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ABSTRACT

Recent work in management accounting offers several novel insights into firms' cost behavior. This study explores whether financial analysts appropriately incorporate information on two types of cost behavior in predicting earnings - cost variability and cost stickiness. Since analysts' utilization of information is not directly observable, we model the process of earnings prediction to generate empirically testable hypotheses. The results indicate that analysts "converge to the average" in recognizing both cost variability and cost stickiness, resulting in substantial and systematic earnings forecast errors. Particularly, we find a clear pattern - inappropriate incorporation of available information on cost behavior in earnings forecasts leads to larger errors in unfavorable scenarios than in favorable ones. Overall, enhancing analysts' awareness of the expense side is likely to improve their earnings forecasts, mainly when sales turn to the worse.

Keywords: cost stickiness; cost variability; analysts' earnings forecasts; expense forecasts

JEL Code: M41, M46, G12

Implications of Cost Behavior for Analysts' Earnings Forecasts

1. Introduction

Recent literature in management accounting has made significant strides in understanding firms' cost behavior, which underlies earnings prediction (Banker and Chen [2006], Weiss [2010]). A thorough understanding of firms' cost behavior is necessary for accurately predicting expenses.[1] Yet, Ertimur, Livnat and Martikainen [2003] decompose earnings forecast errors of financial analysts and report that the magnitude of expense prediction errors of analysts is, on average, twice the magnitude of sales forecast errors made by the analysts. This suggests that analysts' errors in predicting expenses contribute more to earnings forecast errors than errors made in the prediction of sales. This indicates that analysts may not incorporate all aspects of cost behavior information in making their earnings predictions. In this study, we aim to examine this proposition.

We consider two types of cost behavior - cost variability and cost stickiness (Kallapur and Eldenburg [2005] and Anderson, Banker and Janakiraman [2003], respectively).[2] Since analysts' incorporation of cost behavior information is not directly observable, we facilitate an empirical investigation by modeling the process of earnings prediction as 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 utilization of cost behavior results in equal

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[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.

(opposite) earnings forecast errors for favorable and unfavorable sales forecast errors *of equivalent amounts*. However, a systematic error in incorporating available information on 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*. The model offers new tests that facilitate an empirical examination of whether analysts utilize available and relevant information on firms' cost variability and cost stickiness while predicting earnings (in contrast with analysts' potential errors in predicting the probabilities of favorable and unfavorable scenarios).

We utilize a sample of 107,577 firm-quarter observations with available analyst forecasts for both sales and earnings between 1998 and 2011. Our findings suggest that analysts predict firms' expenses with a systematic error. The systematic error in predicting expenses generates a discrepancy 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 2.69 times the mean earnings forecast errors when actual sales exceed the sales forecast by 1.5% to 2% (with opposite signs). Particularly, the evidence suggests that systematic errors in predicting expenses result in substantial earnings forecast errors when sales turn to the worse, i.e., under unfavorable scenarios.

A battery of sensitivity analyses confirms the findings. Specifically, the results hold for subsamples of loss and profit observations, growth firms, subsamples of firms with low or high analyst coverage, and subsamples of firms with low or high intensity of sales, general and administrative costs. The results are insensitive to the timing of the earnings forecasts and hold for individual analysts who perfectly forecast the firm's earnings in the preceding quarter. Further validating our test specifications, we perform a placebo test and find that time-series earnings forecast errors that incorporate information on cost behavior exhibit symmetric earnings forecast 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 suggests a clear pattern - inappropriate incorporation of available information on cost behavior leads to larger earnings forecast errors in unfavorable scenarios than in favorable ones.

Next, we separately investigate analysts' utilization of information on cost variability and cost stickiness. 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. Also, we 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 the inappropriate utilization of cost behavior information has a well-defined pattern - analysts "converge to the average" in recognizing both cost variability and cost stickiness, resulting in systematic errors in forecasting earnings.

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 utilize information on cost variability and cost stickiness with a systematic error, which, in turn, introduces a large earnings forecast error when sales miss expectations and a small earnings forecast error when sales beat expectations by an equivalent amount. The difference is economically meaningful. Taken as a whole, improvements in analysts' ability to utilize information on firms' cost behavior will enhance the accuracy of earnings forecasts, mainly when sales turn to the worse.

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' utilization of cost structures in earnings predictions. 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. He 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.

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 sections 5 and 6, we present the results from our empirical analyses. 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' utilization of available information on firms' cost behavior in predicting future earnings. Since analysts' utilization of information on 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], Calleja, Steliaros, and Thomas [2006], Banker, Byzalov and Chen [2012], Banker, Byzalov, Ciftci and Mashruwala [2012], Banker, Basu, Byzalov and Chen [2012], Chen, Lu, and Sougiannis [2012], Kama and Weiss [2013]). 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

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[3] For instance, suppose a firm faces a uniform sales distribution in the relevant range, say between $800 and $1200, and the expectation is $1,000. Thus, sales in a given period is expected to be $1,100 in a favorable scenario and only $900 in an unfavorable scenario. 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 in the preceding period were $1,000, β=-0.2). The expected expenses under favorable scenario are $650 = $100 + 0.5*$1,100. The expected expenses under the unfavorable scenario are $570 = $100 + 0.5*$900 - 0.2*($900-$1,000). Hence, earnings in the favorable and unfavorable scenarios will be $450 and $330, respectively. If the analysts perfectly understands cost behavior then her earnings forecast is $390. The earnings forecast error in the favorable scenario is $60=$450-$390, and in 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.

