Do Financial Analysts Recognize Firms’ Cost Behavior?

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April 2013

Abstract

This study explores whether financial analysts understand two aspects of cost behavior - cost variability and cost stickiness. Since analysts’ understanding is not directly observable, we model the process of earnings prediction to generate empirically testable hypotheses regarding analysts’ comprehension of cost variability and cost stickiness. Empirical findings suggest that analysts make systematic errors in predicting both variable costs and sticky costs, which undermine their earnings forecasts and mislead investors. Overall, the results provide evidence that analysts understand firms’ cost behavior only to a limited extent.

Keywords: cost stickiness; cost variability; analysts’ earnings forecasts; expense forecasts
JEL Code: M41, M46, G12
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1. Introduction

A wide body of literature in accounting investigates financial analysts’ predictions of earnings. Forecasting earnings, though, requires predicting both sales and expenses (Penman, 2009). A thorough understanding of firms’ cost behavior is necessary for accurately predicting expenses.1 Recent literature in management accounting has made significant strides in understanding firms’ cost behavior, which underlies earnings prediction (Banker and Chen, 2006; Weiss, 2010). Yet, Ertimur, Livnat and Martikainen (2003) decompose earnings forecast errors and report that the magnitude of expense prediction errors is, on average, twice the magnitude of sales forecast errors. This suggests that analysts’ errors in predicting expenses contribute more to earnings forecast errors than errors made in the prediction of sales. However, financial analysts’ understanding of firms cost behavior has been unexplored in the accounting literature. This study aims to address this void.

We consider analysts’ understanding of two aspects of cost behavior - cost variability and sticky costs (Anderson, Banker and Janakiraman, 2003; Balakrishnan and Gruca, 2008).2 Since analysts’ comprehension of cost behavior is not directly observable, we facilitate an empirical investigation by modeling the process of earnings prediction as

1 In an attempt to bridge the financial analyst literature with managerial accounting concepts, we use the terms ‘expense’ and ‘cost’ almost interchangeably, albeit in different contexts. Since the difference between the two terms relates to timing, we assume, without testing, that the differences offset each other over a long period of time and over a large sample.

2 A firm’s costs are characterized as sticky if the firm cuts resources when sales fall less than it increases resources when sales rise by an equivalent amount. Banker and Chen (2006) and Weiss (2010) report that sticky costs matter in predicting future earnings.
a forecast of sales and associated expenses made under favorable and unfavorable sales scenarios. We compare the magnitude of earnings forecast errors between favorable and unfavorable sales forecast errors of equivalent amounts. The model predicts that a perfect understanding of cost behavior results in equal (opposite) earnings forecast errors for favorable and unfavorable sales forecast errors of equivalent amounts. However, a systematic error in understanding cost variability or cost stickiness is likely to lead to a disparity between the magnitudes of earnings forecast errors on favorable and unfavorable sales forecast errors of equivalent amounts. This model offers new tests, which facilitate an empirical examination of whether analysts understand firms’ cost variability and cost stickiness.

We utilize a sample of 87,434 firm-quarter observations with available analyst forecasts for both sales and earnings between 1998 and 2009. Our findings suggest that analysts predict firms’ expenses with a systematic error. The systematic error in predicting expenses generates a disparity in earnings forecast errors between unfavorable versus favorable sales surprises of equivalent amounts. In portfolio tests, for instance, we find that the mean earnings forecast errors when actual sales miss the sales forecast by 1.5% to 2% are 3.07 times the mean earnings forecast errors when actual sales exceed the sales forecast by 1.5% to 2% (with opposite signs). Validating our test specifications, we find that time-series based forecast errors exhibit symmetric errors as predicted by our model, while analysts forecasts exhibit asymmetric errors. This reconfirms our proposition that the asymmetry in analysts’ forecast errors is attributable to analysts’ misunderstanding of cost behavior. Overall, the evidence is inconsistent with analysts’ perfect understanding of firms’ expense behavior.
Next, we investigate analysts’ understanding of cost variability and sticky costs. A surprising result is that analysts only partially recognize the level of cost variability. Our findings indicate that analysts under-estimate variable costs in firms with a high proportion of cost variability and over-estimate variable costs in firms with a low proportion of cost variability. We examine analysts’ recognition of sticky costs and find that analysts tend to under-estimate both sticky costs, as well as anti-sticky costs. That is, they tend to partially ignore cost stickiness. Overall, the findings suggest that analysts understand both cost variability and sticky costs only to a limited extent.

If analysts make systematic errors in predicting future earnings and investors adopt these forecasts, then a trading strategy can exploit these errors. We examine returns to a trading strategy that exploits analysts’ partial understanding of cost behavior. The strategy yields an abnormal return of up to 1.7% per quarter. We interpret this result as suggesting that analysts’ systematic errors mislead investors.

The findings contribute to the literature in several ways. First, it has long been known that understanding firms’ cost behavior is crucial for the prediction of expenses and forecasting earnings (Penman, 2009; Subramanyam and Wild, 2008; Sloan and Lundholm, 2010). Yet, our results suggest that analysts only partially understand cost variability and cost stickiness, which, in turn, introduces systematic errors in their earnings forecasts. The implication of this result is that improvements in analysts’ ability to comprehend firms’ cost behavior can enhance the accuracy of earnings forecasts. Thus, our study emphasizes the expense side as an important source of analyst earnings forecast errors.
Second, empirical accounting research has traditionally been keen to infer unobservable information. This study presents a novel model and new empirical tests, which provide a rigorous premise for the inference of analysts’ understanding of cost patterns. These tests call for future research to examine analysts’ ability to predict other determinants of expenses.

Third, Weiss (2010) argues that analysts cannot reduce the dispersion of the ex-ante earnings distribution implied by cost stickiness because more cost stickiness leads to greater earnings volatility. This leaves open the question of whether analysts understand cost stickiness. Our study extends Weiss (2010) in three ways: (i) we compare earnings forecast errors between favorable and unfavorable sales surprises of equivalent amounts, which enables us to address the open question. Results from examining earnings forecast errors conditioned on sales forecast errors drive the conclusion that analysts’ partial understanding of cost stickiness generates a systematic error in their earnings forecasts, above and beyond the earnings volatility that is mechanically induced by sticky cost structures, (ii) our findings suggest that the relationship between cost stickiness and earnings volatility reported by Weiss (2010) stems primarily from the downside (i.e., when sales miss expectations), and, (iii) importantly, we show that analysts’ partial understanding of the familiar variable costs also induces a systematic error in their forecasts.

Fourth, our findings extend Abarbanell and Lehavy (2003) and a series of subsequent studies that document an asymmetry in the unconditional cross-sectional distribution of earnings forecast errors. Our results offer a new explanation for the asymmetry documented by Abarbanell and Lehavy (2003). By looking at the distribution
of earnings forecast errors conditioned on sales forecast errors, we learn that the asymmetry in the unconditional distribution is partially driven by firms’ differential cost response to favorable versus unfavorable sales surprises. This expands our knowledge of analysts’ forecasting abilities and provides additional insights on the cross-sectional distribution of earnings forecast errors.

Finally, the profitable trading strategy indicates that investors do not adjust analysts’ earnings forecasts to correct for the systematic errors. The findings in this study merge the silos of financial and managerial accounting by integrating the impact of partial understanding of firms’ cost behavior on earnings predictions of both analysts and investors.

The study proceeds as follows. In section 2 we present the analytical model that facilitates our hypotheses and empirical examination. Our test specifications and research design are described in section 3. The data and sample selection procedure are discussed in section 4. In section 5, we present the results from our empirical analyses. The trading strategy is presented in section 6 and we summarize in section 7.

2. Hypothesis development

In this section, we model the process of predicting future earnings to facilitate an empirical investigation of analysts’ understanding of firms’ cost behavior. Since analysts’ comprehension of cost behavior is not directly observable, we develop empirically testable hypotheses. Specifically, we explore the extent to which analysts recognize cost variability and sticky costs in predicting future earnings.

Forecasting future sales and earnings is a complex task requiring several iterative steps. We presume that analysts first predict future sales and then estimate the associated
expenses. For simplicity, suppose an analyst predicts sales in two scenarios: favorable (high demand) and unfavorable (low demand). She then weighs the respective likelihood of each scenario to make her sales forecast. After the analyst completes her sales forecast, she faces the task of estimating the associated expenses in each scenario. Future expenses depend on the pre-committed resources and managers’ discretion to adjust resources in response to the sales surprises. Naturally, firms are likely to adjust resources downward when sales decline, whereas they incur increased costs of supplying rising sales.

Based on the conventional fixed-variable cost model, one would predict that if actual sales exceed sales forecast by $100 then actual expenses will also exceed predicted expenses because variable costs are largely proportional to sales. However, if actual sales are below sales forecast by $100 then actual expenses are lower than predicted expenses by an equivalent amount because variable costs are saved. We presume that financial analysts minimize squared forecast errors and announce expected sales and earnings as their forecasts. Assuming equal likelihood for the two scenarios, the magnitude of the earnings forecast errors on the two scenarios is expected to be equal (with opposite signs).

Recent studies, however, provide evidence that costs increase more when sales rise than they decrease when sales fall by an equivalent amount, i.e., costs are sticky (Anderson, Banker, and Janakiraman, 2003; Balakrishnan, Petersen, and Soderstrom, 2004; Banker, Byzalov and Chen, 2012; Banker, Byzalov, Cifci and Mashruwala, 2012; Banker, Basu, Byzalov and Chen, 2012; Chen, Lu, and Sougiannis, 2012). Again, suppose actual sales exceed sales forecast by $100 in a favorable scenario, and sales are below sales forecast by $100 in an unfavorable scenario. Even if the firm’s (absolute)
cost response differs between the two scenarios, the magnitude of the expense prediction errors are expected to be equal given an equal likelihood of both scenarios. Therefore, the magnitude of the earnings forecast errors in the two scenarios are expected to be equal.\(^3\) The equality of earnings forecast errors in the two scenarios relies heavily on the assumption that the analyst has a perfect understanding of the firm’s sticky costs. If the analyst ignores cost stickiness, she misses the sticky costs incurred by the firm when sales turn to the worse. In this case, the analyst underestimates expected expenses in the unfavorable scenario and, as a result, the expected earnings, i.e., the earnings forecast, is biased upwards.

Modeling the effect of cost behavior on future earnings, Banker and Chen (2006) show that incorporating information on cost behavior into the earnings prediction process results in more accurate earnings forecasts than other time-series models. Yet, Banker and Chen (2006) do not investigate whether financial analysts incorporate information on cost behavior in their earnings predictions.

As with any piece of relevant information, if analysts perfectly recognize firms’ cost behavior then there would be no systematic relationship between earnings forecast

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\(^3\) For instance, suppose a firm faces two scenarios with equal probabilities; sales will be $1,100 in the favorable scenario and only $900 in the unfavorable scenario. Thus, the sales forecast is $1,000. Accordingly, the firm has committed to acquire resources. Fixed costs of the acquired resources is F\(_0\)= $100, variable costs as percentage of sales are v=0.5, and the sticky costs are 20% of the sales decline (sales on the preceding period were $1,000, β=0.2). If the favorable scenario is realized then expenses are $650 = $100 + 0.5*$1,100. Yet, if the unfavorable scenario is realized then expenses are $570 = $100 + 0.5*$900 -0.2*( $900-$1,000). That is, if sales rise by $100, then the firm incurs additional variable costs of $50. However, if sales fall by $100, the firm saves only $30 due to cost stickiness. Earnings on the two scenarios are $450 and $330, respectively. If the analysts perfectly understands cost behavior then her earnings forecast is $390. The earnings forecast error on the favorable scenario is $60=$450-$390, and on the unfavorable scenario is -$60= $330-$390. Incidentally, if there were no cost stickiness for the firm, then, consistent with Weiss (2010), the absolute earnings forecast error would still be equal but smaller i.e. $50. Thus, for two scenarios with equal probabilities, the example illustrates equal magnitudes of the sales and earnings forecast errors.
errors and cost behavior. On the other hand, if analysts do not perfectly recognize either cost variability or sticky costs, then we expect to find a systematic relationship between earnings forecast errors and cost behavior. In the next sub-section, we develop a model that offers empirically testable predictions to examine analysts’ understanding of cost behavior.

