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Cost Behavior and Analysts' Earnings Forecasts

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ABSTRACT: This study examines how firms' asymmetric cost behavior influences analysts' earnings forecasts, primarily the accuracy of analysts' consensus earnings forecasts. Results indicate that firms with stickier cost behavior have less accurate analysts' earnings forecasts than firms with less sticky cost behavior. Furthermore, findings show that cost stickiness influences analysts' coverage priorities and investors appear to consider sticky cost behavior in forming their beliefs about the value of firms. This study integrates a typical management accounting research topic, cost behavior, with three standard financial accounting topics (namely, accuracy of analysts' earnings forecasts, analysts' coverage, and market response to earnings surprises).

Keywords: *analysts; earnings forecasts; sticky costs; asymmetric cost behavior*.

JEL Classifications: *M41; G12*.

I. INTRODUCTION

Management accountants have traditionally focused on cost behavior as an important aspect of profit analysis for managers. Financial analysts, however, estimate firms' future costs in the process of forecasting future earnings. Predicting cost behavior is, therefore, an essential part of earnings prediction. Yet, a potential relationship between firms' cost behavior and properties of analysts' earnings forecasts has not yet been explored. This study integrates the management and financial accounting disciplines by showing effects of cost behavior on: (1) the accuracy of analysts' consensus earnings forecasts, (2) the extent of analyst coverage, and (3) the market response to earnings announcements.

Focusing on cost behavior, I build on the concept of sticky costs (Anderson et al. 2003). Costs are termed sticky if they increase *more* when activity rises than they decrease when activity falls by an equivalent amount. A firm with stickier costs shows a greater decline in earnings when the

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activity level falls than a firm with less sticky costs. The reason is that stickier costs result in a smaller cost adjustment when activity level declines and, therefore, lower cost savings. Lower cost savings result in a greater decrease in earnings. This greater decrease in earnings when the activity levels fall increases the variability of the earnings distribution, resulting in less accurate earnings predictions.

Results, based on a sample of 44,931 industrial firm quarters for 2,520 firms from 1986 through 2005, indicate that sticky cost behavior reduces the accuracy of analysts' consensus earnings forecasts after controlling for environmental uncertainty, the amount of available firm-specific information, the forecast horizon, and industry effects.

Classifying costs into sticky and anti-sticky costs,[1] findings show that analysts' absolute consensus earnings forecasts for firms with sticky cost behavior are, on average, 25 percent less accurate than those for firms with anti-sticky cost behavior. Evidently, cost behavior is an influential determinant of analysts' forecast accuracy. The results are robust to potential managerial discretion that might bias the cost stickiness measure and to estimating cost stickiness over a long time window. The findings extend Banker and Chen (2006), who show that cost behavior explains a considerable part of analysts' advantage over time-series models. These findings are also useful for investors who use consensus earnings forecasts to value firms, as they suggest that stickier costs indicate more volatile future earnings.

Addressing the extent of analyst coverage, I examine the relationship between the accuracy of earnings forecasts and the extent of analyst coverage. While Alford and Berger (1999) and Weiss et al. (2008) document a positive relationship, Barth et al. (2001) report that analysts tend to prefer covering firms with intangible assets characterized by volatile performance. Thus, prior evidence is mixed and this relationship is an open empirical issue. I find that firms with stickier costs (and less accurate earnings forecasts) have lower analyst coverage after controlling for the amount of available information, environmental uncertainty, intensity of R&D expenditures, and additional determinants of supply and demand for analysts' forecasts reported in the literature (e.g., Bhushan 1989; Lang and Lundholm 1996). Findings indicate that firms' cost behavior affects analysts' coverage priorities.

Finally, I examine whether investors behave as if they understand cost stickiness in responding to earnings announcements. As earnings predictability decreases, reported earnings provide less useful information for the prediction of future earnings, such that the earnings response coefficient decreases (e.g., Lipe 1990). If investors recognize cost stickiness to some extent, being aware that cost stickiness diminishes the accuracy of the analysts' earnings forecasts, then stickier cost behavior causes investors to rely less on realized earnings information because of its lower predictive power. Similarly, I find a weaker market response to earnings surprises for firms with stickier cost behavior. Overall, findings indicate that cost behavior matters in forming investors' beliefs regarding the value of the firm.

This empirical examination is facilitated by a new measure of cost stickiness at the firm level developed in this study. I estimate the difference in cost function slopes between upward and downward activity adjustments. While Anderson et al. (2003) and subsequent studies use cross-sectional and time-series regressions to estimate cost stickiness,[2] the new measure developed here puts less demand on the data and allows for testing the sensitivity of results to key cost model assumptions. The new measure corroborates prior evidence on variation among firms' cost sticki-

[1] Costs are termed anti-sticky if they increase *less* when activity rises than they decrease when activity falls by an equivalent amount. See examples in Balakrishnan et al. (2004) and the discussion in Section II.

[2] See, for instance, Banker et al. (2008) and Anderson and Lanen (2007).

ness and provides room for estimating cost stickiness of firms operating in industries with a small number of firms, which limits a meaningful estimation of regression models.[3]

This study expands the scope of cost behavior research. Traditionally, cost behavior has attracted the attention of management accountants interested in decision-making and control. The current results show that financial analysts benefit from understanding cost behavior as well. Further, these findings contribute to our understanding of how analysts use public information reported in financial statements to recognize cost behavior (e.g., Abarbanell and Bushee 1997; Brown et al. 1987).

In sum, this study integrates a typical management accounting research topic, cost behavior, with three standard financial accounting topics. The importance of integrating the two streams of research has long been recognized (Hemmer and Labro 2008).

Hypotheses are developed in Section II, the research design is described in Section III, and the empirical results are in Section IV. Section V offers a concluding remark on the prospects of integrating management and financial accounting research.

II. DEVELOPMENT OF HYPOTHESES

Despite the wide interest in analysts' earnings forecasts, prior research has not yet investigated the relationship between firms' cost behavior and properties of analysts' earnings forecasts, notwithstanding the essential part that cost prediction plays in the process of earnings prediction. Prior empirical studies provide evidence that the accuracy of analysts' earnings forecasts increases in the amount of information available regarding the firm (Atiase 1985; Lang and Lundholm 1996), increases in firm size but not in firm complexity (Brown et al. 1987), and decreases in the level of uncertainty in the firm's production environment (Parkash et al. 1995). Later work by Banker and Chen (2006) reports that cost behavior explains a considerable portion of the analysts' advantage in earnings prediction over various time-series models.

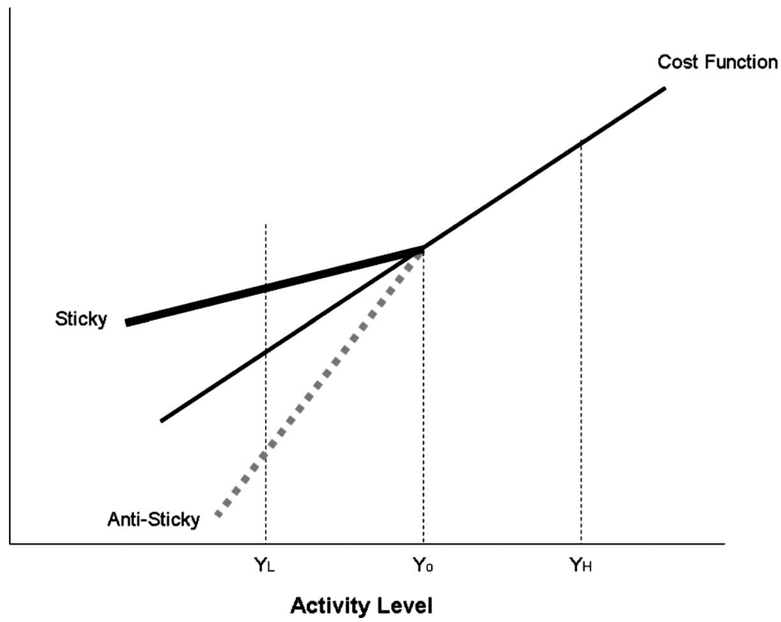
The recently developed concept of sticky costs provides a compelling setting for exploring why and how cost behavior affects the accuracy of analysts' earnings forecasts. Sticky costs indicate that costs tend to "stick" and hence do not go away when activity levels decline. Balakrishnan and Gruca (2008) report that hospital administrators find it hard and expensive to adjust capacity level of core activities downward resulting in sticky costs. Banker and Chen (2006) improve earnings predictions by estimating the excessive costs incurred due to costs being sticky when sales decrease. Anderson et al. (2007) report that cost stickiness causes the ratio of SG&A costs to sales to increase, rather than decrease proportionally with sales, when revenue declines. Overall, prior studies perceive costs as sticky if firms incur disproportionate costs when activity levels decline.

I build on Balakrishnan et al. (2004) to illustrate the intuition underlying the relationship between the extent of cost stickiness and the accuracy of analysts' earnings forecasts. Balakrishnan et al. (2004) argue that the level of capacity utilization affects managers' response to a change in activity level. Thus, if capacity utilization is high, the firm's managers are not likely to immediately cut resources in response to a decrease in activity level because the decrease may be temporary. However, an increase in activity level under high-capacity utilization is likely to cross the available resource threshold and trigger an increase in resources supplied. Assuming high-capacity utilization, the response to a decrease in activity level will be smaller than the response to a similar increase in activity level, resulting in sticky costs—depicted by the bold line in Figure 1.

By contrast, suppose the same firm experiences excess capacity. Its managers are likely to use the slack to absorb the demand from an increase in activity level. However, an additional decrease

[3] For instance, Banker and Chen (2006) exclude from their sample four-digit SIC code industries with less than 20 firms.

FIGURE 1
Cost Asymmetry



The figure depicts sticky and anti-sticky cost functions based on Balakrishnan et al.'s (2004) example. The bold cost function illustrates sticky costs assuming that activity level Y_0 is high-capacity utilization. The dashed cost function illustrates anti-sticky costs assuming excess capacity for activity level Y_0.

in activity level is interpreted as confirming a permanent reduction in demand and triggers a response. Assuming excess capacity, the cost response to an activity level decrease exceeds the cost response to a similar increase in activity level, resulting in anti-sticky costs—depicted by the dashed line in Figure 1.