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 incorporate information on firms' cost behavior then there would be no systematic relationship between earnings forecast 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' incorporation of information on cost behavior.

2.1. Modeling the impact of recognizing 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,

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

and in the unfavorable scenario,

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

We note that the relative magnitude of SFE_H and SFE_L depends on α. 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,

$$C_H = vS_H + F_0, \tag{3}$$

and total costs in the unfavorable scenario as,

$$C_L = vS_L + F_0, \tag{4}$$

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 β 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:

$$X_H = S_H - C_H = S_H - (v\,S_H + F_0), \tag{5}$$

and under an unfavorable sales surprise:

$$X_L = S_L - C_L + \beta\,(\hat{S} - S_L) = S_L - (v\,S_L + F_0 - \beta\,(S_{-1} - S_L)). \tag{6}$$

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

$$\hat{X} = \alpha\,X_L + (1-\alpha)\,X_H. \tag{7}$$

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

$$\hat{X} = \alpha\,X_L + (1-\alpha)\,X_H = (1-v)\,\hat{S} - F_0 + \alpha\,\beta\,(S_{-1} - S_L). \tag{8}$$

The earnings forecast error under a favorable sales surprise is,

$$EFE_H = X_H - \hat{X} = \alpha\,[(1-v)\,(S_H - S_L) - \beta\,(S_{-1} - S_L)] > 0, \tag{9}$$

and under an unfavorable sales surprise is,

$$EFE_L = X_L - \hat{X} = -(1-\alpha)\,[(1-v)\,(S_H - S_L) - \beta\,(S_{-1} - S_L)] < 0. \tag{10}$$

We note that the parameters α, v, and β influence the magnitude of both favorable and unfavorable earnings surprises. As for sales forecast errors, if α=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–(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*:

$$\frac{EFE_L}{SFE_L} - \frac{EFE_H}{SFE_H} = \frac{X_L - \hat{X}}{S_L - \hat{S}} - \frac{X_H - \hat{X}}{S_H - \hat{S}} \tag{11}$$

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

If the analyst correctly estimates α and the cost parameters v, F_0 and β, then equation (11) indicates that the ratio, EFE/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 EFE/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 β, but predicts the probability of the unfavorable scenario with an error. Let α 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:

$$\hat{S}(\Delta\alpha) = (\alpha+\Delta\alpha)S_L + (1-\alpha-\Delta\alpha)S_H. \quad (12)$$

We obtain,

$SFE_H(\Delta\alpha) = S_H - \hat{S}(\Delta\alpha) = (\alpha+\Delta\alpha)(S_H - S_L) > 0$, 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,

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

$EFE_L(\Delta\alpha) = -(1-\alpha-\Delta\alpha)\,[(1-v)(S_H - S_L) - \beta(S_{-1} - S_L)] < 0$.

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

$$\frac{EFE_L(\Delta\alpha)}{SFE_L(\Delta\alpha)} - \frac{EFE_H(\Delta\alpha)}{SFE_H(\Delta\alpha)} = \frac{X_L - \hat{X}(\Delta\alpha)}{S_L - \hat{S}(\Delta\alpha)} - \frac{X_H - \hat{X}(\Delta\alpha)}{S_H - \hat{S}(\Delta\alpha)}$$

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

$$- \left[(1 - v)\left(S_H - S_L\right) - \beta\left(S_{-1} - S_L\right)\right] = 0. \qquad (13)$$

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,

$EFE_H(\Delta v) = \alpha\,[(1-v)\,(S_H - S_L) - \beta\,(S_{-1} - S_L)] + \hat{S}\,\Delta v$, and,

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

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

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.[4,5] 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:

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[4] Continuing the example in footnote 3, 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 - $\hat{S}\,\Delta v$ = 390-1000x0.05 = 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

$$\frac{EFE_L(\Delta v)}{SFE_L} - \frac{EFE_H(\Delta v)}{SFE_H} = \frac{-10}{-100} - \frac{+110}{100} = -1 \quad \neq 0.$$

Alternatively, suppose the analyst under-estimates cost variability by Δv=-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.

