

Predicting Earnings Using a Model Based on Cost Variability and Cost Stickiness

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ABSTRACT: We evaluate the descriptive validity of the cost behavior model for profit analysis using Compustat data. For this purpose, we propose an earnings forecast model decomposing earnings into components that reflect (1) variability of costs with sales revenue and (2) stickiness in costs with sales declines. We evaluate the predictive ability of our model by benchmarking its performance in forecasting one-year-ahead returns on equity against that of two other time-series models based on line item information reported in the income statement and in the statement of cash flows. Specifically, we consider a model that disaggregates earnings into operating income and non-operating income components and another that disaggregates earnings into cash flows and accruals components. While all three models are less accurate than analysts' consensus forecasts that rely on a larger information set, we find that our model provides substantial improvement in forecast accuracy over the other two models that use only the line items in the financial statements. Finally, invoking the market efficiency assumption, we find that earnings forecast errors based on our model have greater relative information content than forecast errors based on the two alternative models based on financial statement information in explaining abnormal stock returns.

Keywords: *analyst forecasts; cost variability; earnings forecasts; fixed costs; market association; predictive content; sticky costs; variable costs.*

Data Availability: *Data used in this study are available from public sources identified in the paper.*

I. INTRODUCTION

Understanding cost behavior is one of the most important aspects of profit analysis for managers. Central to the cost-volume-profit analysis discussed in most managerial accounting textbooks is the traditional model of fixed and variable costs

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(Garrison and Noreen 2002). If this model is descriptively valid, then its estimation using past data should provide a basis for forecasting future earnings. Despite the conceptual importance of incorporating cost behavior in conducting profitability analysis, few empirical studies have systematically examined the forecasting ability of models that explicitly recognize the relation between costs and sales when forecasting future profits. Our purpose is to evaluate the performance of such a cost behavior model in forecasting earnings by benchmarking the predictive performance of our model against that of alternative time-series models using earnings component classifications reported in the income statement and in the statement of cash flows.¹

Prior research addresses the question of forecasting earnings from an external reporting perspective; that is, earnings forecast models are based on line items reported in the income statement (Lipe 1986; Fairfield et al. 1996), on accounting signals calculated from financial statements (Ou and Penman 1989), or on components of earnings such as cash flows and accruals (Sloan 1996). We propose an approach grounded in the management accounting tradition that models earnings as consisting of components proportional to sales increases and decreases, and another unrelated to sales changes. This method of earnings decomposition is motivated by a cost behavior model that recognizes sales as the key driver of profit and variable costs as varying with sales. In addition, we incorporate in our model evidence that cost changes exhibit stickiness in periods of sales decline (Noreen and Soderstrom 1997; Anderson et al. 2003). Cost stickiness refers to the phenomenon that costs decrease less with a sales decrease than they increase with an equivalent sales increase. Economic considerations such as adjustment costs of reducing capacity and ramping up capacity in case sales rebound, motivate managers not to cut back on activity resources in response to a decline in sales to the same extent that they increase resources in response to an increase in sales (Anderson et al. 2003). This asymmetric cost behavior implies asymmetric behavior of earnings with respect to sales changes. Our cost behavior based approach to forecasting earnings is consistent with recent calls to incorporate economic considerations in models characterizing earnings components (Kothari 2001, 151).

Our model based on *cost variability and cost stickiness* (CVCS) is informationally parsimonious, relying only on earnings and sales time-series data. To evaluate the predictive ability of our CVCS model based on information drawn from the financial statements, we benchmark its performance against four other forecast models, including two that rely on information on past earnings components to predict future returns on equity (ROE).² The first model (Fairfield et al. 1996) uses income statement line items to classify earnings into operating income and non-operating income components to generate forecasts of future ROE (hereafter, the OPINC model). The second model (Sloan 1996) predicts future ROE based on past cash flows and accruals components of earnings (hereafter, the CASHFLOW model). The interest in earnings decomposition in forecasting stems largely from the belief that earnings components have different time-series properties and incorporating such information through earnings disaggregation provides a more accurate forecast of future earnings (Fairfield et al. 1996; Kothari 2001). To provide a baseline benchmark, we also consider a simple forecast model based only on past ROE (hereafter, the ROE model). Prior research

¹ We describe our proposed model and other benchmark models as "time-series" models because they are based on a time-series correlation between current and past realizations of components of earnings. However, the empirical estimation of these models may be done on a cross-sectional or pooled basis, rather than on separate time-series data of individual firms to improve precision of the estimated model coefficients.

² We focus on forecasting ROE to be consistent with prior literature (Fairfield et al. 1996; Frankel and Lee 1998). However, results not reported in the paper indicate that the documented superior forecasting performance of our CVCS model relative to other time-series models we consider is robust to forecasting return on assets (ROA).

provides evidence that analysts' earnings forecasts are more accurate than time-series models due to their information advantage in collecting, processing, and aggregating multiple sources of financial and nonfinancial information for forecasting earnings (Brown et al. 1987a; O'Brien 1988). Therefore, we also evaluate the performance of models based on earnings disaggregation relative to that of analysts' consensus forecast to gauge the extent to which different methods of earnings decomposition succeed in capturing some of the analysts' information advantage.

Our primary objective is to evaluate whether models that explicitly incorporate the relationship between cost changes and sales changes are better in capturing the behavior of the earnings time-series than do models that ignore such a relationship between income statement items.³ Using a sample of 8,771 firms in the period 1992–2002, we provide evidence that our proposed CVCS model substantially improves forecast accuracy of one-year-ahead ROE over the ROE, OPINC, and CASHFLOW models. Specifically, we find that the reduction in median absolute forecast errors using our CVCS model relative to the ROE model is about nine times as large as the reduction in median absolute forecast errors using the OPINC or the CASHFLOW model relative to the ROE model. We also find that recognizing cost variability and cost stickiness in earnings decomposition reduces over 30 percent of the advantage in median absolute forecast errors that financial analysts' forecasts display relative to the ROE model.⁴

Invoking the market efficiency hypothesis, we examine whether our CVCS model has greater relative information content in capturing the market's earnings expectations than the other three time-series models. Relative information content is assessed based on the relative strength of the association between forecast errors in ROE from each of these models and the contemporaneous abnormal stock returns. Using a sample of 4,348 firms in the period 1992–2002, we find that our CVCS model also outperforms the other three models in terms of relative information content. The evidence suggests the information in earnings components that pertains to cost variability and cost stickiness is correlated with a part of the information set used in forming the capital market's earnings expectations.

We organize the remainder of the paper as follows. In the next section we discuss earnings forecasting using earnings components and present our contrasting method of earnings decomposition based on cost variability and cost stickiness. We describe the sample and forecast models in Section III, and we report results of forecast accuracy comparisons in Section IV. In Section V, we present tests of relative information content of our model in evaluating the association between earnings forecast errors and abnormal stock returns. Finally, in Section VI we offer concluding remarks and suggest directions for future research.

II. EARNINGS DECOMPOSITION AND FORECASTING

Earnings Forecasting Using Earnings Components

Our study is related to a branch of the earnings forecasting literature concerned with the use of earnings components in predicting future earnings (Brown 1993). Fairfield et al. (1996) and Kothari (2001) suggest that partitioning earnings into components with different

³ We restrict our attention to parsimonious models based only on income statement and cash flow statement data, and do not attempt to develop forecast models (analogous to analysts' forecast models) relying on a wide array of information beyond just financial statements. However, the model structure we develop to link sales changes to cost changes, and consequently to earnings changes, may be augmented to incorporate economy-, industry-, and firm-specific information affecting sales or cost time-series.

⁴ The corresponding reduction in median absolute forecast errors is less than 6 percent for the OPINC and CASHFLOW models.

levels of persistence may enable superior modeling of the earnings process and improve the accuracy of earnings forecasts. Two time-series forecast models using past earnings components to predict future earnings have attracted much attention in the prior literature.⁵ One such model decomposes current earnings into cash flows and accruals components and predicts future earnings using them. Sloan (1996) provides evidence that cash flows have higher persistence than accruals for assessing one-year-ahead earnings but he does not examine the out-of-sample forecasting performance of this model because his focus is on whether the market fully incorporates the information about the differential persistence of cash flows and accruals components. The other earnings-decomposition-based forecast model uses line items in the income statement as the basis for predicting future earnings. Fairfield et al. (1996) find that decomposing earnings into operating income and non-operating income improves the accuracy of one-year-ahead forecasts of returns on equity, relative to a basic model using only aggregate earnings, although further disaggregation does not result in more accurate earnings forecasts.