2.1. Modeling the impact of understanding cost behavior on earnings forecast errors

Modeling the analyst’s prediction process, we presume that the analyst first predicts future sales and then estimates the associated expenses in the two scenarios: favorable (high demand, marked H) and unfavorable (low demand, marked L). Sales are predicted to be \( S_H \) in the favorable scenario and \( S_L \) in the unfavorable scenario. The analyst assigns a probability \( \alpha \in (0,1) \) to the unfavorable scenario and \( 1-\alpha \) to the favorable scenario and announces expected sales as her sales forecast: \( \hat{S} = \alpha S_L + (1-\alpha)S_H \). The sales forecast errors in the favorable scenario are,

\[
SFE_H = S_H - \hat{S} = S_H - [\alpha S_L + (1-\alpha)S_H] = \alpha (S_H - S_L) > 0, \tag{1}
\]

and in the unfavorable scenario,

\[
SFE_L = S_L - \hat{S} = S_L - [\alpha S_L + (1-\alpha)S_H] = -(1-\alpha) (S_H - S_L) < 0. \tag{2}
\]

We note that the relative magnitude of \( SFE_H \) and \( SFE_L \) depends on \( \alpha \). If \( \alpha = 0.5 \) then \( SFE_H = -SFE_L \).

The analyst considers the firm’s cost response in each of the two scenarios. Variable costs are those that change in proportion to changes in sales volume, whereas fixed costs are characterized as those that remain unchanged within a relevant range of sales volume. Variable costs represent the resources that are consumed in a linear
proportion to the produced volume, whereas fixed costs represent the committed resources invested to provide long-term productive capacity and thus are not expected to change with short-term volume fluctuations. This common economic interpretation of different cost components serves as a conceptual basis for modeling cost structure. If the change in costs follows this fixed-variable cost model then we present total costs in the favorable scenario as,

$$C_H = vS_H + F_0,$$  \hspace{1cm} (3)

and total costs in the unfavorable scenario as,

$$C_L = vS_L + F_0,$$  \hspace{1cm} (4)

where $v$ is cost variability measured as a percentage of sales, $0 < v < 1$. Since sales volume is not observable, we model cost variability as percentage of sales, in line with Dechow et al. (1998), Anderson et al. (2003), Banker and Chen (2006), and Weiss (2010). The fixed cost component is $F_0 > 0$, representing the cost of capacity committed in advance.

To model cost stickiness, we follow Banker and Chen (2006) by letting the sticky cost component under an unfavorable sales surprise be: $-\beta(S_{-1} - S_L)$, where $S_{-1}$ is actual sales for the previous period, $S_H > S_{-1} > S_L$, and the parameter $\beta \leq 0$ is an asymmetric percentage cost response, which is a firm-specific parameter that we infer from available public information (as detailed in the next section). In line with the notation in Anderson et al. (2003) and Weiss (2010), a negative value of $\beta$ indicates sticky costs. Thus, $-\beta(S_{-1} - S_L) > 0$ represents the additional costs incurred due to costs being sticky when actual sales are lower than the preceding period. That is, the portion of the costs $-\beta(S_{-1} - S_L)$ is no longer driven down by a decrease in sales when costs are sticky.
We consider accounting earnings, $X$, in each of the two scenarios as predicted by sales net of all costs. Under a favorable sales surprise:

$$X_H = S_H - C_H = S_H - (v_S H + F_0),$$

and under an unfavorable sales surprise:

$$X_L = S_L - C_L + \beta (S_L - S_H) = S_L - (v S_L + F_0 - \beta (S_L - S_H)).$$

If the analyst perfectly recognizes the cost parameters $v$, $F_0$, and $\beta$, then her earnings forecast is,

$$\hat{X} = \alpha X_L + (1- \alpha) X_H.$$

Substituting (5) and (6) into (7) we get

$$\hat{X} = \alpha X_L + (1- \alpha) X_H = (1-v) S_L - F_0 + \alpha \beta (S_L - S_H).$$

The earnings forecast error under a favorable sales surprise is,

$$EFE_H = X_H - \hat{X} = \alpha [(1-v) (S_H - S_L) - \beta (S_L - S_H)] > 0,$$

and under an unfavorable sales surprise is,

$$EFE_L = X_L - \hat{X} = -\alpha [(1-v) (S_H - S_L) - \beta (S_L - S_H)] < 0.$$

We note that the parameters $\alpha$, $v$, and $\beta$ influence the magnitude of both favorable and unfavorable earnings surprises. As for sales forecast errors, if $\alpha=0.5$ then $SFE_H = -SFE_L$.

To develop empirically testable hypotheses, we compare the ratio between the earnings forecast error and the sales forecast error, $EFE/SFE$, under favorable and unfavorable scenarios. We note that an earnings forecast error is the sum of sales forecast error and an expense prediction error i.e., $EFE/SFE = 1\text{–}(\text{expense prediction error/SFE})$. Thus, the ratio $EFE/SFE$ captures the direct impact of the expense prediction error on earnings forecast error per dollar of sales surprise.
\[
\frac{\text{EFE}_L - \text{EFE}_H}{\text{SFE}_L - \text{SFE}_H} = \frac{X_L - \bar{X}}{S_L - \bar{S}} - \frac{X_H - \bar{X}}{S_H - \bar{S}}
\]

(11)

\[
= [(1 - v) (S_H - S_L) - \beta (S_{-1} - S_L)] - [(1 - v) (S_H - S_L) - \beta (S_{-1} - S_L)] = 0.
\]

If the analyst correctly estimates \( \alpha \) and the cost parameters \( v, F_0 \) and \( \beta \), then equation (11) indicates that the ratio, \( \text{EFE}/\text{SFE} \), remains constant over the two scenarios. That is, the magnitudes of the earnings forecast errors under unfavorable and favorable sales surprises of equivalent amounts are equal (but with opposite signs). If the analyst fully recognizes cost behavior and the probabilities of the scenarios, then the pattern of earnings forecast errors reveals a symmetry between unfavorable and favorable earnings forecast errors that are conditioned on sales forecast errors. Hence, the ratio \( \text{EFE}/\text{SFE} \) lends itself as the primary instrument facilitating our empirical investigation of analysts’ understanding of cost behavior.

Now, suppose the analyst perfectly recognizes parameters \( v, F_0 \) and \( \beta \), but predicts the probability of the unfavorable scenario with an error. Let \( \alpha \) be the true probability of the unfavorable scenario and \( \Delta \alpha \in (-\alpha, 1-\alpha) \) be the prediction error. The analyst’s prediction of the probability of the unfavorable scenario is \( \alpha + \Delta \alpha \). The analyst sales forecast given these probabilities is:

\[
\hat{S}(\Delta \alpha) = (\alpha + \Delta \alpha)S_L + (1-\alpha-\Delta \alpha)S_H.
\]

(12)

We obtain,

\[
\text{SFE}_H(\Delta \alpha) = S_H - \hat{S}(\Delta \alpha) = (\alpha + \Delta \alpha) (S_H - S_L) > 0, \text{ and } SFE_L(\Delta \alpha) = -(1-\alpha-\Delta \alpha) (S_H - S_L) < 0.
\]

Both the sales forecast \( \hat{S}(\Delta \alpha) \) and the sales forecast errors are affected by the probability prediction error \( \Delta \alpha \). Similarly,

\[
\text{EFE}_H(\Delta \alpha) = (\alpha + \Delta \alpha) [(1-\nu) (S_H - S_L) - \beta (S_{-1} - S_L)] > 0, \text{ and }
\]
\[ EFE_L(\Delta \alpha) = -(1 - \alpha - \Delta \alpha) [(1 - \nu) (S_H - S_L) - \beta (S_{-1} - S_L)] < 0. \]

But, comparing the ratio EFE/SFE across the two scenarios,

\[
\frac{EFE_L(\Delta \alpha)}{SFE_L(\Delta \alpha)} \cdot \frac{EFE_H(\Delta \alpha)}{SFE_H(\Delta \alpha)} = \frac{x_{L} - \bar{x}(\Delta \alpha)}{x_{L} - \bar{x}(\Delta \alpha)} - \frac{x_{H} - \bar{x}(\Delta \alpha)}{x_{H} - \bar{x}(\Delta \alpha)}
\]

\[
= [(1 - \nu) (S_H - S_L) - \beta (S_{-1} - S_L)]
- [(1 - \nu) (S_H - S_L) - \beta (S_{-1} - S_L)] = 0. \quad (13)
\]

Equation (13) indicates that an error in predicting the probabilities of the two scenarios does not affect the equality of the earnings forecast errors under unfavorable and favorable sales surprises of equivalent amounts. That is, the symmetry between EFE/SFE under unfavorable and favorable sales surprises holds when the analyst predicts the probabilities of the two scenarios with an error. This result allows us to focus on analysts’ understanding of the cost parameters, rather than on the analysts’ prediction of the probabilities of the scenarios.

2.2. Hypotheses

Analysts’ ability to correctly predict firms’ cost variability has not been directly explored in the literature. Assuming that analysts perfectly recognize cost variability and sticky costs while predicting future earnings, equation (11) facilitates an empirically testable hypothesis.

**Hypothesis 1**

If analysts perfectly recognize cost variability and cost stickiness then:

*The magnitude of earnings forecast errors under unfavorable sales surprises is equal to the magnitude of earnings forecast errors under favorable sales surprises of equivalent amounts.*
If analysts perfectly recognize cost variability and cost stickiness then the first hypothesis predicts that the ratio EFE/SFE is equal for favorable and unfavorable sales surprises. A significant difference in earnings forecast errors between unfavorable sales surprises and favorable sales surprises of equivalent amounts is inconsistent with this prediction.

Next, we take a closer look at additional assumptions underlying equation (11). Particularly, we scrutinize the assumption that the analyst perfectly recognizes (i) cost variability, and (ii) sticky costs.

First, suppose that the analyst estimates cost variability with an error. Let $v$ be the true cost variability while $\Delta v \neq 0$ is an estimation error, where $-v < \Delta v < 1-v$. Hence, the analyst predicts $v + \Delta v$. The error in predicting cost variability does not affect $\hat{S}$, $SFE_H$, or $SFE_L$. Accordingly,$$
\frac{EFE_H(\Delta v)}{SFE_H} = \alpha [(1-v) (S_H - S_L) - \beta (S_{-1} - S_L)] + \hat{S} \Delta v,$$
and,
$$\frac{EFE_L(\Delta v)}{SFE_L} = -(1- \alpha) [(1-v) (S_H - S_L) - \beta (S_{-1} - S_L)] + \hat{S} \Delta v.$$ Thus, comparing the ratio EFE/SFE across the two scenarios,

$$\frac{EFE_L(\Delta v)}{SFE_L} - \frac{EFE_H(\Delta v)}{SFE_H} = \frac{X_L - \hat{X}(\Delta v)}{S_L - \hat{S}} - \frac{X_H - \hat{X}(\Delta v)}{S_H - \hat{S}} = \frac{-S \Delta v}{\alpha (1- \alpha)(S_H - S_L)} \neq 0, \quad (14)$$

Equation (14) reveals that an error in predicting cost variability, $\Delta v \neq 0$, generates a differential magnitude of earnings forecast errors between unfavorable and favorable sales surprises of equivalent amounts. In other words, predicting cost variability with an error affects the ratio EFE/SFE in a way that generates an asymmetry between
unfavorable and favorable sales surprises of equivalent amounts. The asymmetry is measured by the difference between the ratios. The following hypothesis summarizes the argument:

**Hypothesis 2**

If analysts predict cost variability with an error then:

The magnitude of earnings forecast errors under unfavorable sales surprises differs from the magnitude of earnings forecast errors under favorable sales surprises of equivalent amounts.