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 β be the true cost stickiness of the firm and Δβ be the error, Δβ≠0. The error in predicting cost stickiness does not affect $\hat{S}$, SFE_H, or SFE_L. We obtain,

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

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

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

Equation (15) indicates that an error in predicting cost stickiness, Δβ≠0, generates a differential magnitude of earnings forecast errors between unfavorable and favorable 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.[6] The following hypothesis summarizes these arguments:

Hypothesis 3

If analysts predict cost stickiness with an error then:

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[6] We continue the example in footnote 3 assuming the analyst estimates sticky costs with an error, Δβ, and perfectly predicts all other parameters. Specifically, the true stickiness is β=-0.2 but the analyst ignores cost stickiness, Δβ=-β=+0.2, and predicts β+Δβ=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/SFE_l – EFE_H/SFE_H = (-70/-100)-(50/100) = +0.2, in line with equation (15).

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.

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? Another study, Kim and Prather-Kinsey [2010], aims to examine whether analyst forecast errors are due their use of a cost model in which they assume an equal growth rate for expenses and sales. However, their analysis is based on examining the relationship between analyst forecast errors and sales growth rates. Hence, their research design does not enable a clear understanding of whether the analysts are making errors in estimating sales growth or in estimating cost behavior.

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.[7]

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

[7] 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.

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 cost variability and cost stickiness 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 a series of tests. 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.

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

$$EFE_H = X_H - \widehat{X} = (1\text{-}v)\ SFE_H - \alpha\ \beta\ (S_{-1} - S_L)], \qquad (9^*)$$

and,

$$EFE_L = X_L - \widehat{X} = (1\text{-v})\ SFE_L + (1-\alpha)\ \beta\ (S_{-1} - S_L)]. \qquad (10^*)$$

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

$$\overset{\wedge}{EFE} = (1 - v)\overset{\wedge}{SFE} \qquad (16)$$

Therefore, we estimate the following regression:

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it} * NEG_{it} + e_{it} \qquad (17)$$

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.

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

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[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 λ_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 $\lambda_2>0$.[9] More importantly, the coefficient λ_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]).[10] 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.

We conduct eight sensitivity analyses of hypothesis 1 to rule out potential alternative explanations for our findings.

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[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. See also Ball [2011].

(i) Loss firms - 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 whether our results are similar for both profit and loss firms. We separate 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. The first hypothesis predicts that $\lambda_3=0$ in each of the two sub-samples.

(ii) Growth firms - Some studies document that a systematic relationship exists between the expected earnings growth of firms, as measured by their book-to-market ratios, and the distribution of analyst forecast errors (e.g., Doukas et al. [2002], La Porta [1996]). Hence we perform a similar analysis for subsamples consisting of high growth (low book-to-market) and low growth (high book-to-market) firms at the beginning of the quarter. We test hypothesis 1 ($\lambda_3=0$) in each of these two subsamples to rule out the alternative explanation that the patterns we see in the distribution of earnings forecast errors is driven by firms' expected earnings growth.

(iii) Analyst coverage - Das et al. [1998] argue that analysts' forecasts for a particular firm are influenced by the number of analysts following that firm. They state two possible reasons for this relationship, (i) competition amongst analysts affects the distribution of forecast errors, and (ii) the number of analysts affects demand and value for non-public information, which in turn can affect the distribution of forecast errors. Hence, we conduct additional analyses by testing hypothesis 1

(λ_3=0) for subsamples formed on the basis of analyst following in the beginning of quarter t.

(iv) Intensity of selling, general, and administrative (SG&A) costs – Early studies focused on SG&A costs for documenting sticky costs (Anderson, Banker and Janakiraman [2003], Noreen and Soderstrom [1997], Anderson, et al. [2007]). We test whether analysts paid more attention to cost structures in firms with high proportion of SG&A costs. We examine the robustness of the results obtained in Table 3 for subsamples formed on the basis of the proportion of SG&A costs on quarter t-1.

(v) Individual analysts - There is considerable research that shows that there are systematic differences in the properties of analysts' forecasts between individual analysts (Mikhail, Walther and Willis [2003]; Tan, Wang and Welker [2011]; Firth, Lin, Liu, and Xuan [2013]). Studies have found that some analysts have consistently more accurate forecasts than others (e.g. Stickel [1992], Sinha, Brown, and Das [1997]). A question that arises then is whether some individual analysts understand cost variability and cost stickiness better than others. To address this question, we test Hypothesis 1 in subsamples divided based on the firm-specific earnings forecast error of individual analysts on the preceding quarter. Specifically, we form subsamples based on the accuracy of firm-analyst earnings forecast accuracy in quarter t-1. Hypothesis 1 (λ_3=0) is then tested separately for these subsamples.

(vi) Timing of the forecasts – We test the sensitivity of the findings to using an early forecast by testing hypothesis 1 (λ_3=0) using the latest consensus earnings forecast available in the *I/B/E/S* Summary files. The latest consensus earnings forecast is generally more accurate than an early one because more information is available on firms performance. We examine whether the availability of more information leads to recognition of cost behavior.

