DP, and XSGA that articulate with the identity OIADP = SALE − DP − XSGA for virtually all Compustat firm-years and firm-quarters. Our (annual) general models (19) and (20) reduce to the special-case models (15) and (16) discussed in many managerial and cost accounting textbooks by substituting the ($SALE_{i,t}/COGS_{i,t}$) for the $EST\_1YR\_SALE\_to\_COGS_{i,t+1}$ and by substituting the $DP_{i,t}$ for [$DP_{i,t}$ − (CHG_1YR_SALE * 0.647 * $DP_{i,t}$)] and the $XSGA_{i,t}$ for [$XSGA_{i,t}$ − (CHG_1YR_SALE * 0.440 * $XSGA_{i,t}$)]. Similarly, our quarterly general models (10) and (11) condense to models (4) and (6), which require the special case of a constant SALE/COGS and fixed DP and XSGA for the referenced and predicted quarters.

Prior research shows that the DP and XSGA are sticky costs while the COGS is much less sticky than either the DP or XSGA. As such, we use the COGS as a proxy for the total variable costs. We introduce a method for adjusting the textbook (base) model to satisfy the constant sales-to-total-variable-costs (SALE-to-COGS) assumption required for the textbook operating leverage to predict future operating income. Also, we follow prior research to compute adjustment factors specific to our studied data for the DP and XSGA sticky costs. These proxies and adjustments culminate in our generalized, full operating-leverage models for quarters (10) and (11) and years (19) and (20) that accommodate the variations in the SALE/COGS ratio, DP, and XSGA between the reference and prediction periods when predicting next-quarter and next-year OIADPs.

Our results support the managerial intuitions that underlie our generalized operating-leverage model, namely, that the textbook operating leverage fails to address the reality of the changes in companies' cogs margin percentages and the stickiness in theoretical total fixed costs.

Educators may use our generalized operating-leverage model to help students better understand the assumptions that constrain the operating-leverage models that most cost and managerial accounting textbooks discuss. Future research may study our full model's performance in predicting next-quarter and next-year OIADPs within the context of firm size and country. Also, future research may validate the model over different economic conditions, firm characteristics, two-year-ahead earnings, and long-term growth, replicating these tests on the DJIA sample of firms. In addition, future research may investigate how S&P's subtraction of the DP from the cogs to derive the COGS affects the stickiness of the COGS compared to the cogs.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Mathematical proof for Equation (3) provided that Assumption 1 (constant sales-to-total variable cost) and Assumption 2 (constant fixed costs) hold for the current period (t) and future period (t + n):

$$\text{operating income}_t + (\text{percent change in sales from t to t + n} * \text{operating leverage}_t * \text{operating income}_t) = \text{future period t + n operating income}$$

where the current period (t) operating $\text{income}_t = S_t - V_t - F_t$; the future period (t + n) operating $\text{income}_t = S_{t+n} - V_{t+n} - F_{t+n}$ (n = 1 for the next period); the current period (t) operating leverage = $(S_t - V_t)/(S_t - V_t - F_t)$; the variable costs (V) are directly proportional to the sales (S) (V = k*S, where k is a constant value); the fixed costs (F) are constant during the t through to the t + n (relevant range); $S_{t+n}/V_{t+n} = S_t/V_t$ (Assumption 1); $F_{t+n} = F_t$ (Assumption 2).

Proof.

$$(S_t - V_t - F_t) + \{[(S_{t+n} - S_t)/S_t] * [(S_t - V_t)/(S_t - V_t - F_t)] * (S_t - V_t - F_t)\}$$
$$(S_t - V_t - F_t) + \{[(S_{t+n} - S_t)/S_t] * [(S_t - V_t)]\}$$

$$\begin{gathered}(S_t - V_t - F_t) + S_{t+n}{*}S_t/S_t - S_t{*}S_t/S_t - S_{t+n}{*}V_t/S_t + S_t{*}V_t/S_t = \\ S_t - V_t - F_t + S_{t+n} - S_t - S_{t+n}{*}V_t/S_t + S_t{*}V_t/S_t \\ - V_t - F_t + S_{t+n} - S_{t+n}{*}V_t/S_t + S_t{*}V_t/S_t = \\ - V_t - (F_t) + S_{t+n} - S_{t+n}{*}(V_t/S_t) + S_t{*}\,(V_t/S_t) =\end{gathered}$$

Substituting using Assumptions 1 and 2 gives the following:

$$\begin{gathered}- V_t - (F_{t+n}) + S_{t+n} - S_{t+n}{*}(V_{t+n}/S_{t+n}) + S_t{*}\,(V_t/S_t) = \\ - V_t - F_{t+n} + S_{t+n} - V_{t+n} + V_t = \\ S_{t+n} - V_{t+n} - F_{t+n}\end{gathered}$$