While these two methods of decomposition seem natural and intuitive from the standpoint of financial reporting, they do not fully exploit the information about the relationships among earnings components suggested by the underlying economics of firms' production processes. We propose an alternative approach to earnings decomposition that reflects the earnings generating process as the outcome of a more primitive sales-generating process. At the operational level, this approach is derived from a management accounting perspective that views accounting income as sales revenue net of variable and fixed expenses, with the explicit recognition of the relationship between revenue and variable expenses. To the extent that variable costs are driven by sales revenue, accounting earnings may be modeled as consisting of two components, the first corresponding to contribution margin varying with sales, and the second corresponding to fixed costs uncorrelated with sales. The focus on sales as the key profit driver allows us to model the earnings process as reflecting the underlying economics of the firms' process of converting resources (costs) into outputs (sales). By relying on such a conceptual framework that highlights the intercorrelation of earnings components, we can incorporate into our forecast model potential asymmetric cost behavior related to sales changes. This constitutes a fundamental difference between our approach and prior earnings-decomposition-based forecast models. In the next section, we discuss in detail how we model such asymmetry (i.e., cost stickiness).

A similar perspective focusing on the prominent role of sales as the driver of earnings is adopted by Dechow et al. (1998), who model earnings, cash flows, and accruals as stochastic processes conditional on a random walk sales-generating process. They argue that sales contracts are more primitive than cash receipts and the modeling of the sales process should precede the modeling of the earnings and cash flows processes. The fundamental analysis of security valuation that uses signals related to inventory, gross margin, receivables, SG&A, order backlog, and labor efficiency that are all benchmarked against sales performance (Lev and Thiagarajan 1993) is also consistent with this sales-centric view of evaluating economic performance.

⁵ As discussed in Kothari (2001), one motivation for studying the properties of earnings components is to assess their incremental information beyond earnings in their association with stock prices. Earnings forecast models based on earnings components are often implicitly assumed in such research contexts, even though some studies may not explicitly examine these models of predictive ability (e.g., Lipe 1986).

Cost Variability and Cost Stickiness (CVCS) Model

We consider accounting earnings (E_t) in period t , measured as sales revenue (S_t) net of costs (C_t):⁶

$$E_t = S_t - C_t \tag{1}$$

Management accounting textbooks describe two basic types of cost behavior patterns: variable costs and fixed costs (Garrison and Noreen 2002). Variable costs are defined as those that change in proportion to changes in sales volume, whereas fixed costs are characterized as those that remain unchanged in a relevant range. From an economic perspective, variable costs represent the flexible productive resources that managers can easily adjust in producing goods and services, whereas fixed costs represent the committed resources invested to provide long-term productive capacity and thus are not expected to change with short-term production volume. Such an economic interpretation of different earnings components serves as a conceptual basis for modeling the earnings-generating process conditional on the relationship between sales and costs. Using this cost model with sales revenue as the cost driver, we express total costs in period t as:

$$C_t = vS_t + F_t \tag{2}$$

where v represents the constant unit variable cost.

It follows from Equations (1) and (2) that:

$$E_t = (1 - v)S_t - F_t \tag{3}$$

We assume that S_t follows a first order autoregressive process and allow the AR(1) coefficient to depend on whether sales decrease in period $t-1$:⁷

$$S_t = \alpha_0 + \alpha_1 S_{t-1} + \epsilon_S \tag{4}$$

where parameter α_1 represents the persistence of sales.

Anderson et al. (2003) document that costs are sticky in that they decrease less with a sales decrease than they increase with a sales increase. Such sticky cost behavior arises if trimming off excess resources when demand declines is relatively more costly than scaling up resources to accommodate increased demand. Under such conditions, managers' rational

⁶ We use S_t to denote sales in dollars instead of volume, and we interpret v as the fraction of sales representing variable costs. Our interpretation is consistent with our empirical forecast model that uses data on sales revenue. Since volume data is unavailable, our study is limited to use of revenue data, which confounds price, volume, and mix changes.

⁷ We are grateful to the referees for suggesting alternative specifications for the sales process that allow the AR(1) coefficient to depend on whether sales decrease in period $t-1$ as in the following two equations:

$$S_t = \alpha_0 + \alpha_1 S_{t-1} + \alpha_2 S_{t-1} D_{t-1} + \epsilon_S$$

and $\Delta S_t = \alpha_0 + \alpha_1 \Delta S_{t-1} + \alpha_2 \Delta S_{t-1} D_{t-1} + \epsilon_S$

where $D_{t-1} = 1$ if sales decline in period $t-1$, and 0 otherwise. The parameter α_2 captures the possibly asymmetric behavior in sales changes. To address the concern that such asymmetric sales behavior confounds our results, we estimated models based on the above two alternative specifications using a pooled sample in 1992-2002 and also on a yearly basis. Our results are robust to these alternative specifications, indicating that the possibly asymmetric sales changes are not a confounding factor in the forecast performance of our CVCS model.

resource adjustment decision entails less reduction of resources when sales decrease than addition of resources when sales increase (Anderson et al. 2003). Unlike the *static* traditional cost model that relates costs only to the contemporaneous level of sales volume independent of costs and volume in the prior period, cost stickiness exemplifies *dynamic* cost behavior that depends on costs and sales in the prior period and the direction of change in sales from the prior period.

We model fixed costs as a first-order autoregressive process specified as:

$$F_t = \beta_0 + \beta_1 F_{t-1} + \beta_2 v(S_{t-1} - S_t)D_t + \varepsilon_F \quad (5)$$

where $D_t = 1$ if sales decline in period t , and 0 otherwise. The term $\beta_2 v(S_{t-1} - S_t)D_t$ in Equation (5) represents the additional amount of costs incurred due to costs being sticky when sales decrease in period t . That is, a portion β_2 of the variable costs in the amount of $v(S_{t-1} - S_t)D_t$ is no longer driven down by a decrease in sales and as a result resembles a "fixed" cost. Costs that may exhibit such "sticky" behavior include skilled labor payroll costs, advertising and sales promotion costs, and branch operating costs.⁸ We recognize cost stickiness in the context of our variable and fixed cost model by allowing the level of fixed costs, F_t , to increase when sales decline.

Substituting S_t and F_t in Equation (3) with Equations (4) and (5), we have:

$$\begin{aligned} E_t &= (1 - v)S_t - F_t \\ &= (1 - v)(\alpha_0 + \alpha_1 S_{t-1} + \varepsilon_S) - (\beta_0 + \beta_1 F_{t-1} + v\beta_2(S_{t-1} - S_t)D_t + \varepsilon_F) \\ &= (1 - v)(\alpha_0 + \alpha_1 S_{t-1} - \varepsilon_S) - \beta_0 - \beta_1((1 - v)S_{t-1} - E_{t-1}) \\ &\quad - v\beta_2(-\alpha_0 + (1 - \alpha_1)S_{t-1} - \varepsilon_S)D_t - \varepsilon_F \\ &= (1 - v)\alpha_0 - \beta_0 + \beta_1 E_{t-1} + (1 - v)(\alpha_1 - \beta_1)S_{t-1} - v\beta_2(1 - \alpha_1)S_{t-1}D_t \\ &\quad + v\beta_2 D_t \varepsilon_S - \varepsilon_F \\ &= \gamma_0 + \gamma_1 D_t + \gamma_2 E_{t-1} + \gamma_3 S_{t-1} + \gamma_4 S_{t-1} D_t + \eta \end{aligned} \quad (6)$$

where:

$$\begin{aligned} \gamma_0 &= (1 - v)\alpha_0 - \beta_0; \\ \gamma_1 &= v\alpha_0\beta_2; \\ \gamma_2 &= \beta_1; \\ \gamma_3 &= (1 - v)(\alpha_1 - \beta_1); \\ \gamma_4 &= v(\alpha_1 - 1)\beta_2; \text{ and} \\ \eta &= v\beta_2 D_t \varepsilon_S - \varepsilon_F. \end{aligned}$$

⁸ Resources that are not mechanically linked to overall activity levels are likely to exhibit sticky behavior. For example, the payroll costs of contract employees could be reasonably viewed as variable with total revenue. However, in a period of sales downturn perceived to be temporary, managers may choose not to reduce the workforce proportionately in order to avoid having to incur additional costs of recruiting and retaining them when sales levels pick up in a subsequent period. Payroll costs for such employees retained in excess of the levels required for the reduced sales activity resemble "fixed costs" more than "variable costs" as traditionally defined.