Second, suppose the analyst estimates cost stickiness with an error. We let $\beta$ be the true cost stickiness of the firm and $\Delta \beta$ be the error, $\Delta \beta \neq 0$. The error in predicting cost stickiness does not affect $\hat{S}$, $SFE_H$, or $SFE_L$. We obtain,

$$EFE_H(\Delta \beta) = \alpha [(1-v) (S_H - S_L) - \beta (S_{-1} - S_L)] - \alpha \Delta \beta (S_{-1} - S_L) > 0, \text{ and,}$$

$$EFE_L(\Delta \beta) = - (1 - \alpha) [(1-v) (S_H - S_L) - \beta (S_{-1} - S_L)] - \alpha \Delta \beta (S_{-1} - S_L) < 0. \text{ Thus, comparing the ratio EFE/SFE across the two scenarios,}$$

$$\frac{EFE_L(\Delta \beta)}{SFE_L} - \frac{EFE_H(\Delta \beta)}{SFE_H} = \frac{X_L - \hat{X}(\Delta \beta)}{S_L} - \frac{X_H - \hat{X}(\Delta \beta)}{S_H} = \Delta \beta \left[\frac{(S_{-1} - S_L)}{(1-\alpha)(S_H - S_L)}\right] \neq 0 \quad (15)$$

Equation (15) indicates that an error in predicting cost stickiness, $\Delta \beta \neq 0$, generates a differential magnitude of earnings forecast errors between unfavorable and favorable

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4 Continuing the example in footnote 4, suppose the analyst over-estimates cost variability, $\Delta v = 0.05$, and perfectly predicts all other parameters. Actual earnings remain unchanged: $X_L = 330$ and $X_H = 450$. But, the analyst’s earnings forecast is $390 - \hat{S} \Delta v = 390-1000 \times 0.05 = 340$. Thus, $EFE_L = 330-340 = -10$, and $EFE_H = 450-340 = +110$. Thus the asymmetry (i.e., the difference between the ratios in equation 14) is $\frac{EFE_L(\Delta v)}{SFE_L} - \frac{EFE_H(\Delta v)}{SFE_H} = \frac{-10}{-100} - \frac{+110}{100} = -1 \neq 0$.

Alternatively, suppose the analyst under-estimates cost variability by $\Delta v = -0.05$. Then the asymmetry equals $+1$.

5 In a similar vein, an error in predicting $F_0$ also distorts the earnings forecast. Therefore, if an analyst predicts the fixed costs parameter, $F_0$, with an error then $EFE_L/SFE_L \neq EFE_H/SFE_H$. Overall, an error in predicting fixed costs is a mirror image of an error in predicting cost variability.
sales surprises of equivalent amounts. The symmetry between earnings forecast errors under unfavorable and favorable sales surprises of equivalent amounts does not hold if the analyst predicts cost stickiness with an error. Overall, if an analyst is not fully aware of sticky costs, then the error in estimating cost stickiness results in a biased earnings forecast, which, in turn, affects the ratio EFE/SFE. The following hypothesis summarizes these arguments:

**Hypothesis 3**

*If analysts predict cost stickiness with an error then:*

*The magnitude of earnings forecast errors under unfavorable sales surprises differs from the magnitude of earnings forecast errors under favorable sales surprises of equivalent amounts.*

Taken as a whole, the model offers two sources for an asymmetry between the ratio EFE/SFE on unfavorable versus favorable sales surprises: errors in predicting cost variability and errors in predicting cost stickiness. If analysts do not perfectly recognize the true cost variability, $\Delta v \neq 0$, or the true cost stickiness, $\Delta \beta \neq 0$, then the results suggest an observable disparity of the earnings forecast errors conditioned on sales surprises between unfavorable and favorable sales surprises. Overall, empirical evidence of an asymmetric conditional earnings forecast errors distribution is inconsistent with analysts’ perfect recognition of firms’ cost variability and cost stickiness.

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6 We continue the example in footnote 4 assuming the analyst estimates sticky costs with an error, $\Delta \beta$, and perfectly predicts all other parameters. Specifically, the true stickiness is $\beta = 0.2$ but the analyst ignores cost stickiness, $\Delta \beta = -0.2$, and predicts $\beta + \Delta \beta = 0$. Actual earnings are: $X_L = 330$ and $X_H = 450$. Ignoring cost stickiness, the analyst’s earnings prediction is 450 on the favorable scenario and 350 on the unfavorable scenario. Her earnings forecast is 400. Thus, $EFE_L = 330 - 400 = -70$, and $EFE_H = 450 - 400 = +50$. We get $EFE_L/EFE_H - EFE_H/EFE_L = (-70/-100) - (50/100) = +0.2$, in line with equation (15).
We note here the subtle, yet important, distinction between Weiss (2010) and our study. Weiss (2010, p. 1445) shows that “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.” That is, sticky costs cause greater earnings forecast errors on both favorable and unfavorable scenarios even if analysts perfectly understand cost stickiness. Weiss (2010) argues that the absolute forecast errors in the two scenarios are expected to be equal (see example provided in footnote 3 for an illustration). Hence, the level of cost stickiness by itself does not affect the symmetry in the ratio EFE/SFE between unfavorable versus favorable sales surprises. The ratio EFE/SFE provides the means for testing analysts’ understanding of the level of firms’ cost stickiness, rather than the impact of sticky or anti-sticky cost structures on the magnitude of earnings forecast errors. Focusing on the symmetry of the ratio, thus, enables our analysis to test an important assumption that is implicit in Weiss (2010); i.e., do analysts perfectly understand cost stickiness?

In another related research, Anderson et al. (2007) estimate an earnings prediction model and find that future earnings are positively related to changes in the SG&A cost ratio in periods when revenue declines, inconsistent with the traditional interpretation of SG&A cost changes. They investigate how changes in SG&A expenses are used as fundamental signals of future performance, not whether investors understand the cost patterns underlying these expenses. Our study addresses this issue by focusing on the
understanding of cost behavior patterns by financial analysts and extends Anderson et al. (2007) by exploring whether investors are misled by analysts.\footnote{Our study also extends Gu, Jain and Ramnath (2006) by presenting plausible causes of “out-of-sync” earnings forecasts, namely, partial understanding of cost behavior.}

Also, our hypotheses should not be confused with prior documentations of an asymmetry in the unconditional distribution of earnings forecast errors. Abarbanell and Lehavy (2003) document an asymmetric distribution of earnings forecast errors and Degeorge et al. (1999) and several subsequent studies report a discontinuity in that distribution. Their approach differs from ours because we compare earnings forecast errors conditional on sales surprises.

Utilizing data on both earnings forecast errors and sale forecast errors allows us to empirically test our research hypotheses. A rejection of hypothesis 1 is inconsistent with analysts’ perfect understanding of cost behavior. Looking into specific cost patterns, the results from testing hypothesis 2 (3) will offer insights on analysts’ understanding of cost variability (cost stickiness).

3. Research design

3.1. Test of Hypothesis 1

If analysts perfectly recognize all cost parameters then Hypothesis 1 predicts symmetric (equal size) earnings forecast errors between unfavorable and favorable sales surprises of equivalent amounts. On the other hand, a significant difference in earnings forecast errors between unfavorable sales surprises and favorable sales surprises of equivalent amounts is inconsistent with analysts’ perfect understanding of cost behavior.
We test the first hypothesis using several methods. First, we create portfolios of favorable and unfavorable sales surprises of equivalent ranges. Specifically, we allocate firm-quarter observations into ten portfolios: five favorable (positive) and five unfavorable (negative) portfolios with equal-size ranges and opposite signs. We then compare the absolute value of mean earnings forecast error for the respective favorable and unfavorable portfolios (e.g., the first portfolio versus the tenth portfolio). Following equation (11), we base our empirical test on the ratio EFE/SFE. The first hypothesis predicts this ratio to have the same value for favorable and unfavorable sales surprises of equivalent amounts. Therefore, evidence of equal mean ratios in the respective portfolios is consistent with the first hypothesis.

To confirm our test specification, we present a placebo test for external validity and verify that the observed asymmetry is indeed attributable to analysts’ misunderstanding of cost behavior. To do this, we utilize a standard seasonal random walk (SRW) model for estimating sales forecasts, and compute earnings forecasts using a model employed in Banker and Chen (2006) that incorporates cost variability and cost stickiness. We expect to obtain the symmetry predicted by equation (11). Obtaining symmetry for the time-series forecasts and asymmetry for the analysts’ forecasts reconfirms our primary argument - the documented asymmetry is driven by analysts’ misunderstanding of cost behavior.

Estimation of regression models is our third approach for testing Hypothesis 1. Specifically, we get the following from substituting equations (1) and (2) in (9) and (10), respectively:

\[
EFE_H = X_H - \hat{X} = (1-\nu) SFE_H - \alpha \beta (S_{1-} S_L)], \quad (9^*)
\]
and,

\[
EFE_L = X_L - \bar{X} = (1-\nu) SFE_L + (1- \alpha ) \beta (S_1 - S_L)]. \quad (10*)
\]

Combining equations (9*) and (10*) and taking expectations we get:

\[
\hat{EFE} = (1 - \nu) \hat{SFE} \quad (16)
\]

Therefore, we estimate the following regression:

\[
EFE_{it} = \lambda_0 + \lambda_1 \text{NEG}_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it} \times \text{NEG}_{it} + e_{it} \quad (17)
\]

where,

\(EFE_{it}\) is the error in analysts’ consensus (median) earnings per share forecast (EPS) of firm \(i\) in quarter \(t\). For the purpose of testing analysts’ understanding of cost behavior, we use the earliest consensus forecast in either the first or the second month of the quarter.\(^8\)

It is computed as the actual EPS minus the consensus (median) EPS forecast deflated by share price at the beginning of the quarter. We only include firm-quarter observations that have both sales and EPS forecasts available from I/B/E/S Summary Files.

\(SFE_{it}\) is the error in analysts’ sales per share forecast. It is computed as actual sales per share minus consensus (median) sales forecast deflated by share price at the beginning of the quarter. Sales per share is computed by dividing sales with the number of common shares outstanding. We use the earliest consensus sales forecast that is available within the first two months of the quarter from I/B/E/S summary files. Consensus sales forecasts are measured in the same month as the EPS forecasts.

\(\text{NEG}_{it}\) is an indicator variable which equals 1 if \(SFE_{it}\) is negative and 0 otherwise. This variable represents conditions where actual sales are below the sales forecast (i.e., negative sales surprise).

\(^8\) We use consensus forecast in the first month of the quarter, when available. If the consensus forecast is not available in the first month of the quarter, we use the consensus forecast in the second month of the quarter.
Estimating an ordinary least squares (OLS) regression model (17) allows for a direct comparison of the errors in analysts’ earnings forecasts under favorable and unfavorable sales surprises of equivalent amounts. Specifically, the linear regression model enables us to estimate the effects of sales surprises of equivalent amounts. The coefficient $\lambda_2$ captures the direct association between analysts’ earnings and sales forecast errors, as predicted by equation (17). If actual sales exceed sales expectations then actual earnings are likely to exceed expected earnings, and vice-versa. Thus, we expect $\lambda_2 > 0$. More importantly, the coefficient $\lambda_3$ measures a potential disparity in the direct association between analysts’ earnings and sales forecast errors for unfavorable versus favorable sales surprises. If analysts perfectly recognize cost behavior then the first hypothesis predicts $\lambda_3 = 0$.

We estimate equation (17) using a pooled cross-sectional regression, including quarterly dummies, and clustering the firm-quarter observations by firm to eliminate autocorrelation and heteroscedasticity as suggested by Petersen (2009). Deflation of the earnings forecast error variable may change the shape of the underlying distribution (Durtschi and Easton, 2005 and 2009). To address this issue, we also estimate equation (17) using earnings and sales forecast errors without deflation. Using undeflated variables enables us to verify whether our results are being driven by the deflation.

Finally, prior studies have reported that the distribution of analyst earnings forecast errors is different for profit firms than for loss firms (Brown, 2001). We perform a contextual analysis to examine the robustness of our empirical evidence. We separate

---

9 We note that errors in sales forecasts are offset by errors made in forecasting expenses. Therefore, when analysts underestimate sales, they are more likely to underestimate expenses as well.

10 Cheong and Thomas (2010) report that high and low price shares exhibit similar magnitudes of analysts’ earnings forecast errors.
our sample into loss and profit firms using forecasted earnings based on the notion that forecasted earnings represent an ex-ante measure of profitability (Gu and Wu, 2003). Loss (profit) observations have negative (zero or positive) values for consensus earnings forecasts. We then estimate equation (17) for profit and loss firms separately. Again, the first hypothesis predicts that $\lambda_3=0$ in each of the two sub-samples.