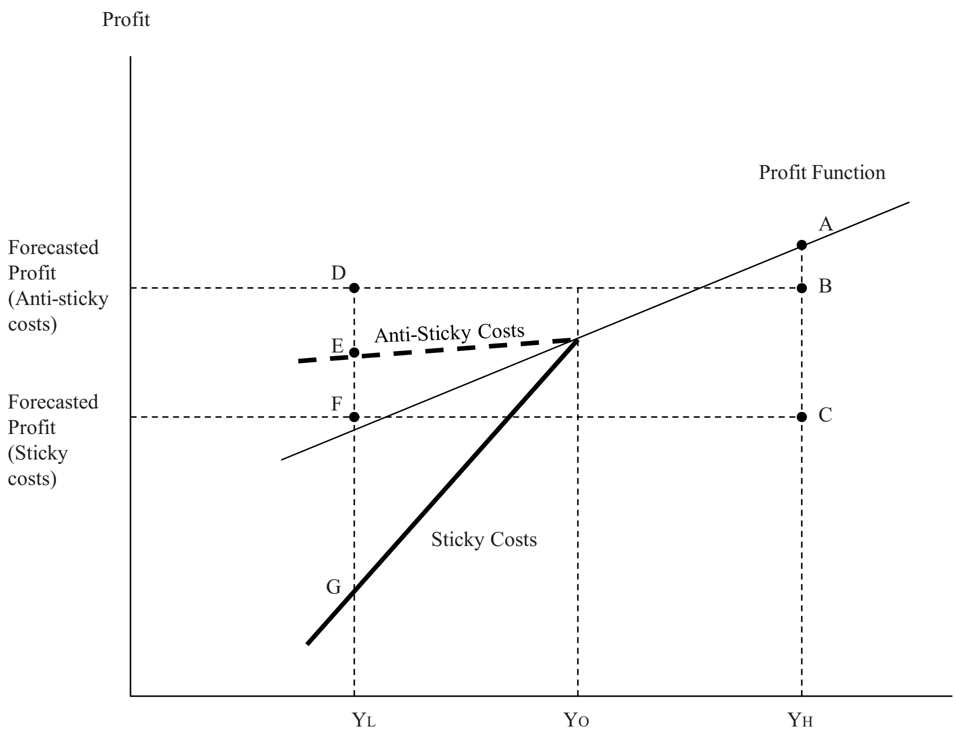
Next, I build on Balakrishnan et al. (2004) to illustrate that stickier costs result in greater earnings variability. Higher capacity utilization yields stickier costs, resulting in lower cost savings and a greater decrease in profits when sales decrease.[4] Assuming that the rest of the distribution of profits is unchanged, this greater decrease in profits increases the variability of the *ex ante* profit distribution.

Now, suppose an analyst predicts future profits. For simplicity, I assume that future activity level will either increase or decrease by an equivalent amount with equal probability. I further suppose that the analyst recognizes cost behavior to a reasonable extent and assume that the analyst forecasts expected profit (e.g., Ottaviani and Sorensen 2006). Other things equal, sticky costs result in lower profits when the activity level declines than anti-sticky costs do. Assuming equal profits when activity levels rise, the analyst's profit forecast is lower under sticky costs than

[4] The terms profits and earnings are used interchangeably in this study.

under anti-sticky costs. For that reason, the *absolute* forecast error when activity levels decline as well as when activity levels rise is greater under sticky costs than under anti-sticky costs. Figure 2 depicts lower profits under sticky costs (assuming high-capacity utilization) than under anti-sticky costs (assuming excess capacity) when activity levels decline: point G is below point E. Lower profits are expected and forecasted under sticky costs than under anti-sticky costs; see profit levels FC and DB, respectively. The *absolute* forecast errors under sticky costs are larger than under anti-sticky costs: AC > AB when the activity level increases and FG > DE when the activity level decreases. The example demonstrates that the absolute forecast errors increase with the extent of cost stickiness.

FIGURE 2
Absolute Forecast Errors are Greater in the Presence of Sticky Costs Than in the Presence of Anti-Sticky Costs



The figure depicts two profit functions following Balakrishnan et al. (2004). The bold profit function assumes sticky costs and the dashed profit function assumes anti-sticky costs. When the activity level declines from Y_0 to Y_L, profits are lower under sticky costs (assuming high-capacity utilization) than under anti-sticky costs (assuming excess capacity): point G is below point E. Expected profits are lower under sticky costs than under anti-sticky costs: see profit levels FC and DB, respectively. The *absolute* forecast errors under sticky costs are larger than under anti-sticky costs: AC > AB on activity level increases and FG > DE on activity level decreases. Overall, the *absolute* forecast errors when activity levels decline, as well as when activity levels increase, are greater under sticky costs than under anti-sticky costs.

The above example is used to illustrate the intuition of the relationship between the extent of cost stickiness and the accuracy of earnings forecasts. This relationship between the extent of cost stickiness and the absolute forecast errors is modeled in the Appendix (consistent with Equation (5) in Banker and Chen [2006]). The Proposition presented in the Appendix indicates a positive relationship between the extent of cost stickiness and the absolute forecast errors. Accordingly, my first hypothesis is:[5]

H1: Increased cost stickiness reduces the accuracy of analysts' consensus earnings forecasts.

Prior literature documents a relationship between the accuracy of analysts' earnings forecasts and the extent of analyst coverage (e.g., Alford and Berger 1999). Recently, Weiss et al. (2008, Table 7) report that firms with high analyst coverage have more accurate earnings forecasts than firms with low analyst coverage. Stickel (1992) reports that members of the Investor All-American Research Team have more accurate forecasts than non-members. Analysts who find this competition to be of major importance are likely to prefer covering firms with less sticky cost behavior to achieve greater expected accuracy.[6]

However, Barth et al. (2001) report high coverage of firms with intangible assets, characterized by low earnings predictability and high earnings forecasts errors. While analysts are motivated to provide investors with more accurate earnings forecasts, they may not shy away from following a firm with low earnings predictability if they have an information advantage with respect to that firm or if the demand for forecasts is higher for that firm. In sum, the empirical evidence on the relationship between the accuracy of analysts' earnings forecasts and the extent of analyst coverage is mixed, and it remains an open empirical issue.

I examine whether sticky cost behavior influences the extent of analyst coverage. Sticky cost behavior will influence analysts' coverage priorities if they recognize the relationship between cost stickiness and accuracy of earnings forecasts hypothesized above. I test a potential relationship between sticky cost behavior and the extent of analyst coverage after controlling for the intensity of research and development, the amount of available information, firm size, environmental uncertainty, and for additional determinants of supply and demand for analysts' forecasts reported in the literature. Because there is no *ex ante* basis for a prediction, the corresponding hypothesis is stated in the null form:

H2: Sticky cost behavior does not affect analyst coverage.

Finally, I examine whether investors recognize cost behavior. If investors have some understanding that firms with stickier costs tend to have less accurate earnings forecasts, then cost behavior is likely to influence their response to surprises in earnings announcements. As earnings predictability decreases, reported earnings provide less useful information for valuation and prediction of future earnings, resulting in a lower earnings response coefficient (e.g., Lipe 1990). Abarbanell et al. (1995) show that the earnings-price response coefficient increases in the forecast precision. If investors recognize that cost stickiness diminishes the accuracy of the analyst's

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[5] To clarify, several studies report a variation in the level of cost stickiness—see Balakrishnan and Gruca (2008), Banker et al. (2008), Anderson and Lanen (2007), and Balakrishnan and Soderstrom (2009). These studies offer explanations for both sticky and anti-sticky cost behavior (e.g., ownership, pessimism/optimism with respect to future demand, core activity). In this study, I build on this variation and show a relationship between the level of cost stickiness and properties of analysts' earnings forecasts.

[6] Examining factors associated with the extent of analyst coverage, Bhushan (1989) finds that the number of analysts covering a firm increases in firm size, O'Brien and Bhushan (1990) report greater coverage in industries with stringent disclosure requirements, and Lang and Lundholm (1996) claim greater coverage of firms with more informative disclosure policies. Frankel et al. (2006), however, find no relation between the informativeness of the analysts' forecasts and the size of the analyst following.

earnings forecasts, then stickier cost behavior causes investors to rely less on realized earnings information because of its low predictive power. The third hypothesis summarizes the argument:

H3: The market response to earnings surprises is weaker for firms with stickier cost behavior.

If H3 holds, then it suggests that investors have some appreciation of the role of cost behavior in determining earnings surprises. In other words, this hypothesis predicts that cost behavior matters in forming investors' beliefs regarding the value of firms.

III. RESEARCH DESIGN

Focusing on asymmetric cost behavior, this study proposes a new measure of cost stickiness at the firm level. Prior studies use a cross-sectional regression model to estimate cost stickiness at the industry level or a time-series regression model to estimate it at the firm level (e.g., Anderson et al. 2003). Taking a different path, this study introduces a direct measure of cost stickiness at the firm level. I estimate the difference between the rate of cost decrease for recent quarters with decreasing sales and the corresponding rate of cost increase for recent quarters with increasing sales:

$$STICKY_{i,t} = \log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i,\underline{\tau}} - \log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i,\bar{\tau}} \quad \underline{\tau}, \bar{\tau} \in \{t, \ldots, t-3\},$$

where $\underline{\tau}$ is the most recent of the last four quarters with a decrease in sales and $\bar{\tau}$ is the most recent of the last four quarters with an increase in sales, $\Delta SALE_{it} = SALE_{it} - SALE_{i,t-1}$, (Compustat #2), $\Delta COST_{it} = (SALE_{it} - EARNINGS_{it}) - (SALE_{i,t-1} - EARNINGS_{i,t-1})$, and *EARNINGS* is income before extraordinary items (Compustat #8).

STICKY is defined as the difference in the cost function slope between the two most recent quarters from quarter $t-3$ through quarter t, such that sales decrease in one quarter and increase in the other. If costs are sticky, meaning that they increase *more* when activity rises than they decrease when activity falls by an equivalent amount, then the proposed measure has a negative value. A *lower* value of *STICKY* expresses *more* sticky cost behavior.[7] That is, a negative (positive) value of *STICKY* indicates that managers are less (more) inclined to respond to sales drops by reducing costs than they are to increase costs when sales rise.

Following prior sticky costs studies, *STICKY* uses a change in sales as an imperfect proxy for the actual activity change because changes in activity level are not observable. Employing sales as a fundamental stochastic variable is in line with Dechow et al. (1998), who suggest a model of earnings, cash flow, and accruals, assuming a random walk sales process. Banker and Chen (2006) also use sales as a fundamental stochastic variable for predicting future earnings.