Unlike E_{t-1} , S_{t-1} , and D_{t-1} , which are all observed at the beginning of period t , the sales decrease dummy variable D_t needs to be estimated before earnings E_t can be forecasted using model (6).⁹ Letting \hat{D}_t denote the estimated value of D_t based on information available at the beginning of period t , \hat{E}_t , the forecasted earnings for period t , is given by:

$$\hat{E}_t = \gamma_0 + \gamma_1 \hat{D}_t + \gamma_2 E_{t-1} + \gamma_3 S_{t-1} + \gamma_4 S_{t-1} \hat{D}_t \quad (7)$$

The forecast model is expressed in terms of observed earnings and sales from prior years. Fixed and variable costs need not to be observed or estimated separately.

III. SAMPLE DATA AND MODEL ESTIMATION

Data

Our sample period spans 1988 through 2002.¹⁰ All four time-series forecast models we consider require information on earnings or components of earnings based on line items from the income statement and the cash flows statement. These annual financial statement data are obtained from the Compustat database. We define earnings as income before extraordinary items (#18) and compute return on owners' equity (ROE) by dividing earnings by beginning book value of equity (#60). We follow Fairfield et al. (1996) to measure the operating income (OPINC) and non-operating income (NOPTAX) components of earnings. Specifically, OPINC is measured as operating income after depreciation (#178) net of interest expense (#15), special items (#17), and minority interest (#49). NOPTAX consists of non-operating income (#61) net of income taxes (#16). Consistent with the accounting accruals literature (Collins and Hribar 2000), we measure the cash flows component (CFO) of earnings based on SFAS No. 95 data reported in the cash flows statement (#308 – #124) and the accruals component (ACCRUALS) as the difference between earnings and cash flows (#18 – #308 + #124).¹¹ Our CVCS model requires, in addition to lagged ROE, information about sales revenue (SALES), which we measure as net sales revenue (#12). OPINC, NOPTAX, CFO, ACCRUALS, and SALES are all scaled by the beginning-of-year owners' equity. We compute analysts' consensus forecasts of one-year-ahead ROE comparable to forecasts generated from the time-series model as the mean analysts' forecasts of earnings per share (EPS) reported on the I/B/E/S database nine months before fiscal year-end, divided by beginning-of-year book value of equity per share.¹²

To mitigate the potential adverse effect of data errors and outliers on the estimation of the time-series models and on the evaluation of forecast accuracy of these models and analysts' forecasts, we restrict our sample to firm-year observations with (1) positive values for owners' equity; (2) absolute values of ROE and lagged ROE less than 1; and (3) absolute

⁹ The actual value of the sales decrease dummy variable in year t is not available when constructing earnings forecast for year t so we cannot use it in any earnings forecast model.

¹⁰ We begin our study period from 1988 because SFAS No. 95 data required for computing cash flows from continuing operations (CFO) were not available prior to 1988. The data on CFO is used to decompose earnings into cash flows and accruals components in the CASHFLOW model (Collins and Hribar 2000).

¹¹ We require the earnings data reported in the statement of cash flows (#123) to be the same as that reported in the income statement (#18) to ensure comparability of cash flows/accruals decomposition of earnings with the operating income/non-operating income decomposition.

¹² This particular measure of analysts' forecasts of one-year-ahead ROE is comparable to forecasts generated from the time-series models using lagged annual data in the sense that the timing of the consensus forecasts roughly coincides with the availability of previous fiscal year's financial statement information. Our method of deriving analysts' forecasts of one-year-ahead ROE from their EPS forecasts follows that of Frankel and Lee (1998).

values of net profit margin (i.e., the ratio of earnings to sales revenue) less than 1.¹³ Since we estimate the time-series forecast models using industry-level (based on four-digit SIC code) random coefficient regressions (discussed in detail in the next subsection), we delete firms from each forecast year and the associated estimation period (i.e., the four years immediately prior to the forecast year) that are in industries with less than 20 firm-year observations available in the estimation period. In order to calculate the forecast errors in ROE from all four time-series models and compare their forecast accuracy performance simultaneously, we require all sample observations to have no missing values for ROE in each forecast year and for the lagged variables: *ROE*, *OPINC*, *NOPTAX*, *CFO*, *ACCRUALS*, and *SALES*.

These sample selection procedures result in a full sample of 39,367 firm-year observations from 8,771 firms over the 11-year forecast period 1992–2002. To evaluate forecast accuracy of the four time-series models relative to that of analysts, we obtain a subsample of 15,500 firm-year observations from 4,334 firms with available analysts' *ROE* forecasts. Descriptive statistics on *ROE* and components of *ROE* for the full sample are reported in Table 1. The median (mean) *ROE* is 0.092 (0.052) and the median (mean) *SALES* is 2.025 (3.021). The median (mean) *OPINC* is 0.109 (0.079), the median (mean) *NOPTAX* is -0.019 (-0.027), the median (mean) *CFO* is 0.175 (0.174) and the median (mean) *ACCRUALS* is -0.106 (-0.122).

TABLE 1
Descriptive Statistics on Return on Equity (ROE) and Components of ROE
Sample Period: 1992–2002 (n = 39,367)

Variable	Median	Mean	Std. Dev.	Q1	Q3
<i>ROE</i>	0.092	0.052	0.250	-0.022	0.173
<i>SALES</i>	2.025	3.021	5.977	1.067	3.677
<i>OPINC</i>	0.109	0.079	0.325	-0.045	0.239
<i>NOPTAX</i>	-0.019	-0.027	0.152	-0.077	0.017
<i>CFO</i>	0.175	0.174	0.517	0.031	0.318
<i>ACCRUALS</i>	-0.106	-0.122	0.505	-0.237	0.000

ROE = return on equity, measured as net income before extraordinary items (Compustat #18) divided by beginning-of-year book value of owners' equity (#60);

SALES = net sales revenue (#12) divided by beginning-of-year book value of owners' equity;

OPINC = operating income (#178 - #15 + #17 - #49) divided by beginning-of-year book value of owners' equity;

NOPTAX = non-operating income (#61) net of income taxes (#16) divided by beginning-of-year book value of owners' equity;

CFO = cash flows from continuing operations (#308 - #124) divided by beginning-of-year book value of owners' equity; and

ACCRUALS = total accruals (#18 - #308 + #124) divided by beginning-of-year book value of owners' equity.

¹³ Our sample screening procedure consists of two steps. The first step screens each *estimation sample* based on all information available up to the end of estimation period (i.e., year $t-4$ to year $t-1$ in our case). This step (estimation and forecasting) is implementable *ex ante* since no information beyond year $t-1$ is used to cull the sample. The second step screens the forecast sample by deleting extreme values of ROE in the forecast year (i.e., year t) to evaluate the predictive performance of competing forecast models. This evaluation is *ex post* since it requires *actual values* of ROE in year t . This step helps alleviate concerns about outliers possibly inflating the average absolute forecast errors and thus obscuring the differential predictive ability of competing forecast models. Our results about the superior predictive ability of our CVCS model hold even when we do not employ any screening of the forecast sample.

Forecast Model Estimation

We benchmark the performance of our CVCS model in forecasting *ROE* against a simple model based only on lagged *ROE* data (the *ROE* model), the *OPINC* model based on lagged operating and non-operating income disaggregation, and the *CASHFLOW* model based on lagged cash flows and accruals components. Specifically, the four time-series *ROE* forecast models we consider are:

$$\text{ROE model: } ROE_t = \gamma_{a0} + \gamma_{a1}ROE_{t-1} + \varepsilon_t \quad (8)$$

$$\text{OPINC model: } ROE_t = \gamma_{b0} + \gamma_{b1}OPINC_{t-1} + \gamma_{b2}NOPTAX_{t-1} + \varepsilon_t \quad (9)$$

$$\text{CASHFLOW model: } ROE_t = \gamma_{c0} + \gamma_{c1}CFO_{t-1} + \gamma_{c2}ACCRUALS_{t-1} + \varepsilon_t \quad (10)$$

$$\begin{aligned} \text{CVCS model: } ROE_t = & \gamma_{d0} + \gamma_{d1}DECRDUM_t + \gamma_{d2}ROE_{t-1} \\ & + \gamma_{d3}SALES_{t-1} + \gamma_{d4}SALES_{t-1}DECRDUM_t \\ & + \varepsilon_t \end{aligned} \quad (11)$$

where *DECRDUM_t* is a sales decrease indicator variable that takes on the value 1 when the unscaled sales revenue in period *t* is less than in period *t*−1, and 0 otherwise.