(vii) Test specification validity (a placebo test) - We use simulations for presenting a placebo test aimed to confirm our test specification. This test offers external validity and verification that the observed asymmetry is indeed attributable to analysts' misunderstanding of cost behavior. To do this, we estimate a seasonal random walk (SRW) model for estimating sales and compute earnings forecasts using a model employed in Banker and Chen [2006] that incorporates cost variability and cost stickiness. To clarify, we perform out-of-sample analysis to calculate earnings and sales forecast errors. Specifically, we first estimate parameters using data from the previous year and use current year data to estimate forecast errors. 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.

(viii) Multiple scenarios – The model predictions are based on assuming two scenarios – a favorable one and an unfavorable one (see section 2). However analysts may consider more than two scenarios in predicting future sales and earnings. Since the number of actual scenarios considered by analysts is not observable, we perform a simulation to gain insights into the sensitivity of the inference to this assumption. The idea is to verify whether the model predictions hold within a relevant range when analysts use multiple scenarios to predict future sales and earnings.

3.2. Tests of Hypotheses 2 and 3

We investigate whether analysts recognize cost variability and cost stickiness, separately, in predicting future earnings based on Hypothesis 2 and 3. We utilize gross margin as a proxy for cost variability.

We utilize gross margin for examining analysts' incorporation of cost variability. Lower margins indicate that sales are associated with higher variable expenses and vice-versa. Therefore, margins capture the extent of cost variability.[11] MARGIN is computed as sales (SALEQ) minus cost of goods sold (COGSQ) divided by sales.

To examine analysts' incorporation 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]:

$$STICKY_{i,t} = log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i\underline{\tau}} - log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i\overline{\tau}} \qquad \underline{\tau}, \overline{\tau} \in \{t, \ldots, t-4\},$$

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

$\Delta SALE_{it}$ = $SALE_{it}$ - $SALE_{it}$, where, SALE is sales revenue (SALEQ from Compustat)

$\Delta COST_{it}$ = ($SALE_{it}$ –$EARNINGS_{it}$) - ($SALE_{it-1}$ – $EARNINGS_{it-1}$), where, EARNINGS is income before extraordinary items (IBQ from Compustat).

[11] Results from estimating the full regression model reported in Table 12 control for industries because gross margin differs across industries, not only within industries.

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 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 STICKY≥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 difference in 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 with quarter dummies and industry dummies to examine our second and third hypotheses:

$$EFE_{it} / SFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2\ DMARGIN_{it} + \lambda_3\ DSTICKY_{it} + \lambda_4\ NEG_{it} * DMARGIN_{it} + \lambda_5 NEG_{it} * DSTICKY_{it} + \lambda_6\ MV_{it} + \lambda_7\ BM_{it} + \lambda_8\ LFLLW_{it} + \lambda_9\ LOSS_{it} + \lambda_{10}\ DISP_{it} + \lambda_{\backslash 11}\ CV_{it} + \lambda_{12}\ INDROE_{it} + \lambda_{13}\ SUE1_{it} + \lambda_{14}\ SUE2_{it} + \lambda_{15}\ LTV_{it} + e_{it} \quad (18)$$

where,

DMARGIN an indicator variable which equals 1 if the firm has high cost variability (below median gross margin, MARGIN) and 0, otherwise. MARGIN is computed as sales (SALEQ) minus cost of goods sold (COGSQ) divided by sales.

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 *I/B/E/S* 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 of NEG captures an asymmetry in EFE/SFE between observations with unfavorable and 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 DMARGIN indicates the difference in the ratio EFE/SFE between firms with high and low cost variability. The coefficient estimate of DSTICKY indicates the difference in EFE/SFE between firms with sticky costs and those with anti-sticky costs. The coefficient estimate of the interaction 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 interaction NEG*DMARGIN as partial understanding of cost variability. That is, Hypothesis 2 predicts that if analysts predict cost variability with a systematic error then $\lambda_4 \neq 0$. In a similar vein, we follow equation (15) and interpret a significant coefficient estimate of the interaction NEG*DSTICKY as partial understanding of cost stickiness. As before, Hypothesis 3 predicts that if analysts predict cost stickiness with a systematic error, then $\lambda_5 \neq 0$.

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. 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]. 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. As an additional proxy for earnings uncertainty, we include the coefficient of variation of earnings per share as per Gu and Wu [2003]. 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. 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 (Hayes [1998]).

4. Sample

We use firm-quarter observations from 1998 to 2011 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, CRSP Merged Files. 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. For estimating regression model (18), we also delete firm-quarter observations where SFE is zero as we use it as a denominator in the EFE/SFE ratio. 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, CRSP Merged 2013 Files that extend until 2012. Our sample ends in 2011 because calculation of some of the control variables in model (18) requires one year-ahead data. There are 107,577 firm-quarter observations in our sample. The STICKY variable is available for 63,603 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 -0.0012 (*p-value*<0.001), suggesting that, on average, the analysts' earnings forecasts are biased (i.e. optimistic). This bias is consistent with prior literature (e.g., Abarbanell and Lehavy [2003], Gu and Wu [2003]). The mean sales forecast error is 0.0004. We obtain the implied expense forecast errors using the sales and earnings forecast errors (XFE = SFE - EFE). The mean expense forecast error is 0.0016 and highly significant (*p-value*<0.001). Between the two components, it is the expense forecast errors that contribute more (i.e. mean expense forecast error is four times larger than the mean sales forecast error) to analysts' earnings forecast errors than the sales forecast errors (*p-value*<0.001). These findings are consistent with Ertimur et al. [2003].