Since analysts estimate total costs in the process of earnings prediction, the stickiness measure concentrates on total costs to gain insights into a potential relationship between stickiness of total costs and the accuracy of analysts' earnings predictions. Investigating how cost stickiness affects analysts' earnings forecasts, I use sales minus earnings. Employing total costs for the analysis also eliminates managerial discretion in cost classifications (Anderson and Lanen 2007). I also assume that costs increase in activity level (as in the adjustment costs model presented in the Appendix). This assumption means that costs move in the same direction as activity and precludes cost increases when activity falls and cost decreases when activity increases (Anderson and Lanen 2007). For this reason, I do not use observations with costs that move in opposite directions in estimating *STICKY*. The ratio form and logarithmic specification make it easier to compare vari-

[7] The estimate of *STICKY* is consistent with the sign of the parameter α, as defined in the model presented in the Appendix. The sign of *STICKY* is also consistent with the stickiness measure, β_2, in Anderson et al. (2003, Model I).

ables across firms, as well as alleviating potential heteroscedasticity (Anderson et al. 2003).

The proposed measure has several advantages. First, and most important for this study, *STICKY* estimates cost asymmetry at the firm level. Thus, it provides means of investigating how cost behavior influences analysts' earnings forecasts. Moreover, it allows for a large-scale study without restricting the analysis to firms with at least ten valid observations and at least three sales reductions during the sample period (see Anderson et al. 2003, 56).[8]

Second, by design, the stickiness of a linear cost function is zero, i.e., $STICKY = 0$, for a traditional fixed-variable cost model with a constant slope for all activity levels within a relevant range. Thus, a zero value indicates that managers change costs symmetrically in response to sales increases and declines.

Third, the proposed cost stickiness measure has a wider scope than that used by Anderson et al. (2003) because it accounts for a difference between proportions of cost changes and allows for cost friction with respect to sales increases. For instance, Chen et al. (2008, 2) argue that empire-building incentives are "likely to lead managers to increase SG&A costs too rapidly when demand increases." They report a positive association between managerial empire building incentives and the degree of cost asymmetry. *STICKY* affords an examination of how cost asymmetry affects the forecast accuracy in the presence of decreases in sales (i.e., as presented by Anderson et al. [2003]) and in the presence of increases in sales.

Nonetheless, there are potential measurement errors in the suggested cost stickiness metric. First, the model assumes a piecewise linear specification of the cost function within the relevant range of activity, which simplifies the analysis and allows for measuring cost stickiness when the upward and downward activity changes do not have the same magnitude. This approximation is consistent with prior studies on sticky costs and is reasonable in the context of investigating a relationship between attributes of cost behavior and properties of analysts' forecasts.

Second, the model assumes a realization of an exogenous state of the world that determines activity level. However, growth or reduction in activity can occur not only because of changes in activity level, but also because of changes in prices of products or resources or other managerial choices (Anderson and Lanen 2007). I restrict the sample to competitive industrial firms to minimize this problem, and later test the sensitivity of results to potential managerial discretion.

To check consistency with prior literature, I compute the suggested measure for two major cost categories investigated in prior literature. Specifically, *COGS-STICKY* and *SGA-STICKY* substitute changes in total costs with changes in cost of goods sold, hereafter *COGS* (Compustat #30) and *SGA* costs (Compustat #1), respectively. The median proportion of *COGS* and *SGA* to sales in my sample is 64.7 percent and 23.1 percent, respectively. However, the accounting classification of *COGS* and *SGA* is open to managerial judgment, which may introduce bias into the cost stickiness estimate of specific cost components. The results should be interpreted in light of this limitation. Taken as a whole, the stickiness measure is expected to provide broad insights into the relationship between cost behavior and properties of analysts' earnings forecasts.

Measuring the accuracy of the analyst consensus forecast, I employ the mean absolute earnings forecast errors as an inverse accuracy measure. This accuracy gauge has been extensively used in the accounting literature (e.g., Lang and Lundholm 1996). Thus, the forecast error is defined as:

$$FE_{it} = \frac{actual\ EPS_{it} - analyst\ consensus\ forecast_{it}}{Price_{i,t-1}},$$

and the absolute forecast error is $ABS\text{-}FE_{it} = |FE_{it}|$, where the analyst consensus forecast is the

[8] In measuring skewness of firm-specific earnings distributions, Gu and Wu (2003) require each firm to have at least 16 quarterly observations.

mean of analyst forecasts for firm *i* and quarter *t* announced in the month immediately preceding that of the earnings announcement. The relatively narrow time window and the short forecast horizon control for the timeliness of the forecasts and mitigate a potential trade-off between timing and accuracy (Clement and Tse 2003).

Testing H1

In testing whether stickier cost behavior results in greater mean absolute analyst consensus earnings forecast error, I control for the amount of available firm-specific information, the inherent uncertainty in the operations environment, and the forecast horizon. The literature reports that an increased amount of available firm-specific information reduces the forecast error. The amount of information acquired by analysts is positively related to firm size (Atiase 1985; Collins et al. 1987; Bhushan 1989). Accordingly, I use firm size as a control variable and expect a negative coefficient. Brown (2001) reports a disparity between the magnitude of earnings surprises of profits and losses. I use an indicator variable to control for losses because they reflect more timely information and are associated with larger absolute forecast errors than are profits. I also follow Matsumoto (2002) and control for potential earnings guidance, which is likely to reduce the forecast error if it results in meeting or slightly beating the consensus earnings forecast.

Environmental uncertainty is likely to influence the forecast accuracy. If the business environment is highly volatile, then one will expect larger forecast errors. I use two proxies for the level of environmental uncertainty. The first is the coefficient of variation in sales, which directly captures sales volatility. The second is analyst forecast dispersion, which measures complementary uncertainty aspects of firms' earnings (Barron et al. 1998). Brown et al. (1987) and Wiedman (1996) report that the accuracy of analysts' forecasts decreases in the dispersion of analysts' forecasts, which is used to proxy for the variance of information observations.

In addition, management accounting textbooks (e.g., Maher et al. 2006) present cost-volume-profit analysis and suggest that firms with a high operating leverage are likely to exhibit high earnings volatility. Lev and Thiagarajan (1993) employ profit margin as a proxy for operating leverage. In an early study, Adar et al. (1977) present a positive relationship between profit margin and forecast error in a cost-volume-profit under uncertainty setting. Operating leverage varies across firms and is likely to depend on the firm-specific business environment, as well as current macroeconomic conditions. The higher the operating leverage of the firm, the higher is the expected error in the analysts' earnings forecast. Therefore, I predict a positive relationship between operating leverage and the magnitude of analysts' earnings forecast errors.

I also control for unexpected contemporaneous seasonal shocks to earnings. An indicator variable, *SEASON*, indicates firm quarters with a positive change in earnings from the same quarter in the prior year. This variable controls for the relation between the change in earnings and the forecast error (Matsumoto 2002). A positive coefficient estimate is predicted.

I estimate the following three cross-sectional regression models with two-digit SIC code industry effects:

Model 1(a)

$$\begin{aligned} ABS\text{-}FE_{it} = {} & \beta_0 + \beta_1 STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} \\ & + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}; \end{aligned}$$

Model 1(b)

$$\begin{aligned} ABS\text{-}FE_{it} = {} & \beta_0 + \beta_1 COGS\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} \\ & + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}; \end{aligned}$$

Model 1(c)

$$ABS\text{-}FE_{it} = \beta_0 + \beta_1 SGA\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it};$$

where:

MV_{it} = log of market value of equity (Compustat #61 × #14) at quarter end;
$LOSS_{it}$ = indicator variable that equals 1 if the reported earnings (Compustat #8) are negative, and 0 otherwise;
$DOWN_{it}$ = as defined in Matsumoto (2002) and equals 1 if unexpected earnings forecasts are negative, and 0 otherwise;
$VSALE_{it}$ = coefficient of variation of sales measured over four quarters from $t-3$ through t;
$DISP_{it}$ = standard deviation of the analysts' forecasts announced for firm i and quarter t in the month immediately preceding that of the earnings announcement, deflated by stock price at the end of quarter $t-1$;
$OPLEV_{it}$ = ratio between $SALE_{it}$, minus $COGS$ (Compustat #30) and $SALE_{it}$; values below 0 or above 1 are winsorized; and
$SEASON_{it}$ = indicator variable that equals 1 if the change in earnings from the same quarter in the prior year (Compustat #8) is positive, and 0 otherwise.

If the above metric captures cost stickiness, then H1 predicts $\beta_1 < 0$ in all three models, where lower values of *STICKY* (*COGS-STICKY*, *SGA-STICKY*) indicate stickier cost behavior.

I further test the sensitivity of the results to the model's assumptions and potential measurement errors in three ways. First, I test the sensitivity of the cost stickiness measure to a longer time window. I compute the ratio of change in total costs to change in sales using data from the most recent eight quarters, $t-7$ through t. I then estimate *M-STICKY*, that is, the difference between the mean slope under downward adjustments and the mean slope under upward adjustments. Thus, *M-STICKY* accounts for downward adjustments and upward adjustments made over eight quarters. Comparing *M-STICKY* with *STICKY* provides insights into the perseverance of firms' cost behavior over a longer window. To check the robustness of the coefficient estimates, I estimate the following regression model:

Model 1(d)

$$ABS\text{-}FE_{it} = \beta_0 + \beta_1 M\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}.$$

Again, if the above metric captures the cost stickiness, then H1 predicts $\beta_1 < 0$ in model 1(d).

Second, I conduct a limited examination of the effects of cost stickiness generated by past decisions, such as technology choice and labor compensation contracts, on absolute forecast errors. Specifically, I consider two forms of managerial discretion: current decisions made in response to realized market conditions in the current quarter t, and past decisions made over quarters prior to quarter t. I view adjustments of activity levels as responses in reaction to realized market conditions, in contrast to prior decisions. Substituting $STICKY_{i,t-1}$ for $STICKY_{i,t}$ allows for estimating the impact of past decisions only. In other words, $STICKY_{i,t-1}$ proxies for the extent of cost stickiness in an earlier quarter, excluding all managerial discretionary choices made in quarter t, such as price discounts or accrual manipulations.