We employ industry-level (based on four-digit SIC code) random coefficient regressions (RCR) to estimate our CVCS model.¹⁴ We allow for stochastic heterogeneity in model parameters for firms in each industry. The coefficients for the firms are random variates drawn from a separate distribution (mean and variance) for each industry. To illustrate, the set of coefficients in Equation (11) is assumed to have the following underlying stochastic structure:

$$\gamma_{di} = \gamma_{di}^{IND} + \delta_{di}^{FIRM}, \quad i = 0, 1, \dots, 4$$

where γ_{di}^{IND} is the mean (constant) for a given industry in which a particular firm belongs and $\delta_{di}^{FIRM} \sim N(0, \sigma_{IND}^2)$ is the firm's deviation from the industry mean. Each δ_{di}^{FIRM} follows a normal distribution with mean 0 and industry-specific variance σ_{IND}^2 . Since we use a pooled sample, there remains residual unexplained variation ε_t in *ROE_t* for each firm in any period *t*. Similar stochastic structure also applies to coefficients in the other three time-series models (i.e., Equations (8)–(10)), allowing us to estimate those coefficients using RCR. We do this to ensure that the four alternative models are evaluated on a comparable basis.

Following Fairfield et al. (1996), we estimate the parameters of all four forecast models for each year on a rolling basis using all available observations from the preceding four-year period.¹⁵ For example, we use data from 1998–2001 to estimate the forecast model

¹⁴ Firm-specific estimation of our CVCS model is not feasible because the model has seven parameters to be estimated and this requires a long time-series of data if firm-level (rather than pooled) estimation is conducted. However, the assumption that model parameters (e.g., cost structure) are constant over time is also difficult to sustain when a long time-series of data is employed to ensure a reasonable number of degrees of freedom for the estimation. Therefore, the compromise we adopt is industry-level estimation with random coefficients for firms in each industry.

¹⁵ This rolling estimation approach is also used in Fairfield et al. (1996). Our method differs from theirs in that we use industry-level random coefficient regressions based on four-year estimation period, whereas they use pooled regressions based on seven-year estimation period.

parameters applicable to constructing the ROE forecast for 2002; we obtain a new set of parameter estimates using data from 1997–2000 in order to derive the ROE forecast for 2001, and so on. Since we consider an 11-year forecast period from 1992–2002, we have 11 corresponding overlapping four-year estimation periods from 1988–2001. This industry-level RCR approach produces, for each model, coefficient estimates of the industry mean and deviation of each individual firm from its industry mean. The estimate of a firm-specific random-effect coefficient is given by the sum of the industry mean and firm-specific deviation.¹⁶ We use this firm-specific estimate to compute the ROE forecast during the forecast period. To illustrate in algebraic terms, the set of RCR coefficient estimates in Equation (11) is expressed as:

$$\hat{\gamma}_{di} = \hat{\gamma}_{di}^{IND} + \hat{\delta}_{di}^{FIRM}, i = 0, 1, \dots, 4$$

where $\hat{\gamma}_{di}^{IND}$ is the estimated industry mean and $\hat{\delta}_{di}^{FIRM}$ is an individual firm's estimated deviation from the industry mean.

Table 2 reports the means and standard deviations of estimated coefficients of the time-series forecast models calculated over the 11 four-year rolling industry-level (based on four-digit SIC code) random coefficient regressions.¹⁷ For the ROE model, the average slope coefficient on ROE_{t-1} is 0.513. The average slope coefficient estimates on $OPINC_{t-1}$ and $NOPTAX_{t-1}$ in the OPINC model are 0.485 and 0.352, respectively. The different slope coefficient estimates on $OPINC_{t-1}$ and $NOPTAX_{t-1}$ suggest that decomposing earnings into operating and non-operating income may provide incremental predictive power for forecasting one-year-ahead ROE. Similarly, the slope coefficients on the cash flows (CFO_{t-1}) and accruals ($ACCRUALS_{t-1}$) components in the CASHFLOW model are different (0.541 and 0.473, respectively).¹⁸

IV. FORECAST ACCURACY COMPARISONS

Main Results

To forecast ROE with our CVCS model, we require in addition to the parameter estimates an indicator of whether sales increase or decrease in the forecast year. This estimator must be based on information available prior to the forecast period. We estimate the sales decrease indicator $DECRDUM_t$, using a logit regression of the following form:

$$\text{Prob}(DECRDUM_t = 1) = \frac{e^y}{1 + e^y} \quad (12)$$

¹⁶ In addition to being firm-specific, the gammas in Equations (8)–(11) and (14)–(17) are indexed by estimation periods because of our rolling estimation method. We omit both firm and time indices in these equations to avoid cumbersome notation.

¹⁷ The summary statistics reported in Table 2 are based on estimated coefficients for individual firms retrieved from the estimation of the random coefficient regression (RCR) model averaged over 8,771 firms in all 432 industries and over the 11 estimation periods. The mean and standard deviation reported in Table 2 are the mean and standard deviation of those coefficient estimates.

¹⁸ Sloan (1996) estimated a similar regression model of earnings on lagged cash flows and accruals. Using pooled estimation, he reported 0.855 and 0.765 as the coefficients on the lagged cash flows and accruals, respectively, and using industry-level estimation, he reported 0.781 and 0.721 as the means of these coefficients. Our results are consistent with Sloan's to the extent that the coefficient estimate on cash flows is greater than that on accruals. Sloan's estimated magnitude of these coefficients may differ from ours because he (1) used a different sample period (from 1962 to 1991); (2) scaled earnings, cash flows, and accruals by average total assets; and (3) used pooled (or industry-level pooled) regressions.

TABLE 2
Coefficient Estimates^a of Time-Series ROE Forecast Models from 11 Four-Year Rolling Industry-Level (four-digit SIC) Random Coefficient Regressions
Sample Estimation Period: 1988–2001

Independent Variable	ROE Model	OPINC Model	CASHFLOW Model	Asy. ROE Model	CVCS Model
	Mean Coeff. Est. (Std. Dev.)	Mean Coeff. Est. (Std. Dev.)	Mean Coeff. Est. (Std. Dev.)	Mean Coeff. Est. (Std. Dev.)	Mean Coeff. Est. (Std. Dev.)
Intercept	0.015 (0.028)	0.013 (0.028)	0.007 (0.025)	0.030 (0.021)	0.042 (0.020)
<i>DECRDUM_t</i>					-0.088 (0.043)
<i>LOSS</i>				-0.054 (0.029)	
<i>ROE_{t-1}</i>	0.513 (0.094)			0.464 (0.064)	0.475 (0.095)
<i>LOSS * ROE_{t-1}</i>				-0.070 (0.106)	
<i>OPINC_{t-1}</i>		0.485 (0.065)			
<i>NOPTAX_{t-1}</i>		0.352 (0.104)			
<i>CFO_{t-1}</i>			0.541 (0.058)		
<i>ACCRUALS_{t-1}</i>			0.473 (0.071)		
<i>SALES_{t-1}</i>					0.002 (0.004)
<i>SALES_{t-1} * DECRDUM_t</i>					-0.008 (0.008)
Average Adj. R ^{2b}	0.2649	0.2911	0.3030	0.2985	0.3676

^a The numbers reported in each cell are the mean and standard deviation (in parentheses) of firm- and period-specific coefficients estimated using the random coefficient regression (RCR) over 8,771 firms in 432 industries and over the 11-year estimation period.

^b Since a goodness-of-fit measure like R² is not well-defined in the context of RCR estimation, the adjusted R²s are obtained from estimating the forecasting models using OLS for each four-digit-SIC industry and each estimation period. The average is calculated across all industries and estimation periods.