3.2. Tests of Hypotheses 2 and 3

We investigate whether analysts recognize cost variability and cost stickiness in predicting future earnings based on Hypothesis 2 and 3. We utilize gross margin as a proxy for cost variability. Gross margin, $\text{MARGIN}$, is defined as sales ($\text{SALEQ}$) minus cost of goods sold ($\text{COGSQ}$) divided by sales. Firms with high gross margin are assumed to have low cost variability and vice-versa.

To examine analysts’ comprehension of sticky costs, we follow Weiss (2010) in measuring the level of firm-specific cost stickiness. This measure estimates the difference between the rate of cost decreases for recent quarters with decreasing sales and the corresponding rate of cost increases for recent quarters with increasing sales. This reflects the literal meaning of sticky costs introduced by Anderson, Banker, and Janakiraman (2003):

$$\text{STICKY}_{i,t} = \log \left( \frac{\Delta \text{COST}}{\Delta \text{SALE}} \right)_{i \tau} - \log \left( \frac{\Delta \text{COST}}{\Delta \text{SALE}} \right)_{i \bar{\tau}} \quad \tau, \bar{\tau} \in \{t, \ldots, t-4\},$$

where $\tau$ is the most recent of the last four quarters with a decrease in sales over quarters $t$ to $t-4$ and $\bar{\tau}$ is the most recent of the last four quarters with an increase in sales over the same period,

$$\Delta \text{SALE}_{it} = \text{SALE}_{it} - \text{SALE}_{it},$$

where, $\text{SALE}$ is sales revenue ($\text{SALEQ}$ from Compustat)
$\Delta \text{COST}_{it} = (\text{SALE}_{it} - \text{EARNINGS}_{it}) - (\text{SALE}_{it-1} - \text{EARNINGS}_{it-1})$, where, EARNINGS is income before extraordinary items (IBQ from Compustat).

STICKY is defined as the difference in the slope of the cost function between the most recent quarter with a sales increase and the most recent quarter with a sales decrease over quarters $t-4$ to $t$. If costs are sticky, meaning that they increase more when sales rise than they decrease when sales fall by an equivalent amount, then $\text{STICKY} < 0$. If costs are anti-sticky, meaning that they increase less when sales rise than they decrease when sales fall by an equivalent amount, then $\text{STICKY} \geq 0$.

We perform both univariate and multivariate tests to investigate analysts’ understanding of cost variability and cost stickiness. Testing Hypotheses 2, we utilize a univariate test for comparing the ratio SFE/EFE across favorable and unfavorable sales surprises in groups of observations with low cost variability (below median) versus high cost variability (above median). Similarly, testing Hypothesis 3, we compare the ratio EFE/SFE across favorable and unfavorable sales surprises in groups of observations with sticky versus anti-sticky costs.

Evidence showing that the disparity in the ratio of SFE/EFE across favorable and unfavorable sales surprises differs between observations with low versus high cost variability, is consistent with predicting cost variability with a systematic error. In a similar vein, evidence that a disparity between the ratio of SFE/EFE across favorable and unfavorable sales surprises differs between observations with sticky versus anti-sticky costs is consistent with predicting sticky costs with a systematic error.
We also estimate the following cross-sectional pooled regression model to examine our second and third hypotheses:

\[
\begin{align*}
EFE_{it} &= \lambda_0 + \lambda_1 \text{NEG}_{it} + \lambda_2 \text{DMARGIN}_{it} + \lambda_3 \text{DSTICKY}_{it} + \lambda_4 \text{SFE}_{it} + \\
&\ldots + \lambda_9 \text{SFE}_{it} \times \text{NEG}_{it} + \lambda_{10} \text{SFE}_{it} \times \text{DMARGIN}_{it} + \lambda_{11} \text{SFE}_{it} \times \text{DSTICKY}_{it} + \\
&\ldots + \lambda_{16} \text{INDROE}_{it} + \lambda_{17} \text{SUE1}_{it} + \lambda_{18} \text{SUE2}_{it} + \lambda_{19} \text{LTV}_{it} + \epsilon_{it}
\end{align*}
\]  

(18)

where,

**DMARGIN** is an indicator variable that equals one if a firm has a high (above median) MARGIN and 0, otherwise. Firms with high gross margins are assumed to have low cost variability.

**DSTICKY** is an indicator variable that equals one if the STICKY measure is negative and 0, otherwise.

**MV** is log market value of equity at the beginning of quarter t. It is computed as share price at the end of quarter (PRCCQ from Compustat) times the number of shares outstanding (CSHOQ from Compustat).

**BM** is book value of equity divided by market value of equity, both measured at the beginning of quarter t.

**LFLLW** is log number of the analysts issuing an earnings forecast in quarter t. It is obtained from the I/B/E/S Detail Files.

**LOSS** is an indicator variable which equals 1 if analysts’ consensus earnings forecast is negative and 0, otherwise.

**DISP** is the standard deviation of the earnings forecasts from IBES Summary Files divided by the share price.

**CV** is coefficient of variation for earnings per share (EPSPXQ from Compustat) over two quarters before and two quarters after quarter t. It is computed as the standard deviation of earnings per share divided by the absolute value of the mean earnings per share.

**INDROE** is industry adjusted ROE (return on equity), computed as average ROE over quarter t+1 to t+4 minus the median ROE of all firms in the same two-digit SIC industry code over the same period. Average ROE is computed as mean income before
extraordinary items (IBQ from Compustat) over t+1 to t+4 divided by mean book value of equity in quarters t+1 and t+4.

SUE1 (SUE2) is first (second) lag of unexpected earnings from a seasonal random walk model divided by share price.

LTV is the logged sum of trading volume from CRSP over the 12 months prior to the month in which the earnings forecast is made.

In equation (18), the coefficient $\lambda_4$ measures the relationship between SFE and EFE. It measures the direct association of sales forecast errors with earnings forecast errors. We expect $\lambda_4$ to be positive and significant. The interaction term SFE*NEG captures an asymmetry in this association between observations with unfavorable sales surprises and observations with favorable sales surprises. A significant coefficient estimate of this interaction term is inconsistent with the first hypothesis.

Testing Hypothesis 2, we focus on firms with high cost variability. The coefficient estimate of SFE*DMARGIN indicates the incremental level of association between sales forecast errors, SFE, and earnings forecast errors, EFE, for firms with high cost variability. The coefficient estimate of the triple interaction SFE*NEG*DMARGIN indicates the incremental asymmetry generated by firms with high cost variability. In line with Hypothesis 2, we follow equation (14) and interpret a significant coefficient estimate of the triple interaction SFE*NEG*DMARGIN as partial understanding of cost variability. That is, Hypothesis 2 predicts that if analysts predict cost variability with a systematic error then $\lambda_8 \neq 0$. In similar vein, we follow equation (15) and interpret a significant coefficient estimate of the triple interaction SFE*NEG*DSTICKY as partial understanding of cost stickiness. As before, Hypothesis 3 predicts that if analysts predict cost stickiness with a systematic error, then $\lambda_9 \neq 0$. 

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Following extant literature, we utilize control variables that can potentially affect earnings forecast errors. Wu (1999) suggests that analysts have stronger incentives to issue optimistic forecasts for smaller firms to facilitate management communication as there is less public information for these firms. Hence, we use market capitalization (MV) as a control for firm size. We expect a positive coefficient on size. Doukas et al. (2002) show that the book to market ratio is negatively related to analysts’ earnings forecast errors. Hence, we control for the book-to-market (BM) ratio which reflects growth opportunities of a firm. Greater analyst following might increase the competition between analysts inducing them to issue more optimistic forecasts. On the other hand, it is often the case that larger firms have more analyst following (Gu and Wu, 2003). Accordingly, we include the log of the number of analysts in quarter t (LFLLW) as a control variable, but we do not have a prediction for the effect of analyst following. Several studies suggest that managers have different incentives to manage losses than profits. These studies show that most of the analyst forecast bias documented in the literature is driven by loss firms (Gu and Xue, 2001). We define losses based on forecasted earnings as per Gu and Wu (2003) and expect a negative sign on loss. Das et al. (1998) suggest that when earnings are more difficult to predict, analysts are more likely to make optimistic forecasts. We utilize analyst forecast dispersion to control for earnings uncertainty and expect a negative sign on it. As an additional proxy for earnings uncertainty, we include the coefficient of variation of earnings per share as per Gu and Wu (2003) and expect a negative sign on it. Firms with good future prospects are less subject to selection bias-induced optimism (Francis and Willis, 2000). Hence, we include INDROE, industry adjusted lead ROE to control for this selection bias and expect a positive sign on it. SUE1
and SUE2 are first and second lags of unexpected earnings from a seasonal random walk model deflated by price. We include these variables to control for analyst underreaction to recent information and expect a positive sign on both. LTV is log of trading volume over past 12 months. We expect a negative sign on this coefficient as trading volume provides greater incentives to issue optimistic forecasts (Hayes, 1998).

4. Sample

We use firm-quarter observations from 1998 to 2009 that have consensus forecasts and actual reports for both sales and earnings available in the first or second month of the quarter from I/B/E/S Summary Files. Share prices at the beginning of the quarter and other balance sheet and income statement data are obtained from Compustat. We base our analyses on analysts’ forecasts announced during the first two months of each quarter to reduce the impact of earnings guidance and earnings management. We delete extreme observations in the top and bottom 1% of deflated and undeflated earnings, sales and expense per share forecast errors. We delete firm-quarter observations with negative sales or negative total expenses. We also delete firm-quarter observations where SFE is zero as we use it as a denominator in the EFE/SFE ratio. 11 Our sample period starts in 1998 because quarterly sales forecasts are rare before 1998. We obtain the data from I/B/E/S and Compustat 2011 files that extend until 2010. Our sample ends in 2009 because calculation of some of the control variables in equation (18) requires one year-ahead data.

11 We replicate all the regression analyses including observations with SFE=0. The spirit of all our results is unchanged.
There are 87,434 firm-quarter observations in our sample. The STICKY variable is available for 58,679 of these observations.

Descriptive statistics of our sample are presented in Table 1. Panel A presents the deflated forecast errors. The mean earnings forecast error is -0.0015 (\(p\)-value<0.001), suggesting that, on average, the analysts’ earnings forecasts are biased. This bias is consistent with prior literature (e.g., Abarbanell and Lehavy, 2003; Gu and Wu, 2003). The mean sales forecast error is -0.0003 and insignificant (\(p\)-value=0.12), which suggests that analysts’ sales forecasts are, on average, unbiased. We obtain the implied expense forecast errors using the sales and earnings forecast errors (\(XFE = SFE - EFE\)). The mean expense forecast error is 0.0012 and highly significant (\(p\)-value<0.001). Between the two components, it is the expense forecast errors that contribute more to analysts’ earnings forecast errors than the sales forecast errors (\(p\)-value<0.001). These findings are consistent with Ertimur et al. (2003). These results suggest that expense prediction errors are influential in the process of forecasting earnings.

Statistics reported in Panel B document the undeflated forecast errors. The mean undeflated earnings forecast error is also negative (-0.0094) and highly significant (\(p\)-value<0.001). On average, actual expenses exceed forecasted expenses (0.0478, \(p\)-value<0.001), and actual sales exceed forecasted sales (0.0385, \(p\)-value<0.001). We note that the mean expense prediction error is larger than the mean sales prediction error (-0.0094 = 0.0385 - 0.0478, \(p\)-value<0.001). Overall, the descriptive statistics indicate that expense prediction errors influence the errors in earnings forecasts, above and beyond the sales forecasts. Altogether, these statistics suggest that our sample characteristics are in line with those reported in the literature.
Panel C presents the descriptive statistics for MARGIN, STICKY and NEG. The mean and median value of STICKY is -0.0370 and -0.0262, suggesting that on average, costs are sticky. The mean value of NEG is 0.4466, suggesting that 44.66% firm quarters have unfavorable sales surprises, while the rest have favorable sales surprises.