Model 1(e)

$$ABS\text{-}FE_{it} = \beta_0 + \beta_1 STICKY_{i,t-1} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}.$$

As before, the hypothesis predicts $\beta_1 < 0$ in model 1(e).

Third, I collect evidence concerning the assumption that analysts understand cost behavior to some extent. If analysts ignore cost stickiness when it exists, then their earnings forecasts will be upward biased. Similarly, if analysts ignore anti-sticky costs when they exist, then their earnings forecasts will be downward biased. However, if analysts understand cost behavior, then the mean forecast error (not absolute error) for firms with sticky costs as well as for firms with anti-sticky costs should *not* be affected by the level of cost stickiness.[9] In other words, if analysts recognize cost behavior, then the extent of cost stickiness will not influence the mean signed forecast error.

Testing H2

To test the association between cost stickiness and analyst coverage, I regress the number of analysts following a firm on its cost stickiness and control variables. The analyses include independent variables to control for the amount of available information, environmental uncertainty, the intensity of research and development expenditures, additional determinants of supply and demand for analysts' forecasts reported in the literature, and year effects and two-digit SIC code industry effects.

Prior literature reports that firm size is a primary determinant of analyst coverage (Bhushan 1989; Hong et al. 2000; Das et al. 2006), perhaps because large firms have more available firm-specific information than small firms (Collins et al. 1987). The extent of information asymmetry between managers and investors is likely to enhance the demand for earnings forecasts, but analysts are required to invest more resources in acquiring information. I use research and development expenditures as a proxy for information asymmetry because firms with more intangible assets exhibit greater information asymmetry (Barth et al. 2001; Barron et al. 2002).

Controlling for uncertainty in the forecasting environment, I employ the coefficient of variation in sales as a direct measure for shocks in demand. In addition, analyst forecast dispersion and the absolute forecast error in the prior quarter are included to measure other aspects of the uncertainty in firms' earnings (Brown et al. [1987] and Matsumoto [2002], respectively). Das et al. (1998) argue that analysts extract higher rents by following less predictable firms, because demand for private information is the highest for these firms, but the accuracy of the forecasts is expected to be lower. Thus, the net effect of uncertainty in the forecasting environment on an increase in the extent of analyst following is ambiguous.

I also control for growth and trading volume (Lang and Lundholm 1996), which provide analysts with greater incentives to cover firms. Finally, Baik (2006) argues that firms experiencing financial distress appear to suffer from self-selection by analysts. Accordingly, I also control for losses.

Using count-data in the dependent variable, I follow Rock et al. (2000) and use the standard negative binomial distribution to estimate regression models 2(a) through 2(c):

9 This argument recognizes that analysts announce expected earnings as their forecast. Even if analysts' forecasts are biased (say, optimistically), there is no reason to believe that their bias depends on the level of cost stickiness.

Model 2(a)

$$FLLW_{it} = \beta_0 + \beta_1 STICKY_{it} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it};$$

Model 2(b)

$$FLLW_{it} = \beta_0 + \beta_1 M\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it};$$

Model 2(c)

$$FLLW_{it} = \beta_0 + \beta_1 STICKY_{i,t-1} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it};$$

where year effects and two-digit SIC code industry effects are added to all models, and:

$FLLW_{it}$ = number of analysts' earnings forecasts announced for firm i and quarter t in the month immediately preceding that of the earnings announcement;
$GROWTH_{it} = (SALE_{it} / SALE_{i,t-4})^{0.25} - 1$;
RD_{it} = Compustat #4 for firm i in quarter t divided by $SALE_{it}$; observations with no values are set equal to 0 and values are winsorized at 1; and
TV_{it} = quarterly trading volume in millions of shares.

Model 2(b) measures cost stickiness based on data from eight preceding quarters and model 2(c) uses a lagged measure of cost stickiness estimated on a prior quarter to strengthen the causality argument.

Market Tests of H3

The third hypothesis predicts that the market response to earnings surprises is weaker for firms with stickier costs than for firms with less sticky costs. To test this hypothesis, I estimate a valuation model that regresses the cumulative abnormal return on the magnitude of earnings surprise and the interaction between earnings surprise and cost stickiness, while controlling for environmental uncertainty. I use contemporaneous estimates of cost stickiness and an earlier quarter estimate in pooled cross-sectional regression models. Additionally:

Model 3(a)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it};$$

Model 3(b)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} COGS\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it};$$

Model 3(c)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} SGA\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it};$$

Model 3(d)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} M\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it};$$

Model 3(e)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} D\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it};$$

Model 3(f)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} STICKY_{i,t-1} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it};$$

where $CAR_{i,t}$ (cumulative abnormal return) is the three-trading-day cumulative value-weighted market-adjusted abnormal return surrounding the earnings announcement for firm *i* in quarter *t*, and, $D\text{-}STICKY_{i,t}$ equals -1 if $STICKY_{i,t} < 0$, and 0 otherwise.

To control for environmental uncertainty, Imhoff and Lobo (1992) use dispersion in analysts' earnings forecasts and show that firms with higher *ex ante* earnings uncertainty exhibit smaller price changes in response to earnings announcements than firms with lower *ex ante* earnings uncertainty. Dispersion in analysts' earnings forecasts is likely to capture additional aspects of earnings predictability other than those related to cost behavior. To control for broad aspects of earnings predictability, I employ both the dispersion in analysts' forecasts, *DISP*, and *VSALE* as control variables in the above models. If the coefficient estimate for the interaction variable becomes statistically significant after controlling by *DISP* and *VSALE*, then this suggests that cost behavior matters in forming investors' beliefs regarding the value of the firm. The earnings response coefficient is predicted to be weaker for firms with stickier cost behavior (i.e., $\beta_2 > 0$).

Sample Selection

The sample includes all industrial firms (SIC codes 2000–3999) from 1986 to 2005. The study is limited to industrial firms for two reasons. First, it allows examination of the effects of a potential variation in cost stickiness of the *COGS* and *SGA* cost components on the accuracy of the earnings forecasts. The homogenous structure of the profit and loss statement among industrial firms allows insights into the effects of sticky cost behavior among major cost components on the accuracy of analysts' earnings forecasts. Second, industrial firms (in contrast to utilities and other regulated industries) generally operate in competitive markets, which partially mitigates the measurement error due to a potential pricing effect, rather than to a volume effect.

The data are obtained from Compustat, I/B/E/S, and CRSP. For each firm quarter, I use the consensus forecast calculated as the average of all forecasts announced in the month preceding that of the earnings announcement. Actual earnings are taken from I/B/E/S, as they are more likely to be consistent with the forecast in treating extraordinary items and some special items (Philbrick and Ricks 1991). Following Gu and Wu (2003), I require stock prices to be at least \$3 to avoid the small deflator problem. Announcement dates are taken from Compustat rather than I/B/E/S, which has more firm quarters with missing announcement dates. In line with the model assumption, I limit the sample to firm-year observations, in which costs and sales change in the same direction. This reduces the sample size by 14.1 percent, resulting in a final sample that consists of 44,931 firm quarters for 2,520 firms.

Descriptive Statistics and Consistency with an Earlier Cost Stickiness Measure

Table 1 presents summary statistics for the relevant variables. The mean (median) value of *STICKY* is -0.0174 (-0.0111). Consistent with prior literature, the mean (median) value of *SGA-STICKY* is -0.0306 (-0.0326). Both means are negative and significant ($p < 0.01$). On average, total costs and *SGA* costs exhibit cost stickiness. The mean (median) value of *COGS* is positive, 0.0187 (0.0063). Thus, on average, *SGA* costs exhibit sticky cost behavior, while *COGS*

TABLE 1

Descriptive Statistics, Pooled over Time 1986–2005

Variables	n	Mean	Std. Dev.	Q1	Median	Q3	% Negative
STICKY	44,931	−0.0174	0.4897	−0.1551	−0.0111	0.1205	53.2
COGS-STICKY	37,521	0.0187	0.4707	−0.1564	0.0063	0.1823	48.7
SGA-STICKY	23,809	−0.0306	0.6944	−0.3870	−0.0326	0.3304	55.1
M-STICKY	44,931	−0.0117	0.2398	−0.0633	−0.0094	0.0501	54.9
FE	44,931	−0.0014	0.0382	−0.0110	0	0.0011	38.3
ABS-FE	44,931	0.0071	0.0118	0.0003	0.0011	0.0034	NA
MV	44,926	4.7037	2.1314	3.1508	4.6328	6.1997	NA
LOSS	44,931	0.1628	0.3692	0	0	0	NA
FLLW	44,931	5.5356	5.1759	2	4	8	NA
DOWN	39,415	0.5702	0.4828	0	1	1	NA
VSALE	44,926	0.1480	0.1478	0.0611	0.1026	0.1752	NA
DISP	44,931	0.0018	0.0328	0.0001	0.0004	0.0012	NA
OPLEV	44,559	0.3670	0.1819	0.2408	0.3530	0.4874	NA
SEASON	44,626	0.6111	0.4875	0	1	1	NA
GROWTH	35,864	0.0418	0.1310	0.0142	0.0247	0.0422	NA
RD	44,931	0.0482	0.0987	0	0	0.0620	NA
TV	42,029	5.3360	8.2114	1.8441	2.2254	6.1813	NA

Variable definitions for each firm i on quarter t:

FE_{it} = difference between reported earnings and the mean (consensus) forecasts announced in the month immediately preceding that of the earnings announcement, deflated by the price at the end of the prior quarter. $ABS\text{-}FE_{it} = |FE_{it}|$;

$STICKY_{it} = \log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i,\underline{\tau}} - \log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i,\bar{\tau}}$, $\underline{\tau}$, $\bar{\tau}\varepsilon\{t, \ldots, t\text{–}3\}$, where $\underline{\tau}$ is the most recent quarter with sales decrease and $\bar{\tau}$ is the most recent quarter with sales increase;

$COST_{it}$ = sales (Compustat #2) minus net earnings (Compustat #8) for firm i in quarter t;

$SALE_{it}$ = Compustat #2 for firm i in quarter t;

$COGS\text{-}STICKY_{it} = \log\left(\frac{\Delta COGS}{\Delta SALE}\right)_{i,\underline{\tau}} - \log\left(\frac{\Delta COGS}{\Delta SALE}\right)_{i,\bar{\tau}}$, $\underline{\tau}$, $\bar{\tau}\varepsilon\{t, \ldots, t\text{–}3\}$, where $\underline{\tau}$ is the most recent quarter with sales decrease and $\bar{\tau}$ is the most recent quarter with sales increase;