ROE model: $ROE_t = \gamma_{a0} + \gamma_{a1}ROE_{t-1} + \epsilon_{at}$

OPINC model: $ROE_t = \gamma_{b0} + \gamma_{b1}OPINC_{t-1} + \gamma_{b2}NOPTAX_{t-1} + \epsilon_{bt}$

CASHFLOW model: $ROE_t = \gamma_{c0} + \gamma_{c1}CFO_{t-1} + \gamma_{c2}ACCRUALS_{t-1} + \epsilon_{ct}$

Asy. ROE model: $ROE_t = \gamma_{d0} + \gamma_{d1}LOSS + \gamma_{d2}ROE_{t-1} + \gamma_{d3}LOSS*ROE_{t-1} + \epsilon_{dt}$

CVCS model: $ROE_t = \gamma_{a0} + \gamma_{d1}DECRDUM_t + \gamma_{a2}ROE_{t-1} + \gamma_{d3}SALES_{t-1} + \gamma_{d4}SALES_{t-1}DECRDUM_t + \epsilon_{dt}$

(continued on next page)

TABLE 2 (Continued)

ROE = return on equity, measured as net income before extraordinary items divided by beginning-of-year book value of owners' equity;
OPINC = operating income divided by the beginning-of-year owners' equity;
NOPTAX = non-operating income net of income taxes divided by beginning-of-year book value of owners' equity;
CFO = cash flows from continuing operations divided by beginning-of-year book value of owners' equity;
ACCRUALS = total accruals divided by beginning-of-year book value of owners' equity;
DECRDUM = a dummy variable that takes the value 1 if sales revenue decreases from prior year, and 0 otherwise;
LOSS = a dummy variable that takes the value 1 if earnings in the prior year are negative, and 0 otherwise; and
SALES = net sales revenue divided by beginning-of-year book value of owners' equity.

where $y = \beta_0 + \beta_1 \Delta REV_{t-1} + \varepsilon$, ΔREV_{t-1} is the percentage change in sales revenue from year $t-2$ to year $t-1$. We estimate the parameters β_0 and β_1 of this logit model on a rolling basis for each forecast year using pooled data from the preceding four-year period.¹⁹ Table 3 shows the estimation results of logit regressions. The estimated mean coefficient on ΔREV_{t-1} across the 11 estimation periods is $\hat{\beta}_1 = -1.865$, and the corresponding mean odds ratio estimate is 0.157. This result indicates that a one percentage point decrease in sales in year $t-1$ is associated with a six-fold (i.e., $1/0.157 \approx 6$) increase in the odds ratio

TABLE 3

Estimation Results of Logit Regression of Sales Decrease Dummy on the Lagged Percentage Change in Sales Revenue From 11 Four-Year Rolling Regressions
Sample Estimation Period: 1988–2001

$$\text{Logit Model: } DECRDUM_t = \frac{\exp(\beta_0 + \beta_1 \Delta REV_{t-1} + \varepsilon_t)}{1 + \exp(\beta_0 + \beta_1 \Delta REV_{t-1} + \varepsilon_t)}$$

Panel A: Coefficient Estimates and Odds Ratio Estimates

<u>Independent Variable</u>	<u>Mean Coeff. Est. (Std. Dev.)</u>	<u>Mean Odds Ratio (Std. Dev.)</u>	<u>Mean Lower Confid. Limit (Std. Dev.)</u>	<u>Mean Upper Confid. Limit (Std. Dev.)</u>
Intercept	-0.743 (0.144)			
ΔREV_{t-1}	-1.865 (0.155)	0.157 (0.024)	0.133 (0.020)	0.185 (0.029)

Panel B: Measures of Association

<u>Mean Percent Concordant (Std. Dev.)</u>	<u>Mean Percent Discordant (Std. Dev.)</u>	<u>Mean Percent Tied (Std. Dev.)</u>
64.190 (0.717)	35.080 (0.704)	0.730 (0.053)

DECRDUM_t = a dummy variable that takes the value 1 if sales revenue decreases in year t , and 0 otherwise;
 and
 ΔREV_{t-1} = percentage change in sales revenue from year $t-2$ to year $t-1$.

¹⁹ To mitigate concerns for undue influence of potential outliers, we deleted observations with absolute value of ΔREV_{t-1} greater than 1 in each round of estimation.

of sales decline in year t . The high concordant measure of 64 percent indicates that this simple and parsimonious logit model (12) performs reasonably well in predicting the direction of change in sales revenue.

We determine the estimated value of the sales decrease dummy variable ($\overline{DECRDUM}_t \equiv \hat{D}_t$) for the forecast period as:

$$\overline{DECRDUM}_t = \begin{cases} 1, & \text{if } \hat{\beta}_0 + \hat{\beta}_1 \Delta REV_{t-1} > 0 \\ 0, & \text{if } \hat{\beta}_0 + \hat{\beta}_1 \Delta REV_{t-1} \leq 0 \end{cases} \quad (13)$$

Our classification scheme based on the zero cutoff in Equation (13) is interpreted as a simple heuristic that predicts a sales decline ($DECRDUM = 1$) if the estimated probability is greater than 50 percent.

The forecast of ROE from our CVCS model is then given by:

$$\overline{ROE}_t = \hat{\gamma}_{a0} + \hat{\gamma}_{d1} \overline{DECRDUM}_t + \hat{\gamma}_{a2} ROE_{t-1} + \hat{\gamma}_{d3} SALES_{t-1} + \hat{\gamma}_{d4} SALES_{t-1} \overline{DECRDUM}_t \quad (14)$$

where, $\hat{\gamma}_{a0}, \hat{\gamma}_{d1}, \dots, \hat{\gamma}_{d4}$ are the five estimated coefficients of the CVCS model in Equation (11).

The ROE forecasts from the ROE model, the OPINC model, and the CASHFLOW model, respectively, are as follows:

$$\overline{ROE}_t = \hat{\gamma}_{a0} + \hat{\gamma}_{a1} ROE_{t-1} \quad (15)$$

$$\overline{ROE}_t = \hat{\gamma}_{b0} + \hat{\gamma}_{b1} OPINC_{t-1} + \hat{\gamma}_{b2} NOPTAX_{t-1} \quad (16)$$

$$\overline{ROE}_t = \hat{\gamma}_{c0} + \hat{\gamma}_{c1} CFO_{t-1} + \hat{\gamma}_{c2} ACCRUALS_{t-1} \quad (17)$$

where $\hat{\gamma}$ s in the above expressions are the estimated coefficients of their corresponding models in Equations (8), (9), and (10).

Based on the estimated parameters of the four forecast models and the estimated direction of change in sales revenue, we obtain four forecasts of ROE in forecast period t (\overline{ROE}_t) as given previously in Equations (14)–(17). The forecast error (FE) is defined as the difference between the actual realization of ROE in year t and the forecasted \overline{ROE}_t :

$$FE_t = ROE_t - \overline{ROE}_t \quad (18)$$

The absolute forecast error (AFE) is the absolute value of the forecast error FE :

$$AFE_t = |FE_t| \quad (19)$$

The statistics on the distribution of AFE for the time-series models are shown in Panel A of Table 4. The CVCS model generates AFE with the smallest median (0.0734), mean (0.1412), first quartile (0.0291), and third quartile (0.1779) of the four time-series models considered. In contrast, the basic ROE model produces AFE with the largest median (0.0805), mean (0.1427), first quartile (0.0340), and third quartile (0.1790). The OPINC and CASHFLOW models represent intermediate cases in terms of their forecast accuracy

TABLE 4
ROE Forecast Accuracy Comparisons among Time-Series Forecast Models Estimated From
11 Four-Year Rolling Industry-Level (four-digit SIC) Random Coefficient Regressions
Sample Forecast Period: 1992–2002 (n = 39,367)

Panel A: Distributions of Absolute Forecast Errors (AFE)

<u>Forecast Model</u>	<u>Median</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Q1</u>	<u>Q3</u>
ROE	0.0805	0.1427	0.1735	0.0340	0.1790
OPINC	0.0797	0.1422	0.1736	0.0334	0.1784
CASHFLOW	0.0797	0.1420	0.1740	0.0337	0.1780
Asy. ROE	0.0791	0.1423	0.1738	0.0328	0.1784
CVCS	0.0734	0.1412	0.1788	0.0291	0.1779

Panel B: Distributions of Pair-Wise Differences in Absolute Forecast Errors (AFE)^a

<u>Base Model</u>	<u>Comparison Model</u>	<u>Median Difference</u>	<u>Mean Difference</u>	<u>Std. Dev. of Difference</u>
ROE	OPINC	0.0002***	0.0005+++	0.0215
ROE	CASHFLOW	0.0005***	0.0006+++	0.0370
ROE	CVCS	0.0052***	0.0010+++	0.0446
OPINC	CASHFLOW	0.0001	0.0001	0.0400
OPINC	CVCS	0.0035***	0.0009+++	0.0431
CASHFLOW	CVCS	0.0031***	0.0008+++	0.0493

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using Wilcoxon signed rank test.