Statistics reported in Panel B document the undeflated forecast errors. The mean undeflated earnings forecast error is also negative (-0.0051) and highly significant (*p-value*<0.001). On average, actual expenses exceed forecasted expenses (0.0517, *p-value*<0.001), and actual sales exceed forecasted sales (0.0467, *p-value*<0.001). We note that the mean expense prediction error is larger than the mean sales prediction error (-0.0051 =0.0467 -0.0517, *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 -0.0111 and -0.0205, suggesting that on average, costs are sticky. The mean value of NEG is 0.4363, suggesting that 43.63% firm quarters have unfavorable sales surprises, while the rest have favorable sales surprises.

[Table 1 about here]

5. Empirical tests of hypothesis 1

5.1. Portfolio analyses

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 -0.0153, while it is 0.0035 for the right-most portfolio. Thus, the absolute value of earnings forecast errors in the left-most portfolio is 4.4

times larger than those in the right-most portfolio. Indeed, the right tail is relatively flat, while the left tail has a steep downward slope. The chart indicates a substantial asymmetry in earnings forecast errors conditioned on sales forecast errors.

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 3.81 (=0.0099/0.0026) times larger in portfolio 1 than in portfolio 10, 2.69 (=0.0043/0.0016) times larger in portfolio 2 than in portfolio 9, 2.50 (=0.0035/0.0014) times larger in portfolio 3 than in portfolio 8, and 2.56 (=0.0023/0.0009) 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.[12]

The right column in Table 2 presents the mean EFE/SFE ratio for each portfolio and the differences between left tail and right tail portfolios. We winsorize the ratio EFE/SFE at the top and bottom 5% to eliminate the impact of extreme observations. The mean ratio for portfolio 1 is 0.2018 whilst that for portfolio 10 is 0.0716. Hence, the mean ratio is 2.82 (=20.18/7.16) 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

[12] 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.

EFE/SFE for unfavorable sales surprises than for favorable sales surprises of equivalent amounts.[13]

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 utilize information on cost behavior with a systematic error.

[Table 2 about here]

5.2. Regression models

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 0.0905 (*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 regression. The coefficient estimate of SFE under favorable sales surprises is significant (0.0101; *p-value*<0.05). The coefficient of the interaction term, SFE*NEG, is positive and significant (0.1834; *p-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 0.0598, while it is 0.0997 in the second column.

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[13] 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.

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 0.0441 (*p-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 0.0129 (*p-value*<0.01) and the coefficient of the interaction term, SFE*NEG, is 0.0669 (*p-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]

5.3 *Sensitivity analyses*

We perform eight contextual analyses to examine the robustness of the results.

(i) Loss firms

We present results from estimating equation (17) for a sub-sample consisting of loss firms in Panel A of Table 4. Analysts forecast losses for only 17,284 observations (16.07% of the sample). The estimated coefficient of the interaction term, SFE*NEG, is positive and significant for deflated variables (0.2306, *p-value*<0.01) and for undeflated variables (0.1460, *p-value*<0.01). Hence, the findings for loss observations reveal significantly greater earnings forecast errors in the presence of unfavorable sales surprises than in the presence of favorable sales surprises of equivalent amounts.[14]

[14] We obtain similar results when we use actual earnings on the preceding quarter to determine profit and loss observations.

Results from estimating equation (17) for a sub-sample of profit observations are presented in Panel B of Table 4. The estimated coefficient of the interaction term, SFE*NEG, is positive and significant for deflated variables (0.1487, *p-value* < 0.01) as well as for undeflated variables (0.0612, *p-value* < 0.01). The findings for profit firms show asymmetric analysts' earnings forecasts errors under favorable sales surprises compared to unfavorable sales surprises of equivalent amounts. Hence, the asymmetry in earnings forecast errors that is documented in Table 3 seems to hold regardless of whether analysts forecast a profit or a loss.

[Table 4 about here]

(ii) Growth firms

Next, we examine the effect of expected future growth of firms on the results obtained in Table 3. Table 5 presents the results of equation (7) for high and low growth firms. We measure firm expected growth using the book-to-market ratio at the beginning of the quarter and exclude negative book-to-market firms. High (low) growth firms are those with low (high) book-to-market ratio. Panel A and B of Table 5 indicates that the interaction of SFE*NEG is positive and significant (*p-value*<0.01) for both high and low growth firms with both deflated and undeflated forecast errors. These results indicate that the asymmetry in earnings forecasts is not driven by expected growth of firms since it is observed for both high growth and low growth firms.