$COGS_{it}$ = Compustat #30 for firm i in quarter t;

$SGA\text{-}STICKY_{it} = \log\left(\frac{\Delta SGA}{\Delta SALE}\right)_{i,\underline{\tau}} - \log\left(\frac{\Delta SGA}{\Delta SALE}\right)_{i,\bar{\tau}}$, $\underline{\tau}$, $\bar{\tau}\varepsilon\{t, \ldots, t\text{–}3\}$, where $\underline{\tau}$ is the most recent quarter with sales decrease and $\bar{\tau}$ is the most recent quarter with sales increase;

SGA_{it} = Compustat #1 for firm i in quarter t;

$M\text{-}STICKY_{it}$ = difference between the mean cost function slope under upward adjustments made on quarters from t–7 through t and the mean cost function slope under downward adjustments made on quarters from t–7 through t;

MV_{it} = log of market value of equity (Compustat #61 × #14) on quarter end;

$LOSS_{it}$ = indicator variable that equals 1 if the reported earnings (Compustat #8) are negative, and 0 otherwise;

$FLLW_{it}$ = number of analysts' earnings forecasts announced for firm i and quarter t in the month immediately preceding that of the earnings announcement;

$DOWN_{it}$ = defined in Matsumoto (2002) and equals 1 if unexpected earnings forecasts are negative, and 0 otherwise;

$VSALE_{it}$ = coefficient of variation of sales measured over four quarters from t–3 through t;

$DISP_{it}$ = standard deviation of the analysts' forecasts announced for firm i and quarter t during the 30 days

(continued on next page)

TABLE 1 (continued)

prior to the earnings announcement, deflated by the stock price at the end of quarter $t-1$;

$OPLEV_{it} = \dfrac{\mathrm{SALE_{it} - COGS_{it}(Compustat\ \#\ 30)}}{\mathrm{SALE_{it}}}$, and values below 0 or above 1 are winsorized;

$SEASON_{it}$ = indicator variable that equals 1 if the change in earnings from the same quarter in the prior year (Compustat #8) is positive, and 0 otherwise;

$GROWTH_{it} = (SALE_{it} / SALE_{i,t-4})^{0.25} - 1$;

RD_{it} = Compustat #4 for firm i in quarter t divided by $SALE_{it}$. Observations with no values are taken at 0 and values are winsorized at 1; and

TV_{it} = trading volume in millions of shares.

exhibit anti-sticky cost behavior.[10] The linear nature of raw materials consumption may partially explain this disparity in cost behavior. Another potential explanation for this finding is that salaries and advertising expenses are likely to be classified as *SGA*. The cost stickiness of total costs is also in line with the negative skewness of the earnings distribution reported by Givoly and Hayn (2000) and Gu and Wu (2003). The standard deviation of *STICKY*, *SGA-STICKY*, and *COGS-STICKY* is 0.4897, 0.6944, and 0.4707, respectively, indicating considerable variation among firms' cost behavior.

Examining whether the classification of per firm cost stickiness tends to remain persistent over time, the likelihood of keeping the same cost classification (either sticky or anti-sticky) over two consecutive quarters is 72.5 percent (not tabulated). The Spearman (Pearson) correlation between *STICKY* and *M-STICKY* reported in Table 2 is 0.48 (0.45), indicating reasonable perseverance over eight quarters. Additionally, the Pearson (Spearman) coefficient between the $STICKY_{i,t-1}$ and $STICKY_{it}$ estimates is 0.43 (0.44), both significant at $\alpha = 1$ percent (not tabulated), indicating that firms' cost behavior is reasonably stable over quarters.

As expected, *STICKY* is significantly and positively correlated with both *COGS-STICKY* and *SGA-STICKY*. The correlation between *COGS-STICKY* and *SGA-STICKY* is also positive and significant, indicating a pattern in firms' cost behavior with respect to total costs and to the two cost constituents. The correlation coefficient between *STICKY* and *ABS-FE* is negative and significant, suggesting a negative relation between the cost stickiness and the absolute analysts' earnings forecast errors.

I concentrate on *SGA* costs to check the consistency of the proposed measure with the stickiness measure and results reported by Anderson et al. (2003). I estimate the stickiness of *SGA* costs using the following cross-sectional regression model for two-digit SIC code industries with at least 25 observations:

Model 4

$$\log\left[\frac{SGA_{it}}{SGA_{i,t-1}}\right] = \lambda_0 + \lambda_1 \log\left[\frac{SALE_{it}}{SALE_{i,t-1}}\right] + \lambda_2 SALEDEC_{it} \log\left[\frac{SALE_{it}}{SALE_{i,t-1}}\right] + \varepsilon_{it}$$

where $SALEDEC_{it}$ equals 1 if $SALE_{it} < SALE_{i,t-1}$, and 0 otherwise.

Anderson et al. (2003) suggest the regression coefficient estimate $\boldsymbol{\lambda_2}$ as a cost stickiness measure. I compute mean *SGA-STICKY* for two-digit SIC code industries and examine the corre-

[10] Similarly, Anderson and Lanen (2007, Table 7) report that, on average, the number of employees, labor costs, and PPE costs are anti-sticky.

TABLE 2
Correlation Coefficients

Variables	FE	ABS-FE	STICKY	COGS-STICKY	SGA-STICKY	M-STICKY	MV	LOSS
FE		0.00	0.18**	0.15**	0.09**	0.11**	0.11**	−0.16**
ABS-FE	−0.26**		−0.03**	−0.04**	−0.01	−0.01**	−0.35**	0.28**
STICKY	0.03**	−0.04**		0.48**	0.40**	0.48**	0.02**	−0.17**
COGS-STICKY	0.02**	−0.04**	0.49**		0.07**	0.32**	0.03**	−0.10**
SGA-STICKY	0.01**	−0.03**	0.43**	0.18**		0.12**	0.01	−0.08**
M-STICKY	0.04**	−0.05**	0.45**	0.36**	0.12**		0.00	−0.09**
MV	0.02**	−0.03**	0.01**	0.02**	0.00	0.01		−0.10**
LOSS	−0.04**	0.06**	−0.15**	−0.08**	−0.08**	−0.07**	−0.10**	
FLLW	0.01**	−0.03**	0.02**	0.02**	0.00	0.02	0.74**	−0.09**
DOWN	0.02	−0.03**	0.04**	0.01	0.02	0.04**	0.01	−0.05**
VSALE	−0.01	0.02**	0.00	0.01	0.00	0.00	−0.02**	0.21**
DISP	0.00	0.25**	0.01	0.00	−0.01	0.00	−0.02**	0.16**
OPLEV	0.01	0.03**	−0.02**	−0.09*	0.02*	−0.01	0.27**	−0.05**
SEASON	0.03**	−0.03**	0.21**	0.16**	0.13**	0.10**	0.09**	−0.33**
GROWTH	0.01**	−0.01**	0.03**	0.04**	0.05**	0.03**	0.08**	−0.05**
RD	−0.02**	0.03**	−0.02**	0.04**	−0.06**	−0.02**	0.09	0.29**
TV	0.02**	−0.03**	0.01	0.01	0.01	0.01	0.70**	−0.04**

Variables	FLLW	DOWN	VSALE	DISP	OPLEV	SEASON	GROWTH	RD	TV
FE	0.05**	0.02	0.03**	−0.02**	0.03*	0.28**	0.01**	0.02**	0.02**
ABS-FE	−0.33**	−0.04**	0.16**	0.24**	0.10**	−0.19**	−0.01**	−0.03**	−0.04**
STICKY	0.00	0.01	0.00	−0.03**	−0.03*	0.26**	0.02**	−0.01	0.01
COGS-STICKY	0.02**	0.02**	0.01	−0.05**	−0.08**	0.18**	0.04**	0.04**	0.00
SGA-STICKY	−0.02**	0.01	0.00	−0.02**	0.00	0.13**	0.05**	−0.04**	0.00
M-STICKY	0.01**	0.05**	0.00	0.02**	−0.02**	0.14**	0.02**	−0.03**	0.02
MV	0.76**	−0.02	−0.07**	0.13**	0.18**	0.09**	0.08**	0.14**	0.72**

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Variables	***FLLW***	***DOWN***	***VSALE***	***DISP***	***OPLEV***	***SEASON***	***GROWTH***	***RD***	***TV***
LOSS	−0.10**	−0.06**	0.25**	0.04**	−0.04**	−0.33**	−0.04**	0.15**	−0.05**
FLLW		−0.07**	−0.08**	−0.01	−0.10**	0.04**	0.03**	0.10**	0.61**
DOWN	0.02		0.04**	0.01	0.02	0.00	0.00	0.05**	0.01
VSALE	−0.14**	0.03**		0.03**	−0.04*	−0.03**	0.33**	0.09**	0.00
DISP	0.34**	0.01	0.02**		0.02**	−0.15**	−0.01**	0.01**	0.00
OPLEV	−0.07**	0.00	0.00	0.04**		−0.05**	0.05**	0.08**	0.01
SEASON	0.05**	0.00	−0.05**	−0.02**	−0.01**		0.12**	−0.06**	0.01
GROWTH	0.04**	0.00	0.34**	−0.01**	0.04**	0.12**		0.09**	0.10**
RD	0.08**	0.06**	0.19**	0.00	0.55**	−0.09**	0.12**		0.13**
TV	0.58**	0.00	0.01	0.01	−0.02	0.00	0.06**	0.18**	

**,* Significant at the 5 percent and 10 percent level, respectively.

Spearman coefficients are reported above the diagonal line and Pearson coefficients below the diagonal line.

Variable definitions are in Table 1.

lation with the estimated λ_2. In addition, I also estimate the correlation with industry-level coefficient estimates reported by Anderson and Lanen (2007, Table 6, Panel B). I note that Anderson et al. (2003) and Anderson and Lanen (2007) use a larger sample comprised of firms with and without analyst coverage and employ annual data. All correlation coefficients reported in Table 3 are positive and significant, indicating consistency between the proposed cost stickiness measure and the earlier evidence on the stickiness of SGA costs.