5. Empirical results

5.1. Results from testing Hypothesis 1

5.1.1. Portfolio test results

We start by plotting analysts’ earnings forecast errors for favorable and unfavorable sales surprises. Figure 1 presents the mean values of earnings forecasts errors for 20 portfolios formed based on the distribution of sales forecast errors, SFE, each quarter. For example, the bottom 5% of observations are allotted to portfolio 1, and the top 5% are allotted to portfolio 20. The mean earnings forecast error for the left-most portfolio is -0.0161, while it is 0.0030 for the right-most portfolio. Thus, the absolute value of earnings forecast errors in the left-most portfolio is 5.3 times larger than those in the right-most portfolio. Indeed, the right tail is almost flat, while the left tail has a steep downward slope. This striking result indicates a substantial asymmetry in earnings forecast errors conditioned on sales surprises.

Table 2 presents the sales and earnings forecast errors for equal ranges of favorable and unfavorable sales surprises. The mean absolute values of earnings forecast errors, EFE, are significantly larger for unfavorable sales surprise portfolios than those for the respective favorable sales surprise portfolios. The absolute value of mean earnings
forecast errors is 4.67 ($=0.0098/0.0021$) times larger in portfolio 1 than in portfolio 10, 3.07 ($=0.0043/0.0014$) times larger in portfolio 2 than in portfolio 9, 3.5 ($=0.0035/0.0010$) times larger in portfolio 3 than in portfolio 8, and 2.75 ($=0.0022/0.0008$) times larger in portfolio 4 than that in portfolio 7. That is, four out of the five portfolio comparisons indicate significantly greater magnitude of earnings forecast errors for unfavorable sales surprises than for favorable sales surprises of comparable amounts.\footnote{We also form portfolios based on undeflated sales forecast errors instead of deflated forecast errors. We find that, similar to the results with deflated forecast errors, the mean earnings forecast errors for the left tail portfolios, 1, 2, 3, and 4 are significantly greater than those in the right tail portfolios, 10, 9, 8, and 7 respectively.}

The last column in Table 2 presents the mean EFE/SFE ratio for each portfolio and the differences between left tail and right tail portfolios. The mean ratio for portfolio 1 is 0.1932 whilst that for portfolio 10 is 0.0615. Hence, the mean ratio is 3.14 ($=19.32/6.15$) times larger for portfolio 1 than for portfolio 10, suggesting that the ratio is much larger for unfavorable sales surprises than for equivalent favorable sales surprises. Similarly, four out of five portfolios (portfolio 1, 2, 3, 4) in the left tail are significantly larger than those in the right tail (portfolios 7, 8, 9, 10) at the 1% level. These findings indicate greater values for the ratio EFE/SFE for unfavorable sales surprises than for favorable sales surprises of equivalent amounts.\footnote{As an exception, portfolio 5 (left tail) has a significantly smaller mean EFE/SFE ratio than that for portfolio 6 (right tail). The two portfolios in the center of the distribution have small denominators (range is [0, +0.005] and [-0.005, 0], respectively), which likely drives this result.}

To confirm the validity of our test specifications, we present results from a placebo test based on time-series forecast errors. Specifically, we utilize a standard seasonal random walk (SRW) model for estimating sales forecasts and compute earnings
forecasts using a model employed by Banker and Chen (2006)\textsuperscript{14} that incorporates cost variability and cost stickiness. Results reported in the right column in Table 2 indicate that the differences in the ratio between favorable and unfavorable sales surprises are not significant in any of the portfolio pairs, in line with the prediction in equation (11). This is in sharp contrast to the significant differences that we find between the corresponding portfolios obtained using analyst forecasts. These findings provide external validity for our test specifications and suggest that the asymmetry in the ratio of EFE/SFE in analyst forecasts is attributable to their partial understanding of cost behavior.\textsuperscript{15}

Overall, the evidence in Table 2 shows a greater magnitude of earnings forecast errors when sales miss expectations than when sales beat expectations by an equivalent amount. This evidence is inconsistent with Hypothesis 1, suggesting that analysts do not perfectly understand cost behavior.

5.1.2. Regression results

The regression coefficients from estimating equation (17) are presented in Table 3. The first two columns report the results with deflated forecast errors. The coefficient estimate of SFE is 0.0884 (\textit{p-value}<0.01), suggesting that, on average, there is a positive association between analysts’ earnings forecast errors and sales forecast errors. In the second column we present the results including the interaction term SFE*NEG in the

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
Variable & Coefficient & \textit{p-value} \\
\hline
SFE & 0.0884 & <0.01 \\
SFE*NEG & -0.0563 & <0.05 \\
\hline
\end{tabular}
\caption{Regression results for equation (17).}
\end{table}

\textsuperscript{14} For brevity, we do not provide details of the procedure of estimating earnings forecasts which incorporate cost variability and cost stickiness. The details can be obtained from Banker and Chen (2006).
\textsuperscript{15} The evidence indicates that analysts’ positive (negative) earnings forecast errors are more frequently accompanied by positive (negative) sales forecast errors than time series forecast errors. Therefore, negative values of EFE/SFE obtained due to opposite error signs reduce the value of the mean ratio for time series errors relative to the corresponding mean ratio for analysts' forecast errors.
regression. The coefficient estimate of SFE under favorable sales surprises is only marginally significant (0.0064; \(p\text{-value}\) <0.10). The coefficient of the interaction term, SFE*NEG, is positive and significant (0.1889; \(p\text{-value}\) <0.01). That is, the association between SFE and EFE under unfavorable sales surprises is significantly different from the association between these two variables under favorable sales surprises. This significant difference suggests that unfavorable sales surprises lead to greater earnings forecast errors than favorable sales surprise of equivalent amounts, which is inconsistent with Hypothesis 1. Also, the addition of the interaction term leads to an increase in the explanatory power of our tests. The adjusted-\(R^2\) in the first column is 0.0620, while it is 0.1056 in the second column.

Checking the sensitivity of the evidence to the deflation of variables, the third and fourth columns in Table 3 present results from estimating equation (17) using undeflated forecast errors (both SFE and EFE). In column III, the association between SFE and EFE without the interaction term is 0.0410 (\(p\text{-value}\) <0.01). When the interaction term SFE*NEG is added to the regression model, results reported in column IV show that the coefficient of SFE is 0.0085 (\(p\text{-value}\) <0.01) and the coefficient of the interaction term, SFE*NEG, is 0.0779 (\(p\text{-value}\) <0.01). Again, the association between SFE and EFE under unfavorable sales surprises is significantly different from the association under favorable sales surprises. The evidence indicates a greater magnitude of earnings forecast errors when sales miss expectations than when sales beat expectations by an equivalent amount, which is inconsistent with Hypothesis 1.

[ Table 3 about here ]
We perform a contextual analysis to examine the robustness of these results to profit and loss observations. Results from estimating equation (17) for a sub-sample of profitable observations are presented in Panel A of Table 4. The estimated coefficient of the interaction term, \( \text{SFE*NEG} \), is positive and significant for deflated variables (0.1610, \( p\text{-value} < 0.01 \)) as well as for undeflated variables (0.0678, \( p\text{-value} < 0.01 \)). The findings for profitable observations show asymmetric analysts’ earnings forecasts errors under favorable sales surprises compared to unfavorable sales surprises of equivalent amounts.

Results from estimating equation (17) for a sub-sample of loss observations are presented in Panel B of Table 4. Analysts forecast losses for only 14,331 observations (16.39\% of the sample). Again, the estimated coefficient of the interaction term, \( \text{SFE*NEG} \), is positive and significant for deflated variables (0.2220, \( p\text{-value}<0.01 \)) and for undeflated variables (0.1493, \( p\text{-value}<0.01 \)). Hence, the findings for loss observations also reveal significantly greater earnings forecast errors in the presence of unfavorable sales surprises than in the presence of favorable sales surprises of equivalent amounts.\(^{16}\)

[ Table 4 about here ]

Taken as a whole, the empirical evidence indicates a greater magnitude of earnings forecast errors when sales miss expectations than when sales beat expectations by an equivalent amount, which is inconsistent with Hypothesis 1. We conclude that Hypothesis 1 is rejected. The empirical evidence is inconsistent with analysts’ perfect recognition of cost behavior.

5.1.3. Tests of Hypotheses 2 and 3

\(^{16}\)We obtain similar results when we use actual earnings to determine profit and loss observations.
We present the results from univariate and multivariate tests of hypotheses 2 and 3 examining analysts’ understanding of cost variability and cost stickiness. Our tests of the second hypothesis build on equation (14). Specifically, Panel A of Table 5 presents the mean and median ratios of EFE/SFE for subsamples with high and low cost variability observations, each split into subsamples of favorable and unfavorable sales surprises. The bottom row shows the difference in the ratio under unfavorable versus favorable sales surprises. The mean difference in the ratio between favorable and unfavorable sales surprises for low cost variability observations is -0.2491 (p-value<0.01). The mean difference in the ratio between favorable and unfavorable sales surprises for high cost variability observations is 0.0540 (p-value<0.01). The difference between these two differences in means is significant at the 1% level. The medians reveal a similar pattern. The results indicate that the difference in the ratio EFE/SFE between unfavorable and favorable sales surprises significantly depends on the extent of cost variability, in line with Hypothesis 2. The evidence suggests that analysts predict cost variability with a systematic error.

There is another compelling insight here. The evidence indicates a positive and significant difference in the mean ratio EFE/SFE between unfavorable and favorable sales surprises for high cost variability firms, 0.0540. From equation (14), this positive difference implies that $\Delta v<0$, suggesting that analysts under-estimate cost variability when cost variability is high (see footnote 6 for an example). In contrast, the evidence indicates a negative and significant difference in the ratio EFE/SFE between unfavorable and favorable sales surprises for low cost variability firms, -0.2491. Based on equation (14), this negative difference implies $\Delta v>0$, suggesting that analysts over-estimate cost
variability when cost variability is low. Overall, the evidence suggests that analysts tend to predict the cross-sectional mean level of cost variability, rather than incorporate available firm-specific information on cost variability into their earnings forecasts. We interpret this evidence as inconsistent with analysts’ full understanding of firms’ cost variability.

We follow a similar path with respect to examining analysts’ prediction of sticky costs. Our tests for hypothesis 3 build on equation (15). Specifically, Panel B of Table 5 presents the mean and median ratio of EFE/SFE for subsamples of sticky and anti-sticky costs firms. The bottom row shows the difference in the ratio under unfavorable and favorable sales surprises. The mean difference in the ratio for sticky costs firms (0.1522, \textit{p-value}<0.01) is significantly greater than the mean difference in the ratio for anti-sticky costs observations (-0.3588, \textit{p-value}<0.01) at the 1% level. The medians reveal a similar pattern. The results indicate that the difference in the ratio EFE/SFE between unfavorable and favorable sales surprises significantly depends on the extent of cost stickiness, in line with Hypothesis 3. Based on equation (15), the evidence suggests that analysts predict sticky costs with a systematic error.

Equation (15) implies that, on average, $\Delta \beta > 0$ for sticky costs observations and $\Delta \beta < 0$ for anti-sticky costs observations (see footnote 6 for an example). Keeping in mind that a greater negative value for $\beta$ expresses more sticky costs, the evidence suggests that analysts under-estimate cost stickiness for observations with sticky costs. That is, analysts predict $\beta$ with a positive error, meaning that their predicted costs are less sticky than actual costs. On the other hand, analysts also under-estimate anti-stickiness for observations with anti-sticky costs. That is, analysts predict $\beta$ with a negative error
meaning that the predicted costs are less anti-sticky than actual costs. The evidence suggests that analysts tend to estimate $\beta$ closer to zero even when the actual level of $\beta$ is either negative (sticky) or positive (anti-sticky). The results are consistent with the interpretation that analysts partially ignore both sticky costs and anti-sticky costs. Overall, the evidence suggests that analysts’ understand sticky costs only to a limited extent.

[ Table 5 about here ]

Next, we present the results from estimating a multivariate regression equation (18) in Table 6. The first two columns present the results using deflated forecast errors, while the third and fourth columns present the results using undeflated forecast errors. In columns I and III we do not include the control variables, whereas in columns II and IV we present coefficient estimates for the full model. In column I, the coefficient estimate of SFE is 0.0156 (p-value<0.05) suggesting a positive association between earnings forecast errors and sales forecast errors. The coefficient estimate of SFE*NEG is positive and significant, 0.0522 (p-value<0.01). That is, the magnitude of earnings forecast errors is, on average, significantly greater when actual sales miss expectations than when actual sales beat expectations by equivalent amounts. This result does not support the first hypothesis and reconfirms our earlier findings.