[Table 5 about here]

(iii) Analyst coverage

Table 6 presents the asymmetry for high and low analyst following firms. Analyst following is the number of analyst following the firm in quarter t generated from *I/B/E/S* Detail Files. Panel A and B of Table 6 indicates that the interaction of SFE*NEG is positive and significant (*p-value*<0.01) for both high and low analyst following firms with both deflated and undeflated forecast errors. These results indicate that earnings forecast asymmetry is observed for firms with high or low analyst coverage.

[Table 6 about here]

(iv) Intensity of SG&A costs

Table 7 presents the asymmetry for firms with high and low proportion of SG&A costs. We measure the level of SG&A as SG&A costs divided by sales revenue in quarter t. We delete the firm-year observations with negative SG&A costs. Panel A and B of Table 7 indicates that the interaction of SFE*NEG is positive and significant (*p-value*<0.01) for both high and low SG&A firms with both deflated and undeflated forecast errors suggesting that earnings forecast asymmetry is not driven by SG&A level.

[Table 7 about here]

(v) Individual analysts

Prior literature documents significant differences among individual analysts in recognizing cost behavior. We investigate whether analysts who made accurate earnings forecasts in quarter t-1 understand cost behavior in quarter t. If they do, then we should find symmetry in earnings forecast errors for these analysts. To examine this issue we first separate analyst-firm-quarter observations into two groups ("zero error" and "error") based on the error in latest individual analyst forecast in the previous quarter. "Zero error" analysts are those with no error in their earnings forecast in quarter t-1, while the "error" analysts had a positive or negative earnings forecast error in quarter t-1. We then estimate equation (17a) for each group using analyst-firm-quarter data.

$$IEFE_{ijt} = \lambda_0 + \lambda_1 INEG_{ijt} + \lambda_2\ ISFE_{ijt} + \lambda_3 ISFE_{ijt} * INEG_{ijt} + e_{ijt} \qquad (17a)$$

$IEFE_{ijt}$ is error in earnings forecast for analyst j, for firm i, in quarter t. Individual analysts forecasts are generated from *I/B/E/S* Detail Files.

$INEG_{ijt}$ is an indicator variable which equals 1 if $IEFE_{ijt}$ is negative and 0, otherwise.

$ISFE_{ijt}$ is error in sales forecast for analyst j, for firm i, in quarter t.

Note, that the variables in equation (17a) are defined based on individual analyst forecasts rather than based on the consensus forecast that was used in Table 3. The estimation results of equation (17a) are provided in Table 8. Panels A and B of Table 8 indicate that the interaction of SFE*NEG is positive and significant (*p-value*<0.01) for both "zero error" and "error" analysts with both deflated and undeflated forecast errors suggesting that the asymmetry in earnings forecasts is observed for both groups of analysts. Hence, our results are confirmed by using data of individual analysts. The results suggest that analysts with no errors in forecasting earnings on the preceding quarter also have asymmetric forecasting errors, suggesting partial understanding of cost behavior.

[Table 8 about here]

(vi) Timing of the forecasts

In our main tests in Table 3 we use the earliest consensus forecast in a given quarter to obtain the forecast errors. We examine the robustness of our results to using the latest consensus forecast in the quarter instead of the earliest consensus forecast. The results are presented in Table 9. The results indicate that the interaction of SFE*NEG remains positive and significant (*p-value*<0.01) for both deflated and undeflated forecast errors. These results suggest that the earnings forecast asymmetry documented in Table 3 is not affected by the forecast horizon.

[Table 9 about here]

(vii) Specification validity – Placebo test

To confirm the validity of our test specifications, we present results from a placebo test based on forecast errors obtained using a time-series prediction model for sales and earnings. Specifically, we utilize a seasonal random walk (SRW) model for estimating sales and compute earnings forecasts using a model employed in Banker and Chen [2006] that incorporates cost variability and cost stickiness. Results reported in the right column in Table 10 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.[15]

[Table 10 about here]

(viii) Multiple scenarios – Simulations

We perform simulations to gain insights into the sensitivity of the inference to the assumption of two scenarios underlying the model predictions. Particularly, we verify whether the model predictions hold within a relevant range when analysts use multiple scenarios to predict future sales and earnings. The simulation follows the example in footnote 3. Forecasting sales, we assume sales on prior period is S_{t-1}=1000. We use a four-scenario sales distribution on period t. A random number evenly distributed between 0 and 100, *R*, is used for generating sales on period t: $S_{t-1}-2R$, $S_{t-1}-R$, $S_{t-1}+R$, and $S_{t-1}+2R$. The analyst perfectly predicts sales on each of the four scenarios. Forecasting costs on each of the four scenarios, we assume cost variability is v=0.5 and cost stickiness is β=-0.2. Therefore, total cost in each scenario is $C_t = 100 + 0.5*S_t - 0.2*(S_t - S_{t-1})$, where $S_t \in \{S_{t-1}-2R, S_{t-1}-R, S_{t-1}+R$, and $S_{t-1}+2R\}$. Earnings in each scenario are predicted as $X_t = S_t - C_t$. Both sales and earnings forecasts are predicted as means assuming

[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.

equal probability for each scenario. The forecast errors are: SFE = S_t – sales forecast, and EFE = X_t – earnings forecast. NEG_t = 1 if $S_t < S_{t-1}$ and zero otherwise.