IV. RESULTS

H1 Results

To test whether stickier cost behavior results in less accurate analysts' earnings forecasts, Table 4 presents the mean and median absolute analysts' earnings forecast errors contingent on sticky ($STICKY < 0$) versus anti-sticky ($STICKY \geq 0$) cost classification. The mean absolute error for firms with sticky cost behavior is 0.0080, whereas that for firms with anti-sticky cost behavior is 0.0060. Thus, forecasts for firms with anti-sticky cost behavior are, on average, more accurate by 25 percent = (0.0080 − 0.0060)/0.0080 than forecasts for firms with sticky cost behavior. The difference is statistically significant ($p < 0.05$). If accurate earnings forecasts are valuable for capital market participants, then the difference is economically meaningful.

Table 5 presents coefficient estimates for the regression models. The coefficient on *STICKY* in model 1(a) is −0.0108, and is statistically significant ($p < 0.001$).[11] The coefficient on *COGS*-

TABLE 3

Correlation Coefficients between Industry Estimates of Cost Stickiness

Variables	Mean $SGA\text{-}STICKY_j$	$\hat{\lambda}_{2,j}$	Anderson-Lanen Coefficient
Mean $SGA\text{-}STICKY_j$		0.562**	0.345**
$\hat{\lambda}_{2,j}$	0.485**		0.467**
Anderson-Lanen Coefficient	0.463**	0.365**	

** Significant at the 5 percent level.

The table presents Spearman (Pearson) coefficients above (below) the diagonal line between three estimates of cost stickiness measured at the two-digit SIC code level: *SGA-STICKY*, an estimate based on a measure suggested by Anderson et al. (2003) and estimates reported by Anderson and Lanen (2007).

Mean $SGA\text{-}STICKY_j$ is the mean value of *SGA-STICKY* across all sample observations at the two-digit SIC code level, j = 20 to 39.

$\hat{\lambda}_{2,j}$ is the coefficient estimate from estimating the regression of the following model using all sample observations at the two-digit SIC code level, j = 20 to 39.

Model 4:

$$\log\left[\frac{SGA_{i,t}}{SGA_{i,t-1}}\right] = \lambda_0 + \lambda_1 \log\left[\frac{SALE_{i,t}}{SALE_{i,t-1}}\right] + \lambda_2\, SALEDEC_{i,t} \log\left[\frac{SALE_{i,t}}{SALE_{i,t-1}}\right] + \varepsilon_{i,t}$$

where $SALEDEC_{i,t}$ equals 1 if $SALE_{i,t} < SALE_{i,t-1}$, and 0 otherwise. $SGA_{i,t}$ is Compustat #1 and *SALE* is Compustat #2.

Anderson-Lanen Coefficients are taken for the respective two-digit SIC code industries from Anderson and Lanen (2007, Table 6, Panel B).

[11] Consistent with the perception of costs as sticky if firms incur disproportionate costs when activity levels decrease, results from an additional regression analysis (untabulated) indicate that cost stickiness boosts absolute earnings forecast errors more when activity levels decrease than when they increase.

TABLE 4

Absolute Forecast Errors (*ABS-FE*) for Firms with Sticky versus Anti-Sticky Cost Behavior

Cost Behavior	Mean	Median	n
Sticky Costs: $STICKY_{it} < 0$	0.0080	0.0012	23,915
Anti-Sticky Costs: $STICKY_{it} \geq 0$	0.0060	0.0010	21,016
Difference	0.0020**	0.0002[a]	

** Significant at the 5 percent level.

[a] Mann-Whitney test indicates a significant difference between the medians at the 5 percent level.

STICKY in model 1(b) is −0.0100, and is statistically significant ($p < 0.001$). The coefficient on *SGA-STICKY* in model 1(c) is −0.0055, statistically significant at $p < 0.002$. Adjusted R^2 values for the regressions vary from 7.5 percent to 17.6 percent. The results support H1, indicating that stickier cost behavior is associated with lower accuracy of analysts' earnings forecasts.

As for the control variables, results for *MV* and *LOSS* are generally consistent with expectations, indicating a positive and significant relationship between the amount of available firm-specific information and forecast error. The coefficient estimate on *DOWN* is insignificant across the regression models, possibly due to differences among analysts in the underlying costs, earnings models, and access to management information: a large number of analysts covering a firm can proxy variation in the underlying costs and profits models, resulting in considerable noise. As expected, the findings for *DISP* and to a limited extent for *VSALE* indicate a positive and significant association between the absolute magnitude of the forecast errors and the uncertainty in the firm's environment of operations and earnings predictability.

OPLEV is positively associated with *ABS-FE*, indicating that operating leverage increases the analysts' earnings forecast errors. The seasonal effect, *SEASON*, is insignificant across the regression models, indicating that analysts recognize the seasonal effect and adjust their forecasts accordingly.

Results for two sensitivity models 1(d) and 1(e) are also reported in Table 5 and provide further insights into additional aspects of the relationship between cost behavior and the accuracy of analyst earnings forecasts. First, I examine the sensitivity of the results to estimating cost stickiness over a longer time period. Accordingly, *M-STICKY* measures cost stickiness based on cost responses over eight quarters. Regression results for model 1(d) indicate a statistically significant negative coefficient on *M-STICKY*, −0.0073 ($p = 0.019$). The result supports H1.

Second, I examine whether past (rather than current) managerial discretion affects the hypothesized relationship. I check whether the regression coefficient estimates are sensitive to discretionary choices made by managers in quarter $t-1$ or earlier by replacing $STICKY_{it}$ in model 1(a) with the cost stickiness measure estimated on quarter $t-1$, $STICKY_{i,t-1}$, which excludes all managerial choices made in quarter t.

Estimating regression model 1(e), the coefficient estimate on $STICKY_{i,t-1}$ is −0.0040 ($p = 0.030$). The negative and significant coefficient estimate indicates that stickier cost behavior observed in a preceding quarter is associated with higher absolute analysts' forecast errors. I conclude that cost stickiness estimated by analysts on a preceding quarter affects the accuracy of the earnings prediction.

Additionally, I examine the incremental effect of *STICKY* over earnings volatility, which is likely to be an all-inclusive noisy variable that incorporates many types of uncertainties (e.g.,

TABLE 5

Regression Coefficients of Analysts' *Absolute* Forecast Error on Cost Stickiness, Control Variables, and Two-Digit SIC-Code Industry Effects

Model 1(a)

$$ABS\text{-}FE_{it} = \beta_0 + \beta_1 STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}$$

Model 1(b)

$$ABS\text{-}FE_{i,t} = \beta_0 + \beta_1 COGS\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}$$

Model 1(c)

$$ABS\text{-}FE_{i,t} = \beta_0 + \beta_1 SGA\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}$$

Model 1(d)

$$ABS\text{-}FE_{i,t} = \beta_0 + \beta_1 M\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}$$

Model 1(e)

$$ABS\text{-}FE_{i,t} = \beta_0 + \beta_1 STICKY_{i,t-1} + \beta_2 MV_{it} + \beta_3 LOSS_{it} + \beta_4 DOWN_{it} + \beta_5 VSALE_{it} + \beta_6 DISP_{it} + \beta_7 OPLEV_{it} + \beta_8 SEASON_{it} + \varepsilon_{it}$$

Variables	Predicted Sign	Model 1(a)	Model 1(b)	Model 1(c)	Model 1(d)	Model 1(e)
Intercept	?	0.0025	0.0035	−0.0062	0.0047	0.0007
		(0.611)	(0.666)	(0.333)	(0.110)	(0.877)
$STICKY_{it}$	−	−0.0108				
		(<0.001)				
$COGS\text{-}STICKY_{it}$	−		−0.0100			
			(<0.001)			

(continued on next page)

TABLE 5 (continued)

Variables	Predicted Sign	Model 1(a)	Model 1(b)	Model 1(c)	Model 1(d)	Model 1(e)
$SGA\text{-}STICKY_{it}$	−			−0.0055		
				(0.002)		
$M\text{-}STICKY_{it}$	−				−0.0073	
					(0.019)	
$STICKY_{i,t-1}$	−					−0.0040
						(0.030)
MV_{it}	−	−0.0008	−0.0007	−0.0006	−0.0005	−0.0008
		(0.030)	(0.044)	(0.048)	(0.050)	(0.006)
$LOSS_{it}$	+	0.0082	0.0122	0.0091	0.0240	0.0095
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$DOWN_{it}$	−	−0.0008	−0.0009	−0.0025	−0.0006	−0.0013
		(0.174)	(0.133)	(0.177)	(0.101)	(0.085)
$VSALE_{it}$	+	0.0013	0.0013	0.0022	0.0030	0.0010
		(0.041)	(0.055)	(0.080)	(0.040)	(0.065)
$DISP_{it}$	+	2.2311	1.8001	4.1311	1.6001	2.2682
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$OPLEV_{it}$	+	0.0090	0.0082	0.0190	0.0090	0.0080
		(0.040)	(0.040)	(0.033)	(0.023)	(0.048)
$SEASON_{it}$	+	0.0001	−0.0001	0.0009	−0.0002	−0.0004
		(0.952)	(0.900)	(0.521)	(0.500)	(0.777)
n		32,563	27,411	16,918	27,811	27,401
Adj. R^2		0.176	0.122	0.075	0.136	0.186

p-values based on two-tailed tests are in parentheses.
Variable definitions are in Table 1.

demand uncertainty and operating leverage). Results (not tabulated) indicate that *STICKY* has an incremental effect on the accuracy of analysts' earnings forecasts above and beyond earnings volatility and the control variables. Overall, the evidence supports the hypothesis.[12]

Furthermore, evidence on the mean forecast error (as opposed to the absolute forecast error) reported in Table 6 offers insights into the validity of the assumption that analysts recognize cost behavior. Results show that the mean forecast error of firms with sticky costs is insignificantly different from that of firms with anti-sticky costs.[13] Thus, the evidence supports the assumption that analysts have at least some understanding of firms' cost behavior.

A final important consideration is that an analyst does not have the ability to reduce forecast errors caused by a dispersion of a firm's *ex ante* earnings distribution. In other words, an analyst cannot influence accuracy implied by cost stickiness because it is a firm-specific feature.[14] Therefore, an analyst cannot reduce the dispersion of the *ex ante* earnings distribution implied by cost stickiness even if she is aware of it in advance.