+++ , ++ , + indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using the t-test.

^a Pair-wise difference in AFE = AFE from the base model – AFE from the comparison model.

measured using distributions of *AFE*. The forecast accuracy improvement of the CVCS model relative to the benchmark ROE model in terms of reduction in median *AFE* is 0.0071 (=0.0805 – 0.0734), which is about nine times as large as the improvement of the OPINC or CASHFLOW models relative to the ROE model (reduction in median *AFE* = 0.0008).

To provide a statistical test of the forecast improvement, following Fairfield et al. (1996), we employ the nonparametric Wilcoxon signed rank test to evaluate the paired differences in *AFE* between two forecast models without imposing restrictive assumptions about the exact form of the underlying distribution (Lehmann 1975; Sheskin 1997).²⁰ Panel B of Table 4 presents pair-wise comparisons of *AFE* among the four models based on the distribution of the difference in *AFE* between any two competing models. Included in each row are the median, mean, and standard deviation of the difference in *AFE* between a comparison model and a base model. Positive (negative) values of the difference in *AFE* indicate that the comparison model generates a lower (higher) level of *AFE* and thus is more (less) accurate in forecasting one-year-ahead *ROE*, as compared to the base model. All the results based on pair-wise comparisons are consistent with those based on comparisons at the median or mean *AFE* in Panel A of Table 4. The median reduction in *AFE* of

²⁰ Since the hold-out samples used in comparing any two competing forecast models consist of the same set of firm-year observations, the appropriate statistical test of relative forecast accuracy is based on a matched sample comparison of AFEs.

the OPINC model relative to the ROE model is 0.0002 ($p < 0.001$).²¹ The CASHFLOW model also provides more accurate forecasts than the ROE model, with a median improvement of 0.0005 ($p < 0.001$). In contrast to the OPINC and CASHFLOW models that exhibit modest forecast accuracy improvement over the ROE model, the CVCS model improves forecast accuracy substantially. The median reductions in the *AFE* of CVCS relative to the ROE, OPINC, and CASHFLOW models are 0.0052 ($p < 0.001$), 0.0035 ($p < 0.001$), and 0.0031 ($p < 0.001$), respectively. Examining the mean differences in *AFE* produces qualitatively similar results.²²

The Table 4 evidence confirms the previous result that disaggregating earnings into its operating and non-operating components leads to more accurate forecasting of one-year-ahead ROE. It also demonstrates that decomposing earnings into cash flows and accruals has a similar impact on ROE forecast accuracy. More importantly, decomposing earnings based on cost variability and cost stickiness provides substantial incremental predictive ability in forecasting future ROE, over and above the forecast improvement of earnings decomposition based on financial statement line items that do not recognize the relation between sales and costs.

The Table 5 results are based on a subsample of firms containing analysts' consensus forecasts. Using the Frankel and Lee (1998) procedure to convert earnings per share (EPS) forecasts to ROE forecasts, we calculate the analysts' *AFE* in ROE based on their EPS forecasts reported on the I/B/E/S database. The statistics on the *AFE* distributions of analysts' forecasts and time-series model forecasts are presented in Panel A of Table 5. Consistent with evidence of analyst earnings forecast superiority *vis-à-vis* time-series models (Brown 1993), the analysts' consensus forecasts are the most accurate, with median (mean) *AFE* of 0.0457 (0.0976), which is 59 percent (80 percent) of the median (mean) *AFE* from the benchmark ROE model (median *AFE* = 0.0775, mean *AFE* = 0.1215). Consistent with the results in Table 4, the CVCS model is the most accurate of the three time-series models based on lagged earnings components, with median (mean) *AFE* of 0.0675 (0.1168). The OPINC and the CASHFLOW models have very similar forecasting performance, with median (mean) *AFE* of 0.759 (0.1205) and 0.760 (0.1206), respectively.

Panel B of Table 5 reports the results of comparing forecast accuracy based on pair-wise differences in *AFE*. The median reductions in matched *AFE* from the OPINC and the CASHFLOW models relative to the ROE model are 0.0005 and 0.0006, respectively, which is less than 3 percent of the median reduction in matched *AFE* from I/B/E/S consensus forecasts (0.0206). In contrast, the median reduction in matched *AFE* from our CVCS model is 0.0113, over half (55 percent) of that attributable to analysts' consensus forecasts. Similar to the Table 4 findings, these results indicate that the OPINC and CASHFLOW models are almost indistinguishable, with median difference of -0.0002 and mean difference of 0.0001. Both differences are statistically significant at 1 percent. In addition, I/B/E/S forecasts beat both the OPINC and CASHFLOW models and, to a lesser extent, the CVCS model, in pair-wise comparisons of forecast accuracy.

To assess the significance of forecast improvement of the three models of earnings decomposition, we calculate the reduction in median and mean *AFE* from the OPINC,

²¹ Fairfield et al. (1996) reported a median reduction of 0.0008 in absolute forecast error using the OPINC model relative to the ROE model.

²² We conducted a *t*-test for the equality of the means of two related samples. The *t*-statistics are all significant at the 0.001 level, indicating that both the OPINC and the CASHFLOW models perform better than the ROE model but worse than the CVCS model. The two-sample *t*-test requires the assumption of normal distribution in both samples. Since the normality assumption is found not to be descriptive of the distributions of *AFE*, we view the *t*-test results as suggestive, not conclusive.

TABLE 5
ROE Forecast Accuracy Comparison between Time-Series Forecast Models and I/B/E/S
Consensus Forecasts^a
Sample Forecast Period: 1992–2002 (n = 15,500)

Panel A: Distributions of Absolute Forecast Errors (AFE)

<u>Forecast Model</u>	<u>Median</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Q1</u>	<u>Q3</u>
ROE	0.0775	0.1215	0.1364	0.0364	0.1511
OPINC	0.0759	0.1205	0.1370	0.0359	0.1490
CASHFLOW	0.0760	0.1206	0.1374	0.0354	0.1499
Asy. ROE	0.0747	0.1202	0.1369	0.0345	0.1511
CVCS	0.0675	0.1168	0.1412	0.0289	0.1454
I/B/E/S	0.0457	0.0976	0.1388	0.0169	0.1156

Panel B: Distributions of Pair-Wise Differences in Absolute Forecast Errors (AFE)^c

<u>Base Model</u>	<u>Comparison Model</u>	<u>Median Difference</u>	<u>Mean Difference</u>	<u>Std. Dev. of Difference</u>
ROE	OPINC	0.0005***	0.0008***	0.0183
ROE	CASHFLOW	0.0006***	0.0009***	0.0309
ROE	CVCS	0.0113***	0.0047***	0.0354
ROE	I/B/E/S	0.0206***	0.0239***	0.1148
OPINC	CASHFLOW	-0.0002	0.0001	0.0335
OPINC	CVCS	0.0075***	0.0037***	0.0387
OPINC	I/B/E/S	0.0190***	0.0229***	0.1153
CASHFLOW	CVCS	0.0075***	0.0038***	0.0437
CASHFLOW	I/B/E/S	0.0230***	0.0230***	0.1158
CVCS	I/B/E/S	0.0105***	0.0192***	0.1049

Panel C: Forecast Improvement over the ROE Model^b

<u>Forecast Model</u>	<u>Accuracy Improvement over the ROE Model</u>		<u>% of Accuracy Improvement of I/B/E/S over the ROE Model</u>	
	<u>Difference in Median AFE</u>	<u>Difference in Mean AFE</u>	<u>Difference in Median AFE</u>	<u>Difference in Mean AFE</u>
OPINC	0.0016	0.0010	5.0	4.2
CASHFLOW	0.0015	0.0009	4.7	3.8
CVCS	0.0100	0.0047	31.4	19.7
I/B/E/S	0.0318	0.0239	100.0	100.0

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using Wilcoxon signed rank test.

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using the t-test.