We simulate sales and earnings forecasts for 100 firms (100 iterations) and estimate regression model (17) in three cases with equal probability for each of the four scenarios:

Case I - The analyst perfectly recognizes both cost stickiness and cost variability (β=-0.2 and v=0.5). Accordingly, costs on each scenario are predicted to be $C_t = 100 + 0.5*S_t - 0.2*(S_t - S_{t-1})$. Case II - The analyst ignores cost stickiness and perfectly recognizes cost variability (β=0 and v=0.5). Costs on each scenario are predicted to be $C_t = 100 + 0.5*S_t$. Case III - The analyst ignores sticky costs (β=0) and erroneously predicts high cost variability (v=0.7). Costs on each scenario are predicted to be $C_t = 100 + 0.7*S_t$.

Table 11 presents results from estimating regression model (17) using simulated data on each of the three cases. In each case, we estimate the regression model using the simulated forecast errors. In line with the model prediction and hypothesis 1, the findings indicate an insignificant coefficient on the interaction SFE* NEG in case I, where the analyst perfectly recognizes both cost stickiness and cost variability. In contrast, the coefficients on the interaction SFE* NEG in cases II and III are significant, indicating errors in recognizing cost variability and cost stickiness as predicted by hypotheses 2 and 3. Once more, the findings support our conclusions.

[Table 11 about here]

Taken as a whole, the evidence in Tables 2-11 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.

6. Empirical tests of hypotheses 2 and 3

We present the results from univariate and multivariate tests of hypotheses 2 and 3 examining analysts' recognition of cost patterns - cost variability and cost stickiness.

6.1 Portfolio tests

Our tests of the second hypothesis build on equation (14). Specifically, Panel A of Table 12 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 high cost variability observations is 0.0543 (*p-value*<0.01). The mean difference in the ratio between favorable and unfavorable sales surprises for low cost variability observations is -0.2919 (*p-value*<0.01). The difference between these two differences in means is 0.3462 and 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, 0.0543. 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 4 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, -0.2919. 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 11 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 (0.1826, *p-value*<0.01) is significantly greater than the mean difference in the ratio for anti-sticky costs observations (-0.4157, *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 β expresses more sticky costs, the evidence suggests that analysts under-estimate cost stickiness for observations with sticky costs. That is, analysts predict β 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 β with a negative error meaning that the predicted costs are less anti-sticky than actual costs. The evidence suggests that analysts tend to estimate β closer to zero even when the actual level of β 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, simply assuming cost symmetry.

[Table 12 about here]

6.2 Regression models

Next, we present the results from estimating a multivariate regression equation (18) in Table 13.[16] The first column reports the estimation results of equation (18) without control variables. Testing the Hypothesis 2, the coefficient estimate of NEG*DMARGIN is 0.2711 (*p-value*<0.01) 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 NEG*DMARGIN as analysts' prediction of cost variability with a systematic error.

We test Hypothesis 3 in a similar way. The coefficient estimate of NEG*DSTICKY is 0.6412 (*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 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. Thus, the addition of control variables does not alter our conclusions.

[Table 13 about here]

6.3. Additional robustness tests

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[16] 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. As a result, the sample size reduces from 107,577 firm-quarter observations to 49,091 firm-quarter observations.

Several robustness checks corroborate these findings. First, 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.

Second, we replicate the analyses using consensus analyst forecasts in all three months of the quarter instead of the first two months. Third, we use Fama and MacBeth [1973] regressions rather than using pooled estimation as per Table 3. Our findings are essentially the same.

Taken as a whole, the empirical evidence suggests that financial analysts "converge to the average" in recognizing understand both cost variability and cost stickiness. As a result, analysts make systematic errors in the estimation of firms' cost variability and cost stickiness, resulting in systematic errors in their earnings forecasts.

7. Concluding remarks

In this study, we examine whether inappropriate utilization of information on cost behavior leads to analysts' earnings forecast errors. The study presents new tests, which provide a rigorous premise for the inference of analysts' incorporation of cost structures. 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 incorporating available information on firms' cost behavior. The results suggest that correctly predicting expenses has a substantial impact on the accuracy of earnings forecasts.

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.

References

Abarbanell, J. and Lehavy, R. "Biased Forecasts or Biased Earnings? The Role of Reported Earnings in Explaining Apparent Bias and Over/Underreaction in Analysts' Earnings Forecasts." *Journal of Accounting and Economics*, 36 (2003): 105-146.

Anderson, M.A., Banker, R. D. and Janakiraman, S. "Are Selling, General, and Administrative Costs Sticky." *Journal of Accounting Research*, 41 (2003): 47-63.