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17 Our variable choice for this regression model results in a smaller sample for three reasons. First, computations of STICKY and DSTICKY require data availability in quarters t-4 through t, computation of INDROE requires data availability on quarters t+1 through t+4, computation of SUE2 (SUE1) requires data availability on quarters t-6(t-4), and computation of LTV requires trading volume data availability 12 months prior to the forecast announcement date. Second, computing DISP requires at least three forecasts. Third, we follow Weiss (2010) in excluding observations with opposite cost responses in computing STICKY (i.e., cost increases when sales miss expectations or cost decreases when sales exceed expectations). As a result, the sample size reduces from 87,434 firm-quarter observations to 48,207 firm-quarter observations.
Testing the Hypothesis 2, the coefficient estimate of SFE*NEG*DMARGIN is 0.0446 (p-value<0.05) suggesting an incremental asymmetry generated by firms with high cost variability. In line with Hypothesis 2, we interpret a significant coefficient estimate of the triple interaction SFE*NEG*DMARGIN as analysts’ prediction of cost variability with a systematic error.

We test Hypothesis 3 in a similar way. The coefficient estimate of SFE*NEG*DSTICKY is 0.0853 (p-value<0.01) suggesting an incremental asymmetry generated by firms with high cost stickiness. Consistent with Hypothesis 3, we interpret a significant coefficient estimate of the triple interaction SFE*NEG*DSTICKY as analysts’ prediction of cost stickiness with a systematic error.

Column II presents the results when we include the control variables. The direction of the results is similar, suggesting that analysts predict cost variability and cost stickiness with a systematic error. The coefficient estimates of the control variables are generally significant and in the expected direction. LTV (MV), though, has a positive (negative) sign in contrast to our expectation of a negative (positive) sign. Also, LOSS and INDROE do not have any significant associations with earnings forecast errors. Thus, the addition of control variables does not alter our conclusions. Columns III and IV report the results from replicating the analyses with undeflated forecast errors, which support our earlier conclusions.

[ Table 6 about here ]

Several robustness checks corroborate these findings. First, we utilize EFE/SFE as the dependent variable to offer an alternative empirical specification for testing the models in equations (11), (14), and (15). Thus, we replace EFE with EFE/SFE as the
dependent variable in estimating equation (18), while removing SFE from the right-hand side. We find (not reported) that the coefficient estimates of NEG*DMARGIN and NEG*DSTICKY remain positive and significant at the 1% level.

Second, we perform a sensitivity check (not reported) to consider the robustness of our findings to data availability restrictions imposed by the STICKY measure. We utilize a substitute cost stickiness measure suggested by Weiss (2010) that is based on financial information reported in the past eight quarters, t-7 through t. Cost stickiness is then measured as the difference in the mean slope under downward adjustments and the mean slope under upward adjustments made over the past eight quarters. The tenor of our evidence is not altered using this alternative specification. Third, we replicate the analyses using consensus analyst forecasts in all three months of the quarter instead of the first two months. Our findings are essentially the same.

Taken as a whole, the empirical evidence suggests that financial analysts understand firms’ cost behavior only to a limited extent. The evidence suggests that analysts make systematic errors in the estimation of firms’ cost variability and cost stickiness. Predicting cost parameters with systematic errors generates a systematic bias in earnings forecasts announced by analysts.

6. Trading strategy

The accounting literature frequently employs analysts’ earnings forecasts as a proxy for investors’ expectations of future earnings (Kothari, 2001). If analysts make systematic errors in incorporating information on cost behavior in the process of predicting future earnings, then investors may be misled by biased earnings forecasts. Assuming that
market expectations of future earnings echo analysts’ earnings forecasts, a trading strategy can profitably exploit these errors. Particularly, analysts’ systematic errors in the estimation of firms’ cost variability and cost stickiness, which generate a systematic bias in earnings forecasts, calls for a profitable trading strategy. Therefore, we test the ability of portfolios formed on the cross-sectional distribution of cost variability and cost stickiness to predict future abnormal stock returns.

The idea underlying the strategy is to employ available information on cost variability and cost stickiness to project future abnormal returns. Sticky costs reflect a slow adjustment of resources in response to changes in sales. The literature reports that adjustment costs (Anderson et al., 2003) and managers’ reluctance to fire employees (Dierynck, Landsman and Renders, 2012) cause cost stickiness leading to slow cost adjustment in response to changes in the levels of sales. Anti-sticky costs, however, express firms’ ability to promptly adjust costs in response to changes in the level of sales (Weiss, 2010). Therefore, sticky costs are predicted to yield, on average, negative abnormal returns whereas anti-sticky costs are predicted to yield, on average, positive abnormal returns.

Cost variability, on the other hand, represents the extent of proportional (linear) cost responses to changes in sales. Thus, cost variability reflects symmetric cost adjustments made in response to equivalent increases or decreases in the level of sales. Since sales growth is more frequent than sales decreases,\(^\text{18}\) low cost variability is

\(^{18}\text{Actual sales for 63.3\% of our full sample of firm-quarter observations exceed the respective actual sales in the preceding quarter.}\)
predicted to yield, on average, positive abnormal returns because it provides the means to take greater advantage of sales growth given the higher margins.

The strategy we implement relies on the construction of zero-investment portfolios (Fama and MacBeth, 1973). We split the full sample observations into portfolios. For each quarter, we calculate the quintile based on MARGIN, for each firm. Specifically, we rank the values of MARGIN into quintiles (0,4) and divide the quintile number by four so that the quintile rank takes a value ranging between 0 and 1 (quintile ranks change with 0.25 increments). That is, we transform the variable MARGIN into MARGIN\textsuperscript{quin}. We follow the same procedure for quintile ranks of STICKY and generate STICKY\textsuperscript{quin}. Following prior studies (e.g., Livnat and Santicchia, 2012), we measure cumulative size-adjusted abnormal returns, SAR, from two days after earnings announcement of quarter t till one day after earnings announcement of quarter t+1. The long window allows investors to absorb the accounting information reported in the earnings announcement as well as in the financial statements reported later. We also control for other variables that may be associated with future abnormal stock returns: MV\textsuperscript{quin} and BM\textsuperscript{quin}. MV\textsuperscript{quin} is the quintile rank of market value of common equity measured at the beginning of the quarter calculated similar to MARGIN\textsuperscript{quin}. BM\textsuperscript{quin} is the quintile rank of the book-to-market ratio measured at the beginning of the quarter. We estimate the following regression:

\[
\text{SAR}_{t+1} = \beta_0 + \beta_1 \text{MARGIN}_{t}^{\text{quin}} + \beta_2 \text{STICKY}_{t}^{\text{quin}} + \beta_3 \text{MV}_{t}^{\text{quin}} + \beta_4 \text{BM}_{t}^{\text{quin}} + \epsilon_{t+1} \quad (19)
\]

The coefficient \(\beta_1\) (\(\beta_2\)) represents the size-adjusted abnormal return to a zero-investment portfolio formed to exploit the information in the cost variability (cost
stickiness) variables. The portfolio weights are determined without foreknowledge of future abnormal returns, resulting in executable trading strategies. The abnormal returns represented by the coefficients are comparable to abnormal returns to a zero-investment portfolio with long (short) positions in firms with the lowest (highest) quintiles of cost variability and in firms with the lowest (highest) quintiles of sticky costs. Simply said, the strategy goes long on firms with the lowest cost variability and the most anti-sticky costs, while going short on firms with the highest cost variability and the most sticky costs.

Results from estimating the regressions reported in the first column of Table 7 show a positive and significant relation ($\beta_1=1.29\%$, $p$-value$<0.01$) between MARGIN and future abnormal returns. Similarly, the coefficient estimate reported in the second column of Table 7 shows a positive and significant relation ($\beta_2=0.81\%$, $p$-value$<0.05$) between STICKY and future abnormal returns. The coefficient estimates from estimating the full model reported in column IV indicate quarterly abnormal returns of 1.76% for a trading strategy based on cost variability and 0.84% for a trading strategy based on cost stickiness (both significant at the 1% level). The findings are both statistically and economically significant. Results reported in the fourth column of Table 7 also indicate that the incremental abnormal returns related to MARGIN and STICKY persist after controlling for book-to-market and size.

[ Table 7 about here ]

The findings allow for merging the accounting silos of managerial and financial accounting. The results suggest that to the extent that analysts’ earnings forecasts reflect the market expectations for future earnings, investors are misled by analysts.
7. Concluding remarks

In this study, we examine whether sales and earnings forecasts made by financial analysts reflect perfect understanding of cost behavior. The study presents new empirical tests, which provide a rigorous premise for the inference of analysts’ understanding of cost patterns. Facilitating an empirical investigation, our model suggests that if financial analysts make no errors in estimating variable costs or sticky costs, then the earnings forecast errors should be symmetric across favorable and unfavorable sales surprises of equivalent amounts. Our findings, though, show earnings forecast errors that are significantly smaller when sales beat expectations than when sales miss expectations by an equivalent amount. This empirical evidence is inconsistent with analysts perfectly understanding firms’ cost behavior. These tests call for future research to examine analysts’ ability to predict other determinants of expenses.

The paper ties two distinct literature streams – one that seeks to understand how financial analysts forecast earnings, and the other that explores cost behavior rooted in the principles of management accounting. The results of this synthesis inform and provide new insights for both literature streams. For the analyst literature, this provides a fresh look at the role of expense prediction in the forecasts of earnings. Specifically, analysts can make less biased and more accurate forecasts if they take into account variable and sticky costs.
References


Figure 1
Asymmetry in Earnings Forecast Errors between Favorable and Unfavorable Sales Surprises

This figure presents the mean values of earnings forecasts errors for 20 portfolios of sales forecast errors, SFE. The definition of variables is in Table 1.
### Table 1
**Descriptive Statistics**

#### Panel A: Deflated Forecast Errors

<table>
<thead>
<tr>
<th></th>
<th>P10</th>
<th>Q1</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>Q3</th>
<th>P90</th>
<th>STD</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFE</td>
<td>-0.0074</td>
<td>-0.0014</td>
<td>-0.0015</td>
<td>0.0000</td>
<td>0.0017</td>
<td>0.0052</td>
<td>0.0185</td>
<td>-23.27***</td>
</tr>
<tr>
<td>SFE</td>
<td>-0.0204</td>
<td>-0.0047</td>
<td>-0.0003</td>
<td>0.0006</td>
<td>0.0062</td>
<td>0.0195</td>
<td>0.0436</td>
<td>-1.54</td>
</tr>
<tr>
<td>XFE</td>
<td>-0.0180</td>
<td>-0.0046</td>
<td>0.0012</td>
<td>0.0006</td>
<td>0.0065</td>
<td>0.0211</td>
<td>0.0436</td>
<td>7.20***</td>
</tr>
<tr>
<td>EFE_SFE</td>
<td>-0.7728</td>
<td>-0.0429</td>
<td>0.2316</td>
<td>0.0937</td>
<td>0.4815</td>
<td>1.4627</td>
<td>1.0900</td>
<td>62.82***</td>
</tr>
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</table>

#### Panel B: Undeflated Forecast Errors

<table>
<thead>
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<th>MEAN</th>
<th>MEDIAN</th>
<th>Q3</th>
<th>P90</th>
<th>STD</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFE</td>
<td>-0.1100</td>
<td>-0.0267</td>
<td>-0.0094</td>
<td>0.0096</td>
<td>0.0300</td>
<td>0.0900</td>
<td>0.1573</td>
<td>-17.57***</td>
</tr>
<tr>
<td>SFE</td>
<td>-0.3348</td>
<td>-0.0824</td>
<td>0.0385</td>
<td>0.0114</td>
<td>0.1289</td>
<td>0.4181</td>
<td>0.6818</td>
<td>16.68***</td>
</tr>
<tr>
<td>XFE</td>
<td>-0.2971</td>
<td>-0.0756</td>
<td>0.0478</td>
<td>0.0105</td>
<td>0.1299</td>
<td>0.4293</td>
<td>0.6799</td>
<td>21.10***</td>
</tr>
</tbody>
</table>

#### Panel C: Other Variables

<table>
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<tr>
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<th>Q1</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>Q3</th>
<th>P90</th>
<th>STD</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>MARGIN</td>
<td>0.1324</td>
<td>0.2485</td>
<td>0.4265</td>
<td>0.4066</td>
<td>0.6033</td>
<td>0.7604</td>
<td>0.2353</td>
<td>536***</td>
</tr>
<tr>
<td>STICKY</td>
<td>-1.427</td>
<td>-0.4991</td>
<td>-0.0370</td>
<td>-0.0262</td>
<td>0.4167</td>
<td>1.353</td>
<td>1.2700</td>
<td>-7.06***</td>
</tr>
<tr>
<td>NEG</td>
<td>0</td>
<td>0</td>
<td>0.4466</td>
<td>0</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.4971</td>
<td>266***</td>
</tr>
</tbody>
</table>

* *, **, *** indicate statistically significant at 10%, 5%, 1%, respectively. T-statistics are reported in parentheses.