^a ROE forecasts calculated based on analysts' consensus forecasts of earnings per share reported on I/B/E/S database nine months before the fiscal year end.

^b Forecast improvement is measured as the difference in median or mean absolute forecast errors between two forecast methods.

^c Pair-wise difference in AFE = AFE from the base model – AFE from the comparison model.

CASHFLOW, and CVCS models, respectively, as a percentage of the reduction in AFE of analysts' forecasts, all benchmarked against the ROE model. The differential forecast accuracy between analysts' forecasts and the ROE model reflects the total "information gap"

existing between the basic time-series model that uses only aggregate historical earnings information and financial analysts who utilize a significantly richer set of information, possibly including information contained in earnings components, in making earnings forecasts. The results are shown in Panel C of Table 5. The CVCS model improves forecast accuracy in median *AFE* by 0.0100 relative to the ROE model, representing 31.4 percent of the total improvement of analyst consensus forecasts over the ROE model (reduction in median *AFE* = 0.318). In contrast, the corresponding figures for the OPINC and the CASH-FLOW models are only 5.0 percent and 4.7 percent, respectively.

Taken together, these results in Table 5 indicate that earnings decomposition that recognizes cost variability and cost stickiness provides substantial incremental predictive content in forecasting one-year-ahead ROE relative to earnings decomposition that ignores such properties of earnings components. The evidence on the forecasting performance of our CVCS model relative to the more accurate analysts' consensus forecasts suggests a promising line of inquiry to examine if cost behavior information is a source of financial analysts' advantage over time-series models.

Loss Firms

Prior work in the accounting literature demonstrates that losses have lower earnings response coefficient (ERC) than profits, suggesting that the former is not as persistent as the latter due to the liquidation option (Hayn 1995). Our CVCS model contains a term that captures the differential impact of sales increase and decrease on future earnings. To the extent that the direction of sales changes is correlated with the sign of earnings, the observed superior forecasting performance of our CVCS model may be confounded.²³ To test this possibility, we augment the simple baseline ROE model (Equation (8)) to allow for differential persistence of profits and losses. This asymmetric ROE model is specified as follows:

$$ROE_t = \gamma_{e0} + \gamma_{e1}LOSS + \gamma_{e2}ROE_{t-1} + \gamma_{e3}LOSS*ROE_{t-1} + \varepsilon_t \quad (8')$$

$$\text{where } LOSS = \begin{cases} 1, & \text{if } ROE_{t-1} < 0 \\ 0, & \text{if } ROE_{t-1} \geq 0 \end{cases}$$

We expect the revised ROE model in Equation (8') to produce more accurate earnings forecasts than the simple ROE model in Equation (8) that does not distinguish between positive and negative earnings. More importantly, we expect the CVCS model to perform better than the asymmetric ROE model if our CVCS model captures an aspect of the earnings process beyond the liquidation option.

In estimating the asymmetric ROE model in Equation (8') and forecasting one-year-ahead ROE, we follow the procedure described in the section titled "Forecast Model Estimation" to provide earnings forecasts on a comparable basis. Descriptive statistics on absolute forecast errors from the asymmetric ROE model are reported in Panel A of Tables 4 and 5. As expected, the asymmetric ROE model generates more accurate earnings forecasts than the simple ROE model. In Panel A, Table 4, for the full sample, the median (mean) *AFE* of the asymmetric ROE model is 0.0791 (0.1423), while the median (mean) *AFE* of the simple ROE model is 0.0805 (0.1427). Results reported in Panel A of Table 5 for the subsample of observations with available I/B/E/S forecasts are quantitatively similar to those in Table 4: the median (mean) *AFE* of the asymmetric ROE model is 0.0747

²³ We are grateful to an anonymous referee for suggesting we examine the possibly confounding effect of differential persistence of profits and losses.

(0.1202), while the median (mean) *AFE* of the simple ROE model is 0.0775 (0.1215). Such improvement in forecasting accuracy, however, does not fully explain the superior performance of our CVCS model: the median (mean) *AFE* of the CVCS model is 0.0734 (0.1412) for the full sample and 0.0675 (0.1168) for the I/B/E/S subsample. These results suggest that by incorporating asymmetric cost behavior, our CVCS model captures an aspect of the earnings process that is not a mere manifestation of the liquidation option.

V. ASSOCIATION WITH ABNORMAL STOCK RETURNS

In the previous two sections, we focus on forecast accuracy when comparing our CVCS model with the ROE, OPINC, and CASHFLOW models. Another performance criterion widely used in capital market research when evaluating earnings forecast models is based on the association of earnings forecast errors (i.e., unexpected earnings conditioned on a forecast model) with contemporaneous stock returns (Fried and Givoly 1982; Brown et al. 1987b; O'Brien 1988). This performance criterion reflects the informativeness (or information content) of an earnings forecast model in capturing investors' earnings expectations. Under our maintained assumption that the market's expectation is informationally efficient, the closer a selected model comes to mimicking the market's expectations, the less noise there is in forecasts from the model in representing unobservable market expectations, and thus the higher the association we expect to observe between the forecast errors from the model and the contemporaneous abnormal stock returns (Foster 1977). Therefore, the strength of the association between forecast errors and abnormal returns provides a yardstick to measure the relative information content of alternative earnings forecast models.

Prior research finds that forecast models with superior accuracy are not necessarily superior on the association dimension (Hughes and Ricks 1987; O'Brien 1988) so we evaluate the performance of the CVCS model based on the association between its forecast errors and contemporaneous stock returns, and compare it with the associations using the ROE, OPINC, CASHFLOW, and analyst models. We follow Dechow (1994) in evaluating the relative information content by using the likelihood ratio test proposed by Vuong (1989) for the following five simple regression models:

$$RET_t = \alpha_{a0} + \alpha_{a1}FE_t^{ROE} + \varepsilon_{at} \quad (20)$$

$$RET_t = \alpha_{b0} + \alpha_{b1}FE_t^{OPINC} + \varepsilon_{bt} \quad (21)$$

$$RET_t = \alpha_{c0} + \alpha_{c1}FE_t^{CASHFLOW} + \varepsilon_{ct} \quad (22)$$

$$RET_t = \alpha_{d0} + \alpha_{d1}FE_t^{CVCS} + \varepsilon_{dt} \quad (23)$$

$$RET_t = \alpha_{e0} + \alpha_{e1}FE_t^{IBES} + \varepsilon_{et} \quad (24)$$

where RET_t is the size- and book-to-market-adjusted contemporaneous annual stock returns (Fama and French 1992), and FE_t^{ROE} , FE_t^{OPINC} , $FE_t^{CASHFLOW}$, FE_t^{CVCS} , and FE_t^{IBES} are the forecast errors based on the ROE, the OPINC, the CASHFLOW, the CVCS models and I/B/E/S analyst consensus forecasts, respectively. The advantage of using Vuong's (1989) test is that it provides directional inferences as to which of two competing models is closer to the true underlying model without assuming that one model is the true one. The Vuong test is particularly suitable when the models being compared have significant explanatory power, as is true in our case (Vuong 1989; Dechow 1994).

We obtain information on the portfolio returns formed conditioned on size (market value of equity) and the book-to-market ratio to compute abnormal returns. The sample we use for the market association analysis is the intersection of the sample firms used above to compare earnings forecasts, and the CRSP database from which we obtain data on stock returns. We omit firms without December 31 fiscal year-ends and firm-year observations whose absolute abnormal stock returns exceed 100 percent. We also exclude observations with the most extreme 1 percent of forecast errors of each model. Our final sample is 8,745 firm-years from 2,747 firms from 1992 to 2002.²⁴

Table 6 presents the correlation coefficients between forecast errors and abnormal stock returns. The Pearson (Spearman) correlations are above (below) the diagonal. The CVCS model produces forecast errors that are the most highly correlated with abnormal returns among the four time-series models we consider (Pearson $\rho = 0.350$, Spearman $\rho = 0.375$), while I/B/E/S analyst forecast errors are more highly correlated with abnormal returns (Pearson $\rho = 0.387$, Spearman $\rho = 0.459$) than any of the time-series model. The fact that the four time-series models generate highly correlated forecast errors is not surprising since they are conditioned on similar information sets, but the superior performance of the CVCS model relative to the other three time-series models obtains despite the near-unity correlations among them.