□

Appendix B

Applying ABJ Methodology to Compute Sticky Factors for XSGA and DP Quarterly

ABJ developed an empirical model that measures changes in the XSGA resulting from contemporaneous changes in the SALE and that differentiates between periods when the SALE increases and decreases. After adding an indicator variable (*Decrease_Dummy*) that equals 1 when the SALE decreases between t − 1 and t, and 0 otherwise, the ABJ model is as follows:

$$\begin{gathered}\log\,[XSGA_{i,t}/XSGA_{i,t-1}] = \beta_0 + \beta_1 \log\,[SALE_{i,t}/SALE_{i,t-1}] \\ + \beta_2 * \text{Decrease\_Dummy}_{i,t} * \log\,[SALE_{i,t}/SALE_{i,t-1)}] + \varepsilon_{i,t}\end{gathered}$$

ABJ found that the annual XSGA increased, on average, by 0.55 percent for each 1 percent increase in the SALE but decreased by just 0.35 percent for each 1 percent decrease in the SALE for the annual Compustat data studied from 1979 to 1998.

We follow ABJ's methodology to compute the average percentage increases for the sticky COGS, DP, and XSGA using quarterly data from the fourth quarter of 2005 through to the third quarter of 2022. We study the COGS and DP in addition to the XSGA considered by ABJ because these are the three aggregate costs in (1) that articulate with the OIADP for quarterly Compustat data.

Table A1 displays the results based on the three regression specification models shown above.[3]

Table A1. Results for regressing changes in COGS, DP, and XSGA on changes in SALE using ABJ's methodology with S&P's Compustat quarterly data for all companies for fiscal quarters (t) from 2005 quarter 2 to 2021 quarter 4.

Regression Specification Models based on ABJ:

$$\log\,[COGS_{i,t}/COGS_{i,t-3}] = \beta_0 + \beta_1 \log[SALE_{i,t}/SALE_{i,t-3}] + \beta_2 * Decrease\_Dummy_{i,t-3\text{ to }t} * \log\,[SALE_{i,t}/SALE_{i,t-3})] + \varepsilon_{i,t}$$

$$\log\,[DP_{i,t}/DP_{i,t-1}] = \beta_0 + \beta_1 \log[SALE_{i,t}/SALE_{i,t-1-3}] + \beta_2 * Decrease\_Dummy_{i,t-3\text{ to }t} * \log\,[SALE_{i,t}/SALE_{i,t-3})] + \varepsilon_{i,t}$$

$$\log\,[XSGA_{i,t}/XSGA_{i,t-1}] = \beta_0 + \beta_1 \log\,[SALE_{i,t}/SALE_{i,t-1}] + \beta_2 * Decrease\_Dummy_{i,t} * \log\,[SALE_{i,t}/SALE_{i,t-1})] + \varepsilon_{i,t}$$

Coefficient Estimates (t-statistics)

Dependent Variable	N	Adj. R-Square	% Increase in Dependent Variable for 1% increase in Sales (β_1)	SALE Change Decrease Dummy (β_2)	% Decrease in Dependent Variable for 1% Decrease in Sales ($\beta_1 + \beta_2$)	β_1 *p*-value (t value)	β_2 *p*-value (t value)
COGS	241,043	0.445	0.879	−0.162	0.717	0.000 296.380	0.001 −36.064
DP	241,043	0.105	0.484	−0.279	0.205	0.000 139.327	0.000 −52.839
XSGA	241,043	0.150	0.377	−0.142	0.235	0.000 154.402	0.000 −38.349

The Table A1 results show that the SALE (adjusted coefficient of determination; henceforth, "adj. R-square" = 0.445) has more explanatory power for predicting the next-quarter COGS than for predicting either the DP (adj. R-square = 0.105) or XSGA (adj. R-square = 0.150). The XSGA's estimated value for β_1 of 0.377 (t-statistic = 154.402) indicates that, on average, XSGA increase by 0.377% per 1% increase in the quarterly SALE. The XSGA's estimated value of β_2, equal to −0.142 (t-statistic = −38.349), supports the XSGA's stickiness on a quarterly basis. The XSGA's $\beta_1 + \beta_2 = 0.235$ indicates that XSGA decrease, on average, by 0.235% per 1% decrease in the quarterly SALE. Following similar procedures for the DP, we find that, on average, the quarterly DP increases by 0.484% per 1% increase in the quarterly SALE but decreases only 0.205% per 1% decrease in the SALE.