**Definition of Variables:**
This table presents the descriptive statistics for deflated and undeflated forecast errors over 1998-2009.
There are 87,434 firm-quarter observations in the sample that have data in Compustat with consensus sales and earnings per share forecast available in I/B/E/S Summary Files. SFE is error in analysts’ sales per share forecast in quarter t. Deflated sales forecast errors are computed as actual sales per share minus consensus (median) sales forecast deflated by share price (PRCCQ from Compustat) at the beginning of the quarter. Sales per share is computed by dividing sales with common shares outstanding (CSHOQ from Compustat) at the end of quarter t. We use the earliest consensus sales forecast within the quarter from I/B/E/S Summary Files. We include sales forecasts made before the third month of the quarter (i.e. either first or second month of the quarter included). Undeflated forecast errors are calculated in a similar way except
not being deflated by share price. EFE is error in analysts’ consensus (median) earnings per share forecast (EPS) in quarter t. It is computed as actual EPS minus consensus (median) EPS forecast deflated by share price at the beginning of the quarter. Consensus forecasts are measured in the same month as sales forecasts. We only include firm-quarter observations that have both sales and EPS forecasts available from I/B/E/S Summary Files. XFE is error in analysts’ implied expense per share forecasts computed as implied expense forecast per share minus implied actual expense per share divided by share price. Implied expense forecast per share is computed as sales forecast per share minus the earnings per share forecast. Implied actual expense per share is also computed in the same way. Consensus forecasts are measured in the earliest month in the quarter consensus sales forecast is available from I/B/E/S Summary Files. EFE_SFE is the ratio of EFE to SFE. STICKY is the defined as in Weiss (2010). MARGIN is operating leverage, which is computed as sales (SALEQ) minus cost of goods sold (COGSQ) divided by sales (Weiss, 2010). NEG is an indicator variable which equals 1 if SFE<0 and 0, otherwise.
# Table 2

**Distribution of Analysts’ Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts**

This table presents the mean deflated sales and earnings forecast errors for equivalent ranges of sales forecast errors. The definitions of variables are provided in Table 1. The third column shows the mean value of EFE/SFE ratios from analyst forecasts. The last column shows the ratio of EFE, from model used by Banker and Chen (2006) that incorporates cost variability and cost stickiness, to SFE from a seasonal random walk model (SRW).

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>N</th>
<th>Ranges of Sales Forecast Errors Portfolios (SFE)</th>
<th>Analysts Forecasts</th>
<th>Time-series Forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean Forecast Errors</td>
<td>Mean Ratio For EFE/SFE</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sales Error (SFE)</td>
<td>Earnings Error - (EFE)</td>
</tr>
<tr>
<td>1 – low</td>
<td>8,913</td>
<td>&lt; -0.020</td>
<td>-0.0536</td>
<td>-0.0098</td>
</tr>
<tr>
<td>2</td>
<td>2,364</td>
<td>[-0.020, -0.015)</td>
<td>-0.0174</td>
<td>-0.0043</td>
</tr>
<tr>
<td>3</td>
<td>3,597</td>
<td>[-0.015, -0.010)</td>
<td>-0.0123</td>
<td>-0.0035</td>
</tr>
<tr>
<td>4</td>
<td>6,491</td>
<td>[-0.010, -0.005)</td>
<td>-0.0072</td>
<td>-0.0022</td>
</tr>
<tr>
<td>5</td>
<td>17,687</td>
<td>[-0.005, 0)</td>
<td>-0.0020</td>
<td>-0.0007</td>
</tr>
<tr>
<td>6</td>
<td>23,546</td>
<td>[0, +0.005)</td>
<td>0.0020</td>
<td>0.0004</td>
</tr>
<tr>
<td>7</td>
<td>8,731</td>
<td>[+0.005, +0.010)</td>
<td>0.0072</td>
<td>0.0008</td>
</tr>
<tr>
<td>8</td>
<td>4,601</td>
<td>[+0.010, +0.015)</td>
<td>0.00123</td>
<td>0.0010</td>
</tr>
<tr>
<td>9</td>
<td>2,848</td>
<td>[+0.015, +0.020)</td>
<td>0.00173</td>
<td>0.0014</td>
</tr>
<tr>
<td>10 – high</td>
<td>8,656</td>
<td>≥ +0.020</td>
<td>0.0519</td>
<td>0.0021</td>
</tr>
</tbody>
</table>

| Asymmetry Tests * |     |                                               |                     |                      |                        |
|                   | abs(5) – abs(6) |                                               | -0.0000             | 0.0002               | -0.2764                | -0.0129               |
|                   |                 |                                               | (-1.07)             | (1.14)               | (-9.61)***             | (-1.30)               |
|                   | abs(4) – abs(7) |                                               | 0.0000              | 0.0011               | 0.0703                 | 0.0109                |
|                   |                 |                                               | (1.08)              | (4.45)***            | (2.71)***              | (0.61)                |
|                   | abs(3) – abs(8) |                                               | 0.0000              | 0.0020               | 0.1067                 | 0.0083                |
|                   |                 |                                               | (0.45)              | (5.64)***            | (4.93)***              | (0.30)                |
|                   | abs(2) – abs(9) |                                               | 0.0000              | 0.0025               | 0.1171                 | 0.0342                |
|                   |                 |                                               | (0.71)              | (5.25)***            | (4.95)***              | (0.90)                |
|                   | abs(1) – abs(10)|                                              | 0.0017              | 0.0072               | 0.1263                 | -0.0200               |
|                   |                 |                                               | (0.49)              | (8.70)***            | (8.98)***              | (-1.41)               |

* *, **, *** indicate statistically significant at 10%, 5%, 1%, respectively. t-statistics are reported in parentheses.
a - The means and t-statistics of the asymmetry tests are computed based on variation of 48 quarterly differences between the absolute magnitude of the mean errors in each of the two portfolios. The t-statistics for asymmetry tests are computed based on the Fama and MacBeth (1973) procedure.
b – For the time-series forecast errors, the earnings forecast error, EFE, is computed using a time-series model employed in Banker and Chen (2006) that incorporates cost variability and cost stickiness. The sales forecast error, SFE, is estimated based on a seasonal random walk model (SRW).
Table 3  
Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts

EFE_{it} = \lambda_0 + \lambda_1 \text{NEG}_{it} + \lambda_2 \text{SFE}_{it} + \lambda_3 \text{SFE}_{it} \ast \text{NEG}_{it} + \epsilon_{it} \quad (17)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Deflated variables</th>
<th>Undeflated variables</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.0007</td>
<td>0.0019</td>
</tr>
<tr>
<td></td>
<td>(-1.17)</td>
<td>(3.43)***</td>
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<tr>
<td>NEG</td>
<td>-0.0018</td>
<td>(-7.34)***</td>
</tr>
<tr>
<td>SFE</td>
<td>0.0884</td>
<td>0.0064</td>
</tr>
<tr>
<td></td>
<td>(6.53)***</td>
<td>(1.77)*</td>
</tr>
<tr>
<td>SFE* NEG</td>
<td>0.1889</td>
<td>(11.01)***</td>
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<tr>
<td>Clustering</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter Dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adjusted - R^2</td>
<td>0.0620</td>
<td>0.1056</td>
</tr>
<tr>
<td>N</td>
<td>87,434</td>
<td>87,434</td>
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</table>

*, **, *** indicate statistically significant at 10%, 5%, 1%, respectively. t-statistics are reported in parentheses.

Notes:
This table presents the association between sales forecast errors and earnings forecast errors. The variables are defined in Table 1. We estimate pooled cross-sectional regressions based on equation (17). Firm-quarter observations are clustered by firm to eliminate autocorrelation and heteroscedasticity as per Petersen (2009).
Table 4  
Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts– Contextual Analysis

$$EFE_{it} = \lambda_0 + \lambda_1 \text{NEG}_{it} + \lambda_2 \text{SFE}_{it} + \lambda_3 \text{SFE}_{it} \ast \text{NEG}_{it} + e_{it}$$

(17)

Panel A: Profit Observations

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<thead>
<tr>
<th>Variables</th>
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</thead>
<tbody>
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<td></td>
<td>I</td>
<td>II</td>
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<tr>
<td>Intercept</td>
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<td>0.0021</td>
</tr>
<tr>
<td></td>
<td>(-0.71)</td>
<td>(9.22)***</td>
</tr>
<tr>
<td>NEG</td>
<td>-0.0012</td>
<td>-0.0374</td>
</tr>
<tr>
<td></td>
<td>(-5.28)***</td>
<td>(-18.58)***</td>
</tr>
<tr>
<td>SFE</td>
<td>0.0859</td>
<td>0.0071</td>
</tr>
<tr>
<td></td>
<td>(6.99)***</td>
<td>(1.68)*</td>
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<tr>
<td>SFE* NEG</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(9.33)***</td>
<td></td>
</tr>
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<td>Clustering</td>
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<td>Yes</td>
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<tr>
<td>Quarter Dummies</td>
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<td>Yes</td>
</tr>
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Panel B: Loss Observations

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</thead>
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<td>I</td>
<td>II</td>
</tr>
<tr>
<td>Intercept</td>
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<td></td>
<td>(-5.43)***</td>
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<td></td>
<td>(-7.22)***</td>
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<tr>
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<tr>
<td></td>
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<td>(0.98)</td>
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<td>SFE* NEG</td>
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<tr>
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</tr>
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<td>Adjusted - $R^2$</td>
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<td>14,331</td>
</tr>
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</table>

*, **, *** indicate statistically significant at 10%, 5%, 1%, respectively. $ t $-statistics are reported in parentheses.
Notes:
This table presents the association of sales and earnings forecast errors for profit and loss firms. Loss (profit) firms have a negative (zero or positive) consensus (median) earnings forecast. The variables are defined as in Table 1. We estimate pooled cross-sectional regressions based on equation (17). Firm-quarter observations are clustered by firm to eliminate autocorrelation and heteroscedasticity as per Petersen (2009).
Table 5  
The Effects of Cost Variability and Sticky Costs - Portfolio Analyses

Panel A (B) presents the mean and median value of ratio of EFE/SFE for high and low cost variability (sticky and anti-sticky) conditional on the sign of sales forecast errors (i.e. NEG=1 (NEG=0) for negative (positive) sales forecast errors). The mean values of differences are computed using the average of 48 quarterly means over 1998-2009. The t-statistics are computed based on the Fama and MacBeth (1973) procedure.

Panel A: Cost Variability Effect

\[
\frac{\text{EFE}_L - \text{EFE}_H}{\text{SFE}_L - \text{SFE}_H} = \frac{\bar{X}_L - \bar{X}_H}{\bar{L}_S - \bar{H}_S} = \frac{-\Delta \bar{X}}{\bar{S}_L + \bar{S}_H - 1 - \alpha \bar{S}_L \bar{S}_H - \alpha \bar{S}_L \bar{S}_H}. \tag{14}
\]

<table>
<thead>
<tr>
<th>Low Cost Variability (MARGIN above median)</th>
<th>High Cost Variability (MARGIN below median)</th>
<th>Difference (Low-High)</th>
<th>Difference (Low-High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Unfavorable sales surprises (NEG=1)</td>
<td>0.1253</td>
<td>0.0594</td>
<td>0.1855</td>
</tr>
<tr>
<td>Favorable sales surprises (NEG=0)</td>
<td>0.3744</td>
<td>0.2073</td>
<td>0.1316</td>
</tr>
<tr>
<td>Difference (1-0)</td>
<td>-0.2491***</td>
<td>-0.1479***</td>
<td>0.0540***</td>
</tr>
</tbody>
</table>

*, **, *** indicate statistically significant at 10%, 5%, 1%, respectively. t-statistics are reported in parentheses.