Table 7 contains results of the test of relative information content. Panel A reports regression results on the association between abnormal stock returns and forecast errors

TABLE 6
Correlation Coefficients^a (p-values in parentheses) between Abnormal Stock Returns (RET)^b and Forecast Errors (FE)^c in Returns on Equity (ROE) Based on Four Time-Series Forecast Models and I/B/E/S Consensus Forecasts
Sample Period: 1992–2002 (n = 8,745)

	<i>RET</i>	<i>FE^{ROE}</i>	<i>FE^{OPINC}</i>	<i>FE^{CASHFLOW}</i>	<i>FE^{CVCS}</i>	<i>FE^{IBES}</i>
<i>RET</i>		0.342 (0.000)	0.338 (0.000)	0.331 (0.000)	0.350 (0.000)	0.387 (0.000)
<i>FE^{ROE}</i>	0.362 (0.000)		0.993 (0.000)	0.978 (0.000)	0.992 (0.000)	0.702 (0.000)
<i>FE^{OPINC}</i>	0.360 (0.000)	0.990 (0.000)		0.975 (0.000)	0.985 (0.000)	0.701 (0.000)
<i>FE^{CASHFLOW}</i>	0.348 (0.000)	0.971 (0.000)	0.965 (0.000)		0.973 (0.000)	0.697 (0.000)
<i>FE^{CVCS}</i>	0.375 (0.000)	0.984 (0.000)	0.975 (0.000)	0.959 (0.000)		0.723 (0.000)
<i>FE^{IBES}</i>	0.459 (0.000)	0.652 (0.000)	0.652 (0.000)	0.641 (0.000)	0.675 (0.000)	

^a Pearson correlation coefficients are above the diagonal, and Spearman correlation coefficients are below the diagonal.

^b Abnormal stock returns are measured as size and book-to-market adjusted returns, or annual raw returns less portfolio returns matched on size (market value of equity) and book-to-market (the ratio of book value of equity to market value of equity).

^c *FE^{ROE}*, *FE^{OPINC}*, *FE^{CASHFLOW}*, *FE^{CVCS}*, and *FE^{IBES}* are forecast errors based on the ROE, OPINC, CASHFLOW, CVCS models, and I/B/E/S consensus analysts' forecasts, respectively.

²⁴ Results are similar to those reported here for the relative performance of the four time-series models when we use a larger sample of 17,170 firm-years that includes observations for which I/B/E/S data are not available.

TABLE 7
Regression Results of Abnormal Returns^a on Forecast Errors (FE)^b and Results of Vuong's
Test of Relative Information Content of Four Time-Series Forecast Models and I/B/E/S
Consensus Forecasts
Sample Period: 1992–2002 (n = 8,745)

Panel A: Simple Regression of Abnormal Returns on Forecast Errors (FE)

<u>Independent Variable</u>	<u>Coeff. Est. (t-statistic)</u>	<u>Coeff. Est. (t-statistic)</u>	<u>Coeff. Est. (t-statistic)</u>	<u>Coeff. Est. (t-statistic)</u>	<u>Coeff. Est. (t-statistic)</u>
Intercept	-0.002 (-0.60)	-0.001 (-0.26)	-0.001 (-0.18)	0.013 (1.22)	0.025 (4.71)
FE^{ROE}	0.829 (34.03)				
FE^{OPINC}		0.818 (33.53)			
$FE^{CASHFLOW}$			0.803 (32.76)		
FE^{CVCS}				0.845 (34.95)	
FE^{IBES}					1.020 (39.21)
Adj. R ²	0.1169	0.1139	0.1093	0.1225	0.1495

Panel B: Results of Vuong's Test of Relative Information Content

<u>Competing Forecast Models</u>		<u>Vuong's Z-statistic^c</u>	<u>p-value</u>
ROE	vs. OPINC	-3.22	0.002
ROE	vs. CASHFLOW	-4.66	0.000
ROE	vs. CVCS	5.45	0.000
ROE	vs. I/B/E/S	4.76	0.000
OPINC	vs. CASHFLOW	-2.62	0.009
OPINC	vs. CVCS	6.29	0.000
OPINC	vs. I/B/E/S	5.22	0.000
CASHFLOW	vs. CVCS	7.12	0.000
CASHFLOW	vs. I/B/E/S	5.85	0.000
CVCS	vs. I/B/E/S	4.04	0.000

^a Size and book-to-market adjusted returns equal annual raw returns less portfolio returns matched on size (market value of equity) and book-to-market (the ratio of book value of equity to market value of equity).

^b FE^{ROE} , FE^{OPINC} , $FE^{CASHFLOW}$, FE^{CVCS} , and FE^{IBES} are forecast errors based on the ROE, OPINC, CASHFLOW, CVCS models, and I/B/E/S consensus analysts' forecasts, respectively.

^c Vuong's Z-statistic is based on the likelihood ratio test developed by Vuong (1989) for non-nested model selection; a significant positive (negative) Z-statistic indicates that the first (second) forecast model is rejected in favor of the other forecast model.

in return on equity based on various forecast models. The highest adjusted R² of 0.1495 is achieved when abnormal returns are regressed on I/B/E/S analyst forecast errors, followed by forecast errors based on the CVCS model (adjusted R² = 0.1225). In Panel B, results based on pair-wise comparison indicate that the relative information content of the I/B/E/S analyst forecast is significantly greater than that of any of the mechanical forecast models. However, among the four time-series models we consider, Vuong's test rejects all

three benchmark models when each of them is compared against the CVCS model. Specifically, Vuong's Z-statistic is 5.45 ($p < 0.001$) for the comparison between the ROE model and the CVCS model, 6.29 ($p < 0.001$) for the comparison between the OPINC model and the CVCS model, and 7.12 ($p < 0.001$) for the comparison between the CASHFLOW model and the CVCS model, all in favor of the CVCS model. In sum, these findings are consistent with the CVCS model having greater relative information content in measuring market's earnings expectations than other time-series forecast models that do not exploit the information in the relation between sales and cost items in the financial statements.

VI. CONCLUDING REMARKS

We propose an earnings forecast model (CVCS) that recognizes cost variability with sales changes and cost stickiness when sales decline. Unlike models of disaggregated earnings based on reporting classifications, our model stems from a management accounting perspective that emphasizes interactions among earnings components. The core of our model is the relation between sales and expenses embodied in the traditional fixed and variable cost behavior model. In addition, CVCS incorporates recent research that documents sticky cost behavior—the fact that costs do not decrease as much with sales decreases as they increase with sales increases.

Our CVCS model predicts one-year-ahead returns on equity better than do other models based on line items reported in income statements and statements of cash flows. Our CVCS model bridges over 30 percent of the information advantage financial analysts possess in forecasting one-year-ahead ROE over a basic time-series model that uses information on historical aggregate earnings. In contrast, the OPINC and CASHFLOW models bridge less than 6 percent of analysts' superior forecast accuracy over the basic ROE model. Invoking the assumption of market efficiency, we find that our model performs better than the other three time-series models when evaluated based on the association between the earnings surprise measured by forecast errors relative to these models and contemporaneous abnormal stock returns. Thus, the evidence suggests that earnings forecasts using our CVCS model better represent the market's earnings expectations than those using other models based on financial statement line items.

Our study raises several interesting questions to be explored in future research. As our association analysis is predicated on the maintained assumption of market efficiency, we do not address the issue of whether the stock market fully captures the information content of cost variability and cost stickiness relevant for forecasting future earnings. Although cost variability is a concept that is generally well understood, evidence on cost stickiness was largely anecdotal until recently. The extent to which investors have rational expectations about the impact of cost stickiness on future earnings over a longer horizon remains an open question.

Our objective is to consider a parsimonious model based only on income statement data. Promising research opportunities include expanding the scope of our model to incorporate additional information such as new product introduction or plant closures available to investors that may impact the earnings forecasts. In addition, the manner in which we model the impact of sticky cost behavior could be extended to consider its impact on the amount of accruals and related balance sheet items in order to develop a better understanding of the valuation process.

Our study documents that the simple cost variability and cost stickiness model has predictive content for the analysis of future profitability. Since such cost behavior models underlie some management accounting systems for budgeting and variance analysis, this

documentation is important in validating the basic premise supporting their design and indicating the importance of incorporating sticky cost behavior in improving their design. By emphasizing the importance of understanding cost behavior in forecasting earnings, our study points to the rich potential for future research integrating heretofore disparate streams of work in managerial and financial accounting.

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