H2 Results

Results showing that firms with stickier cost behavior have lower analyst coverage are presented in Table 7. Findings in Panel A indicate that, on average, 5.459 analysts follow firms with sticky cost behavior while 5.622 analysts follow firms with anti-sticky cost behavior. The difference of about 3 percent is statistically significant ($p < 0.05$). Panel B reports the results of three regression models, 2(a), 2(b), and 2(c). The coefficients on $STICKY_{it}$, $M\text{-}STICKY_{it}$ and

TABLE 6

Forecast Errors (*FE*) for Firms with Sticky versus Anti-Sticky Cost Behavior

Cost Behavior	Mean	Median	n
Sticky Costs: $STICKY_{it} < 0$	−0.0016	0	23,915
Anti-Sticky Costs: $STICKY_{it} \geq 0$	−0.0012	0	21,016
Difference	−0.0004[a]	0	

[a] Insignificant at the 10 percent level.

[12] Results of further analyses also support H1. First, findings from estimating model 1 with a differential slope coefficient on negative stickiness (i.e., sticky costs) indicate a minor and marginally significant difference between the coefficients of negative and positive values of *STICKY* on *ABS-FE*. Second, checking for a potential seasonality effect, I also computed the stickiness measure using cost responses relative to the same quarter of the preceding year. These findings support H1.

[13] To see the intuition, suppose, on the contrary, that an analyst ignores cost stickiness. Consequently, her forecast will be upward biased in case of sticky costs (forecast error = reported earnings − forecast < 0) because she *under-estimates* costs on demand falls. In a similar vein, her forecast will be downward biased in case of anti-sticky costs (forecast error = reported earnings – forecast > 0) because she *over-estimates* costs on demand falls. Thus, sticky costs trigger a negative mean forecast error and anti-sticky costs trigger a positive mean forecast error (i.e., bias, not absolute forecast error).
However, results reported in Table 6 indicate that the mean forecast error is *not* significantly different for observations with sticky versus anti-sticky costs. Therefore, the data support the assumption that analysts recognize cost stickiness to some extent.

[14] Lys and Soo (1995) demonstrate that the inherent difficulty in predicting earnings is associated with large forecast errors (see also Kross et al. 1990). Alford and Berger (1999, 219) suggest a proxy for "analysts' *ability* to predict company's earnings" (emphasis added). In contrast, firm-specific sticky costs increase the *ex ante* dispersion of the firm's earnings distribution. The correlation between *STICKY* (*M-STICKY*) and this proxy (using Equation (1) in Alford and Berger 1999, 223) is −0.07 (0.04), suggesting that the two variables do not pick up the same phenomena.

TABLE 7

Association of Cost Behavior with Analyst Coverage

Panel A: Mean Number of Analysts Following Firms with Sticky versus Anti-Sticky Cost Behavior.

Cost Behavior	Mean Number of Analyst Coverage	n
Sticky Costs: $STICKY_{it} < 0$	5.459	23,915
Anti-Sticky Costs: $STICKY_{it} \geq 0$	5.622	21,016
Difference	0.163**	

Panel B: Regression of the Number of Analysts Following Firms on Cost Stickiness, Control Variables, Year Effects and Two-Digit SIC-Code Industry Effects

Model 2(a)

$$FLLW_{it} = \beta_0 + \beta_1 STICKY_{it} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it}$$

Model 2(b)

$$FLLW_{it} = \beta_0 + \beta_1 M\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it}$$

Model 2(c)

$$FLLW_{it} = \beta_0 + \beta_1 STICKY_{i,t-1} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it}$$

Variables	Model 2(a)	Model 2(b)	Model 2(c)
Intercept	0.0500	0.0448	0.0586
	(<0.001)	(<0.001)	(<0.001)
$STICKY_{it}$	0.0211		
	(0.031)		
$M\text{-}STICKY_{it}$		0.0144	
		(0.042)	
$STICKY_{i,t-1}$			0.0216
			(0.033)
MV_{it}	0.3174	0.3188	0.3171
	(<0.001)	(<0.001)	(<0.001)
RD_{it}	0.2196	0.2977	0.2633
	(<0.001)	(<0.001)	(<0.001)
$VSALE_{it}$	−0.4133	−0.5001	−0.4702
	(<0.001)	(<0.001)	(<0.001)
$DISP_{it}$	0.6735	0.6448	0.7116
	(<0.001)	(<0.001)	(<0.001)
$ABS\text{-}FE_{it}$	−0.0854	−0.0998	−0.0796
	(0.023)	(0.046)	(0.045)
$GROWTH_{it}$	−0.0067	−0.0444	0.0360
	(0.786)	(0.171)	(0.219)
TV_{it}	0.1551	0.1881	0.1776
	(<0.001)	(<0.001)	(<0.001)

(continued on next page)

Panel B: Regression of the Number of Analysts Following Firms on Cost Stickiness, Control Variables, Year Effects and Two-Digit SIC-Code Industry Effects

Model 2(a)

$$FLLW_{it} = \beta_0 + \beta_1 STICKY_{it} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it}$$

Model 2(b)

$$FLLW_{it} = \beta_0 + \beta_1 M\text{-}STICKY_{it} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it}$$

Model 2(c)

$$FLLW_{it} = \beta_0 + \beta_1 STICKY_{i,t-1} + \beta_2 MV_{it} + \beta_3 RD_{it} + \beta_4 VSALE_{it} + \beta_5 DISP_{it} + \beta_6 ABS\text{-}FE_{it} + \beta_7 GROWTH_{it} + \beta_8 TV_{it} + \beta_9 LOSS_{it} + \varepsilon_{it}$$

Variables	Model 2(a)	Model 2(b)	Model 2(c)
$LOSS_{it}$	−0.0059	−0.0055	−0.0023
	(0.094)	(0.111)	(0.188)
n	35,857	31,532	31,662
Pseudo-R^2	43.18%	45.81%	44.07%

** Significant at the 5 percent level.

The regression model was estimated using a standard negative binomial distribution because the dependent variable (*FLLW*) is count-data. The dispersion parameter was estimated by maximum likelihood. p-values are reported in parentheses. The pseudo-R^2, also named McFadden's R^2, is the log-likelihood value on a scale from 0 to 1, where 0 corresponds to the constant-only model and 1 corresponds to perfect prediction (a log-likelihood of 0).

Variable definitions are in Table 1.

$STICKY_{i,t-1}$ are positive and highly significant. Keeping in mind that lower values of *STICKY* indicate stickier cost behavior, the findings reject the null H2.[15]

As for the control variables, the coefficient estimates of *MV* and *TV* are positive and significant, in line with prior research. The coefficient estimates of the proxies for environmental uncertainty show mixed results. The coefficients of *VSALE* and *ABS-FE* are negatively and significantly associated with the analyst following, while the coefficient of *DISP* is positive and significant. The coefficients of *GROWTH* and *LOSS* are insignificant.

The coefficient estimate of *RD* is also positive and highly significant, consistent with Barth et al. (2001). To further check the robustness of the cost behavior effect, I separately examine the cost stickiness effect on analyst coverage for firms with and without R&D expenditures. Results (not tabulated) indicate that cost stickiness is significantly associated with analyst coverage for firms with and without R&D expenditures. In sum, the evidence indicates that firms with stickier cost behavior have lower analyst coverage.

Lower coverage for firms with stickier costs and more volatile earnings may seem counterintuitive if analysts strive to meet a high demand for earnings forecasts for firms that have less predictable earnings. However, the analysts' attitude toward large negative forecast errors can

[15] The analysis implicitly assumes that an equivalent effort is expended for estimating sticky and anti-sticky costs. This assumption is sensible in this context because cost stickiness is estimated from public information reported in financial statements.

partially explain their coverage preferences. Ample evidence shows substantial declines in share price following a negative forecast error (e.g., Bartov et al. 2002).[16] To some extent, analysts' short- and long-term benefits are affected by their relationships with managers of covered firms (Lim 2001). Therefore, all else being equal, analysts are likely to prefer covering firms with low *ex ante* probability of large negative forecast errors. Risk aversion reflected in a conventional concave loss-utility function captures these preferences. This interpretation implicitly assumes some disparity in risk attitude to large negative forecast errors between investors and analysts or, alternatively, that investors recognize cost stickiness to a limited extent.

H3 Results

Table 8 presents results from testing whether the market response to earnings surprises is weaker for firms with stickier cost behavior. In line with the prior literature, coefficient estimates β_1 in all regression models are positive and highly significant, indicating a positive market response to earnings surprises. The estimated coefficients for the interaction variable are positive and significant when cost stickiness relates to total costs (models 3(a) and 3(d)), but only marginally significant when cost stickiness relates to *SGA* costs (model 3(c)), and insignificant with respect to stickiness of *COGS* (model 3(b)). Additionally, results from estimating model 3(e), which uses an indicator variable for the classification of costs as sticky versus anti-sticky, support H3.

The findings suggest that investors recognize and consider cost stickiness with respect to total costs, but not the stickiness of cost components. The explanatory power in the models ranges between 1.8 percent and 2.9 percent, which is in line with prior literature (e.g., Gu and Wu 2003). To strengthen the evidence, I take a predictive rather than contemporaneous approach in estimating cost stickiness. Model 3(f) shows a lower market reaction to earnings surprises for firms with less sticky costs estimated on the preceding quarter (note that $STICKY < 0$ indicates sticky costs). Taken as a whole, the findings corroborate Banker and Chen (2006) and indicate a weaker market response to earnings surprises for firms with stickier cost behavior, supporting H3.

These results contribute to the ongoing debate on investor rationality by documenting that investors are able to process accounting information and partially infer cost behavior in a rational manner. With respect to the control variables, coefficient estimates for *DISP* are generally insignificant and coefficient estimates for *VSALE* are only marginally significant. Thus, dispersion of analysts' forecasts and variation of sales may not serve as appropriate proxies for *ex ante* earnings predictability as perceived by investors. This argument is supported by Diether et al. (2002), who interpret dispersion in analysts' earnings forecasts as a proxy for differences in opinion about the stock (e.g., due to the employment of different valuation models). While forecast dispersion may indicate different opinions or the use of different forecasting models, cost stickiness serves as a proxy for more volatile earnings due to firm-specific cost structures. Thus, the two proxies capture different aspects of earnings predictability.[17] Overall, findings indicate that investors have at least some understanding of firms' cost behavior in responding to earnings surprises.