Panel B: Sticky Costs Effect

\[
\frac{\text{EFE}_L - \text{EFE}_H}{\text{SFE}_L - \text{SFE}_H} = \frac{\bar{X}_L - \bar{X}_H}{\bar{L}_S - \bar{H}_S} = \Delta \bar{\beta} \left[ \frac{(S_{L-1} - S_L)}{(1 - \alpha(S_H - S_L))} \right]. \tag{15}
\]

<table>
<thead>
<tr>
<th>Sticky Costs</th>
<th>Anti-Sticky Costs</th>
<th>Difference (sticky – anti-sticky)</th>
<th>Difference (sticky – anti-sticky)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Unfavorable sales surprises (NEG=1)</td>
<td>0.2610</td>
<td>0.1334</td>
<td>-0.0286</td>
</tr>
<tr>
<td>Favorable sales surprises (NEG=0)</td>
<td>0.1088</td>
<td>0.0604</td>
<td>0.3302</td>
</tr>
<tr>
<td>Difference (1-0)</td>
<td>0.1522***</td>
<td>0.0730***</td>
<td>-0.3588***</td>
</tr>
</tbody>
</table>

*, **, *** indicate statistically significant at 10%, 5%, 1%, respectively. t-statistics are reported in parentheses.
Table 6
The Effects of Cost Variability and Sticky Costs – Regression Analyses

\[
\text{EFE}_t = \lambda_0 + \lambda_1 \text{NEG}_t + \lambda_2 \text{DMARGIN}_t + \lambda_3 \text{DSTICKY}_t + \lambda_4 \text{SFE}_t + \lambda_5 \text{SFE}_t \times \text{NEG}_t + \lambda_6 \text{SFE}_t \times \text{DMARGIN}_t + \lambda_7 \text{SFE}_t \times \text{DSTICKY}_t + \lambda_8 \text{NEG}_t \times \text{DMARGIN}_t + \lambda_9 \text{NEG}_t \times \text{DSTICKY}_t + \lambda_{10} \text{NEG}_t \times \text{DMARGIN}_t \times \text{DSTICKY}_t + \lambda_{11} \text{NEG}_t \times \text{SFE}_t \times \text{DMARGIN}_t + \lambda_{12} \text{NEG}_t \times \text{SFE}_t \times \text{DSTICKY}_t + \lambda_{13} \text{NEG}_t \times \text{DMARGIN}_t \times \text{DSTICKY}_t + \lambda_{14} \text{NEG}_t \times \text{DMARGIN}_t \times \text{DSTICKY}_t + \lambda_{15} \text{NEG}_t \times \text{DMARGIN}_t \times \text{DSTICKY}_t + \lambda_{16} \text{NEG}_t \times \text{DMARGIN}_t \times \text{DSTICKY}_t + e_t
\]

<table>
<thead>
<tr>
<th></th>
<th>Deflated Forecast Errors</th>
<th>Undeflated Forecast Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0019</td>
<td>0.0029</td>
</tr>
<tr>
<td></td>
<td>(3.42)***</td>
<td>(3.23)***</td>
</tr>
<tr>
<td>NEG</td>
<td>-0.0014</td>
<td>-0.0014</td>
</tr>
<tr>
<td></td>
<td>(-7.24)*****</td>
<td>(-6.78)**</td>
</tr>
<tr>
<td>DMARGIN</td>
<td>0.0006</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(3.45)*****</td>
<td>(1.50)</td>
</tr>
<tr>
<td>DSTICKY</td>
<td>-0.0014</td>
<td>-0.0014</td>
</tr>
<tr>
<td></td>
<td>(-8.58)*****</td>
<td>(-7.89)**</td>
</tr>
<tr>
<td>SFE</td>
<td>0.0159</td>
<td>0.0291</td>
</tr>
<tr>
<td></td>
<td>(2.26)**</td>
<td>(3.05)**</td>
</tr>
<tr>
<td>SFE*DMARGIN</td>
<td>0.0092</td>
<td>0.0103</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>SFE*DSTICKY</td>
<td>-0.0186</td>
<td>-0.0214</td>
</tr>
<tr>
<td></td>
<td>(-2.37)**</td>
<td>(-1.83)**</td>
</tr>
<tr>
<td>SFE* NEG</td>
<td>0.0522</td>
<td>0.0151</td>
</tr>
<tr>
<td></td>
<td>(3.28)**</td>
<td>(0.86)</td>
</tr>
<tr>
<td>SFE<em>NEG</em>DMARGIN</td>
<td>0.0446</td>
<td>0.0404</td>
</tr>
<tr>
<td></td>
<td>(2.13)**</td>
<td>(1.99)**</td>
</tr>
<tr>
<td>SFE<em>NEG</em>DSTICKY</td>
<td>0.0853</td>
<td>0.0870</td>
</tr>
<tr>
<td></td>
<td>(3.64)**</td>
<td>(3.62)**</td>
</tr>
<tr>
<td>MV</td>
<td>-0.0003</td>
<td>-0.0015</td>
</tr>
<tr>
<td></td>
<td>(-2.79)**</td>
<td>(-1.37)</td>
</tr>
<tr>
<td>BM</td>
<td>-0.0009</td>
<td>-0.0134</td>
</tr>
<tr>
<td></td>
<td>(-1.70)**</td>
<td>(-3.56)**</td>
</tr>
<tr>
<td>LFLLLW</td>
<td>-0.0004</td>
<td>-0.0057</td>
</tr>
<tr>
<td></td>
<td>(-4.74)**</td>
<td>(-4.70)**</td>
</tr>
<tr>
<td>LOSS</td>
<td>0.0002</td>
<td>-0.0018</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(-0.44)</td>
</tr>
<tr>
<td>DISP</td>
<td>-0.6302</td>
<td>-4.3941</td>
</tr>
<tr>
<td></td>
<td>(-4.47)**</td>
<td>(-3.89)**</td>
</tr>
<tr>
<td>CV</td>
<td>-0.0001</td>
<td>-0.0014</td>
</tr>
<tr>
<td></td>
<td>(-2.79)**</td>
<td>(-6.58)**</td>
</tr>
<tr>
<td>INDROE</td>
<td>0.0016</td>
<td>0.0313</td>
</tr>
<tr>
<td></td>
<td>(1.21)</td>
<td>(2.95)**</td>
</tr>
<tr>
<td></td>
<td>SUE1</td>
<td>0.0068</td>
</tr>
<tr>
<td>-------</td>
<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.94)**</td>
</tr>
<tr>
<td>SUE2</td>
<td>0.0061</td>
<td>0.0644</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.74)*</td>
</tr>
<tr>
<td>LTV</td>
<td>0.0005</td>
<td>0.0040</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5.32)***</td>
</tr>
</tbody>
</table>

Clustering | Yes | Yes | Yes | Yes |
Quarter Dummies | Yes | Yes | Yes | Yes |
Adjusted - R² | 0.1012 | 0.1488 | 0.1375 | 0.1640 |
N | 48,207 | 48,207 | 48,207 | 48,207 |

* *, **, *** denote statistical significance at 10%, 5%, 1%, respectively. t-statistics are reported in parentheses.

**Definition of Variables:**
This table presents the results from pooled OLS estimation of equation (18). DSTICKY is an indicator variable that equals one if the STICKY measure is negative and 0, otherwise. STICKY is defined as in Weiss (2010). DMARGIN is an indicator variable which equals 1 if the firm has low gross margin (MARGIN) and 0, otherwise. MARGIN is computed as sales (SALEQ) minus cost of goods sold (COGSQ) divided by sales. MV is log market value of equity at the beginning of quarter t, computed as share price (PRCCQ from Compustat) times the number of shares outstanding (CSHOQ from Compustat). BM is book to market ratio at the beginning of quarter t, computed as book value of equity (SEQQ from Compustat) divided by market value of equity. LFLLW is log number of the analysts issuing an earnings forecast in quarter t. It is generated from I/B/E/S Detail Files. LOSS is an indicator variable which equals 1 if analysts’ consensus earnings forecast is negative and 0, otherwise. DISP is standard deviation of earnings forecast from IBES Summary Files divided by share price. CV is the coefficient of variation for earnings per share (EPSPXQ from Compustat) over two quarters before and two quarters after quarter t. It is computed as standard deviation of earnings per share divided by absolute value of the mean. INDROE is industry adjusted ROE (return on equity), computed as average ROE over quarter t+1 to t+4 minus median ROE of all firms in the same two-digit SIC industry code over the same period. Average ROE is computed as average income before extraordinary items (IBQ from Compustat) over t+1 to t+4 divided by average book value of equity in quarter t+1 and t+4. SUE1 (SUE2) is first (second) lag of unexpected earnings from seasonal random walk model divided by share price. LTV is log of sum of trading volume from CRSP over the 12 months prior to the month in which the earnings forecast is made. We include 47 quarter dummies over our sample period to control for time effects in our estimation. All other variables are as defined in Table 1. Firm-quarter observations are clustered by firm to eliminate autocorrelation and heteroscedasticity as per Petersen (2009).
Table 7
Abnormal Stock Returns from a Trading Strategy

\[ \text{SAR}_{t+1} = \beta_0 + \beta_1 \text{MARGIN}^{\text{quin}}_t + \beta_2 \text{STICKY}^{\text{quin}}_t + \beta_3 \text{MV}^{\text{quin}}_t + \beta_4 \text{BM}^{\text{quin}}_t + \epsilon_{t+1} \quad (19) \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.0424*</td>
<td>0.0689**</td>
<td>0.0638**</td>
<td>0.0596**</td>
</tr>
<tr>
<td></td>
<td>(1.74)</td>
<td>(2.38)</td>
<td>(2.20)</td>
<td>(2.03)</td>
</tr>
<tr>
<td>MARGIN\text{quin}</td>
<td>0.0129***</td>
<td>0.0137***</td>
<td>0.0176***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.83)</td>
<td>(3.42)</td>
<td>(4.02)</td>
<td></td>
</tr>
<tr>
<td>STICKY\text{quin}</td>
<td></td>
<td>0.0081**</td>
<td>0.0082**</td>
<td>0.0084***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.47)</td>
<td>(2.47)</td>
<td>(2.54)</td>
</tr>
<tr>
<td>MV\text{quin}</td>
<td></td>
<td></td>
<td></td>
<td>-0.0116***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-4.09)</td>
</tr>
<tr>
<td>BM\text{quin}</td>
<td></td>
<td></td>
<td></td>
<td>0.0124***</td>
</tr>
<tr>
<td>Clustering</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adjusted \text{- R}^2</td>
<td>0.83%</td>
<td>1.05%</td>
<td>1.07%</td>
<td>1.20%</td>
</tr>
<tr>
<td>N</td>
<td>83,477</td>
<td>56,494</td>
<td>56,271</td>
<td>55,026</td>
</tr>
</tbody>
</table>

*, **, *** statistically significant at 10%, 5%, 1%, respectively. t-statistics are reported in parentheses.

**Definition of Variables:**
The table presents the regression estimates of equation (19). Firm-quarter observations are clustered by firm to eliminate autocorrelation and heteroscedasticity as per Petersen (2009). SAR is the size-adjusted cumulative abnormal return over quarter t+1 (i.e. returns are accumulated starting from two days after earnings announcement of quarter t until one day after earnings announcement of quarter t+1). STICKY\text{quin} is the quintile rank of STICKY. The quintile numbers (0, 4) are divided by 4 so that the bottom quintile has a value of 0 and the top quintile has a value of 1. MARGIN\text{quin} is the quintile rank of MARGIN calculated in a similar way. MV\text{quin} is the quintile rank of MV. BM\text{quin} is the quintile rank of BM. The remaining variables are as defined in Table 6.