The 18% difference between the COGS estimates of 0.879 for β_1 and 0.717 for $\beta_1 + \beta_2$ indicates that the COGS varies more symmetrically with increases and decreases in the SALE than either the DP (57% difference between 0.484 β_1 and 0.205 $\beta_1 + \beta_2$) or XSGA (38% difference between 0.377 β_1 and 0.235 $\beta_1 + \beta_2$).

Appendix C

Applying ABJ Methodology to Compute Sticky Factors for XSGA and DP Annually

Similar to Table A1 in Appendix B for the quarterly analysis, Table A2 displays our computations of the annual sticky factors for the COGS, DP, and XSGA. We followed ABJ, Shust and Weiss (2014), and Chen et al. (2019) to compute these factors using our study's annual data for the fiscal years 2005 through 2021.

The results in Table A2 in Appendix C indicate that the SALE (adj. R-square = 0.589) has more explanatory power for predicting the next-year COGS than for predicting either the next-year DP (adj. R-square = 0.267) or XSGA (adj. R-square = 0.310). The XSGA's estimated average value for a β_1 of 0.440 (t-statistic = 245.616) indicates that, on average, XSGA increase by 0.44% per 1% increase in the annual SALE. The XSGA's $\beta_1 + \beta_2 = 0.309$ indicates that XSGA decrease, on average, by 0.31% per 1% decrease in the annual SALE. These results are comparable to ABJ's findings that the XSGA increase, on average, by 0.55% for a 1% SALE increase but decrease by only 0.35% for a 1% decrease in the SALE. Following similar procedures for the DP, we find that, on average, the annual DP increases by 0.64% per 1% increase in the annual SALE but decreases only 0.39% per 1% decrease in the SALE.

For the COGS, the absolute value of β_2 (0.046) is only 5.2% of β_1 (0.880), indicating that the annual COGS generally varies symmetrically with respect to increases and decreases in the SALE.

This finding strongly supports the choice of the COGS as a proxy for the variable costs in Figure 1. By contrast, the absolute difference between β_1 and $\beta_1 + \beta_2$ is 39.3% for the DP and 29.8% for the XSGA, indicating that both the annual DP and XSGA are sticky costs.

In conclusion, financial analysts, investors, managers, and other practitioners who use S&P's Compustat data to forecast companies' future earnings may benefit from using our generalized operating-leverage model to forecast companies' next-quarter and next-year operating incomes.

Table A2. Results for regressing changes in COGS, DP, and XSGA on changes in SALE using ABJ's methodology with S&P's Compustat annual data for all companies for fiscal years 2005 through 2021.

Regression Specification Models based on ABJ:

$$\log[COGS_{i,t}/COGS_{i,t-1}] = \beta_0 + \beta_1 \log[SALE_{i,t}/SALE_{i,t-1}] + \beta_2 * Decrease\_Dummy_{i,t} * \log[SALE_{i,t}/SALE_{i,t-1}] + \varepsilon_{i,t}$$

$$\log[DP_{i,t}/DP_{i,t-1}] = \beta_0 + \beta_1 \log[SALE_{i,t}/SALE_{i,t-1}] + \beta_2 * Decrease\_Dummy_{i,t} * \log[SALE_{i,t}/SALE_{i,t-1}] + \varepsilon_{i,t}$$

$$\log[XSGA_{i,t}/XSGA_{i,t-1}] = \beta_0 + \beta_1 \log[SALE_{i,t}/SALE_{i,t-1}] + \beta_2 * Decrease\_Dummy_{i,t} * \log[SALE_{i,t}/SALE_{i,t-1}] + \varepsilon_{i,t}$$

			Coefficient Estimates (t-statistics)				
Dependent Variable	N	Adj. R-square	% Increase in Dependent Variable for 1% Increase in Sales (β_1)	SALE Change * Decrease Dummy (β_2)	% Decrease in Dependent Variable for 1% Decrease in Sales ($\beta_1 + \beta_2$)	β_1 *p*-value (t value)	β_2 *p*-value (t value)
COGS	188,808	0.589	0.880	−0.046	0.834	0.000 404.713	0.001 −11.050
DP	188,808	0.267	0.647	−0.254	0.393	0.000 227.362	0.000 −46.695
XSGA	188,808	0.310	0.440	−0.131	0.309	0.000 245.616	0.000 −38.125

Notes

1 Bostwick et al. (2016) found that S&P subtracts (DP − AM) from the cogs to derive the COGS when entities disclose and quantify the allocation of amortization (AM) but not depreciation.

2 For all observations, we require OIADP − (SALE − COGS − DP − XSGA) < 0.001 and SALE, COGS, DP, and XSGA values > 0.

[3] In the results that follow, we revisit the same company quarters in Tables 3–5 as analyzed in Table 1.

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