V. A CONCLUDING REMARK

The study utilizes a managerial accounting concept, sticky costs, to gain insights into how firms' cost behavior affects (1) the accuracy of analysts' earnings forecasts, (2) analysts' selection of covered firms, and (3) the market response to earnings announcements. While implications of cost behavior are of primary interest to management accountants, this study employs a manage-

[16] Kinney et al. (2002) provide a different view, which finds considerable variation in returns for firms reporting positive or negative surprises.
[17] See Dichev and Tang (2009) and Frankel and Litov (2009) for additional aspects of earnings predictability.

TABLE 8
Effect of Sticky Cost Behavior on Stock Market's Reaction to Earnings Surprises

Model 3(a)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it}$$

Model 3(b)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} COGS\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it}$$

Model 3(c)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} SGA\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it}$$

Model 3(d)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} M\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it}$$

Model 3(e)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} D\text{-}STICKY_{it} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it}$$

Model 3(f)

$$CAR_{it} = \beta_0 + \beta_1 FE_{it} + \beta_2 FE_{it} STICKY_{i,t-1} + \beta_3 DISP_{it} + \beta_4 VSALE_{it} + \varepsilon_{it}$$

Variable	Model 3(a)	Model 3(b)	Model 3(c)	Model 3(d)	Model 3(e)	Model 3(f)
Intercept	0.0208	0.0197	0.0256	0.0355	0.0011	0.0244
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.066)	(<0.001)
FE_{it}	0.2929	0.3326	0.3636	0.3467	0.4377	0.3745
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$FE_{it}STICKY_{it}$	0.0166					
	(0.033)					
$FE_{it}COGS\text{-}STICKY_{it}$		0.0238				
		(0.141)				
$FE_{it}SGA\text{-}STICKY_{it}$			0.0089			
			(0.077)			
$FE_{it}M\text{-}STICKY_{it}$				0.0202		
				(0.038)		
$FE_{it}D\text{-}STICKY_{it}$					0.0366	
					(0.040)	
$FE_{it}STICKY_{i,t-1}$						0.0244
						(0.048)

(continued on next page)

TABLE 8 (continued)

Variable	Model 3(a)	Model 3(b)	Model 3(c)	Model 3(d)	Model 3(e)	Model 3(f)
$DISP_{it}$	0.9202	0.8333	1.0284	1.0196	1.1280	1.1017
	(0.151)	(0.095)	(0.156)	(0.640)	(0.251)	(0.233)
$VSALE_{it}$	0.0120	0.0377	0.0095	0.0111	0.0267	0.0212
	(0.048)	(0.089)	(0.090)	(0.050)	(0.055)	(0.075)
Adj. R^2	0.029	0.018	0.019	0.027	0.028	0.019
n	43,777	37,389	23,666	38,121	43,777	37,119

p-values based on two-tailed tests are in parentheses.

Variable Definitions:
CAR_{it} = cumulative market-adjusted returns (raw return minus value-weighted CRSP return) measured over three trading days surrounding earnings announcement, from the day before to the day after; and
$D\text{-}STICKY_{it}$ = -1 if $STICKY_{it} < 0$, and 0 otherwise.

Definitions of the other variables are in Table 1.

ment accounting concept for addressing research questions usually raised by financial accountants. Although such a multi-disciplinary approach has not been common in the prior literature, the findings of this study suggest that combining the perspectives of management and financial accounting can be fruitful. Further research is expected to build on this approach in exploring multi-disciplinary accountings topics. Integrating management and financial accounting research is likely to benefit both disciplines.

APPENDIX

Employing cost stickiness as a yardstick, I develop a simple two-period model to predict a relationship between the level of cost stickiness and the accuracy of analysts' earnings forecasts. The primitive model input in the first period is a set of prior beliefs on the state of the world, say demand y, which is a realization of a random variable $\tilde{y}$, drawn from a distribution function, $\Phi(y)$, with a strictly positive and symmetric density, $\phi(y)$, over the support $[\bar{y} - \lambda, \bar{y} + \lambda]$, $\bar{y} > \lambda > 0$. The second-period revenue function, $R(y)$, is assumed to be differentiable, increasing and concave.[18] Costs in the second period are modeled by:

$$C(y, \bar{y}, \alpha) = \begin{cases} f + (v + \alpha)y & \text{if } y < \bar{y} \\ f + \text{v}y + \alpha\bar{y} & \text{if } y \geq \bar{y} \end{cases}$$

f = a fixed cost of production, $f \geq 0$;
v = a variable cost per product unit, $v \geq 0$; and

[18] The revenue function depends on previously made managerial choices, like product price. See also Balakrishnan and Sivaramakrishnan (2002).

α = level of cost stickiness per product unit, $-v < \alpha < R'(\bar{y}) - v$.

The parameter α captures the level of cost stickiness in adjusting resources to changes in the activity level. If $\alpha < 0$, then costs increase *more* when activity rises than they decrease when activity falls by an equivalent amount; that is, a negative value of α indicates sticky costs. If $\alpha > 0$, then costs increase *less* when activity rises than they decrease when activity falls by an equivalent amount; that is, a positive value of α indicates anti-sticky costs. The difference between the cost of an upward activity adjustment and the cost of an equivalent downward activity adjustment depends only on α:[19]

$$[C(\bar{y}+1) - C(\bar{y})] - [C(\bar{y}) - C(\bar{y}-1)] = [v(\bar{y}+1) + \alpha\bar{y} - v\bar{y} - \alpha\bar{y}] - [v\bar{y} + \alpha\bar{y} - (v+\alpha)(\bar{y}-1)]$$
$$= -\alpha.$$

I use cost of adjustments to expand the conventional fixed-variable cost model and estimate stickiness of firms' cost functions. My approach follows Wernerfelt (1997), who shows that the magnitude of an adjustment cost drives the form of the organization, and Balakrishnan and Gruca (2008), who show that cost stickiness is greater for cost functions that relate to an organization's core competency. Rothschild (1971) models properties of convex (concave) adjustment cost structures that result in asymmetric cost functions due to the cost of producing marginal unit increases (decreases) in the activity level.

In my model, the earnings function, $\Pi(y,\alpha) = R(y) - C(y,\alpha)$, is strictly increasing in y and transforms demand y realized in the second period into earnings. The *ex ante* earnings expectations in the first period are denoted $\hat{\Pi}(\tilde{y}, \alpha)$. In the second period, the firm truly reports its realized earnings, $\Pi(y,\alpha)$.

An analyst is delegated the task of producing accurate estimates of a firm's earnings expectations and the forecast is honest, as in, for example, Ottaviani and Sorensen (2006). In the first period, the analyst announces $\hat{\Pi}(\tilde{y}, \alpha)$ as her most accurate forecast, if her error loss function is symmetric and concave (e.g., a quadratic loss function).[20] Focusing on the absolute earnings forecast error as an accuracy gauge, the proposition below proves a negative relationship between the level of cost stickiness and the mean absolute earnings forecast error. That is, higher values of α, i.e., less sticky cost behavior, result in lower mean absolute analyst forecast errors.

Proposition

$E[|\Pi(\tilde{y}, \alpha) - \hat{\Pi}(\tilde{y}, \alpha)|]$ decreases in α.

Proof

The proof is based on Jensen's inequality:

$$\text{Let FE}(y,\alpha) = \Pi(y,\alpha) - \hat{\Pi}(y,\alpha) = \begin{cases} R(y) - f - (v+\alpha)\text{y} - \hat{\Pi}(\tilde{y},\alpha) & \text{if y} < \bar{y}, \\ \text{R}(y) - f - \text{vy} - \alpha\bar{y} - \hat{\Pi}(\tilde{y},\alpha) & \text{otherwise}. \end{cases}$$

Define $y^{\#}(\alpha)$: $\Pi(y^{\#}(\alpha), \alpha) = \hat{\Pi}(\tilde{y}, \alpha)$. Thus, $FE(y, \alpha) \le 0$ for all $y \in [\bar{y} - \lambda, y^{\#}(\alpha)]$.

[19] I note that cost stickiness does not depend on the operating leverage of the firm because the fixed cost component, f, does not influence the level of cost stickiness.
[20] A discussion on the properties of a symmetric error loss function appears in Beja and Weiss (2006).

$$E[|FE(\tilde{y},\alpha)|] = \int_{\bar{y}-\lambda}^{y^{\#}(\alpha)} -\mathrm{FE}(y,\alpha)\phi(y)\mathrm{dy} + \int_{y^{\#}(\alpha)}^{\bar{y}+\lambda} FE(y,\alpha)\phi(y)\mathrm{dy} = -2\int_{\bar{y}-\lambda}^{y^{\#}(\alpha)} FE(y,\alpha)\phi(y)\mathrm{dy}$$

$$+\int_{\bar{y}-\lambda}^{\bar{y}+\lambda} FE(y,\alpha)\phi(y)\mathrm{dy} = -2\int_{\bar{y}-\lambda}^{y^{\#}(\alpha)} FE(y,\alpha)\phi(y)\mathrm{dy} > 0$$

Jensen's inequality implies $\alpha_1 \geq \alpha_2 \Rightarrow y^{\#}(\alpha_1) \geq y^{\#}(\alpha_2)$, and, $FE(y, \alpha_2) \leq \mathrm{FE}(y, \alpha_1)$ for all $y \in [\bar{y} - \lambda, y^{\#}(\alpha_2)]$.

Suppose $\alpha_1 \geq \alpha_2$. Hence:

$$E[|FE(\tilde{y},\alpha_2)|] - E[|FE(\tilde{y},\alpha_1)|] = -2\int_{\bar{y}-\lambda}^{y^{\#}(\alpha_2)} FE(y,\alpha_2)\phi(y)\mathrm{dy} + 2\int_{\bar{y}-\lambda}^{y^{\#}(\alpha_1)} FE(y,\alpha_1)\phi(y)\mathrm{dy}$$

$$= 2\left[\int_{\bar{y}-\lambda}^{y^{\#}(\alpha_2)} (FE(y,\alpha_1) - FE(y,\alpha_2))\phi(y)\mathrm{dy}\right]$$

$$-2\int_{y^{\#}(\alpha_2)}^{y^{\#}(\alpha_1)} FE(y,\alpha_1)\phi(y)\mathrm{dy} \geq 0.$$

Based on the proposition, I argue that cost stickiness is a determinant of the accuracy of analysts' earnings forecasts. Specifically, more sticky costs increase the spread of the *ex ante* distribution of earnings, which increases the *ex ante* volatility of reported earnings. For that reason the proposition motivates H1: Increased cost stickiness reduces the accuracy of analysts' consensus earnings forecasts.

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