Anderson, M.A., Banker, R.D., Huang, R. and Janakiraman, S. "Cost Behavior and Fundamental Analysis of SG&A Costs." *Journal of Accounting, Auditing, and Finance*, 22 (2007): 1-28.

Balakrishnan, R. and Gruca, T. S. "Cost stickiness and Core Competency: A Note." *Contemporary Accounting Research*, 25 (2008): 993-1006.

Balakrishnan, R., Petersen, M. and Soderstrom, N. "Does Capacity Utilization Affect the "Stickiness" of COst?" *Journal of Accounting, Auditing and Finance* 19 (2004): 283-99.

Ball, R. T. "Discussion of Why Do EPS Forecast Error and Dispersion Not Vary with Scale? Implications for Analyst and Managerial Behavior." *Journal of Accounting Research*, 49 (2011): 403–412.

Banker, R., Byzalov, D. and Chen, L. "Employment Protection Legislation, Adjustment Costs and Cross-Country Differences in Cost Behavior." *Journal of Accounting and Economics* (2012): forthcoming.

Banker, R. D., Byzalov, D., Ciftci, M. and Mashruwala, R. "The Moderating Effect of Prior Sales Changes on Asymmetric Cost Behavior." Working paper, Temple University, 2012.

Banker, R., Basu, S., Byzalov, D. and Chen, J.Y.S. "Asymmetric Timeliness of Earnings: Conservatism or Sticky Costs?" Working paper, Temple University, 2012.

Banker, R. and Chen, L. "Predicting Earnings Using a Model Based on Cost Variability and Cost Stickiness." *The Accounting Review*, 81 (2006): 285-307.

Brown, L.D. "A Temporal Analysis of Earnings Surprises: Profits Versus Losses." *Journal of Accounting Research*, 39 (2001): 221-241.

Calleja, K., Steliaros, M. and Thomas, D. C. "A Note on Cost Stickiness: Some International Comparisons." *Management Accounting Research*, 17 (2006): 127-140.

Chen, C.X., Lu, H. and Sougiannis, T. "The Agency Problem, Corporate Governance, and the Asymmetrical Behavior of Selling, General, and Administrative Costs." *Contemporary Accounting Research*, 29 (2012): 252-282.

Cheong, F.S., and Thomas, J. "Why Do EPS Forecast Errors and Dispersion Not Vary With Scale? Implications for Analyst And Managerial Behavior." *Journal of Accounting Research*, 49 (2010): 359-401.

Das, S., Levine, C.B. and Sivaramakrishnan, K. "Earnings Predictability and Bias in Analysts' Earnings Forecasts." *The Accounting Review*, 73 (1998): 277-294.

Dechow. P., Kothari, S.P. and Watts, R. "The Relation between Earnings and Cash Flows." *Journal of Accounting and Economics*, 25 (1998): 133-168.

Degeorge, F., Patel, J. and Zeckhauser, R. "Earnings Management to Exceed Thresholds," *Journal of Business*, 72 (1999): 1-33.

Doukas, J.A., Kim, C. and Pantzalis, C. "A Test of the Errors–in–Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts." *Journal of Finance*, 57 (2002): 2143-2165.

Durtschi, C. and Easton, P. "Earnings Management? The Shapes of the Frequency Distributions of Earnings Metrics Are Not Evidence Ipso Facto." *Journal of Accounting Research*, 43 (2005): 537-592.

Durtschi, C. and Easton, P. "Earnings Management? Erroneous Inferences Based on Earnings Frequency Distributions." *Journal of Accounting Research,* 47 (2009): 1249-1281.
Ertimur, Y., Livnat, J. and Martikainen, M. "Differential Market Reactions to Revenue And Expense Surprises." *Review of Accounting Studies*, 8 (2003): 185-211.
Fama. E., and Macbeth, J. "Risk, Return and Equilibrium: Empirical Tests." *Journal of Political Economy,* 38 (1973): 607-636.
Firth, M., Lin, C., Liu, P. and Xuan, Y. "The Client Is King: Do Mutual Fund Relationships Bias Analyst Recommendations?" *Journal of Accounting Research*, 51(2013): 165–200.
Francis, J., and Willis, R.H. "A Multivariate Test of Incentive, Selection and Judgmental Explanations for Analyst Bias." Working Paper, Duke University, 2000.
Gu, Z., Jain, P.C. and Ramnath, S. "In-sync Or Out-Of-sync? The Joint Information in Revenues and Expenses." Working paper, University of Minnesota, 2006.
Gu, Z., and Wu, J. "Earnings Skewness and Analyst Forecast Bias." *Journal of Accounting and Economics,* 35 (2003): 5-29.
Gu, Z., and Xue, J. "Earnings Levels, Earnings Changes and Analyst Forecast Bias: Another Look." Working paper, Carnegie Mellon University, 2001.
Hayes, R. "The Impact of Trading Commission Incentives on Analysts' Stock Coverage Decisions and Earnings Forecasts." *Journal of Accounting Research*, 36 (1998): 299–320
La Porta, R. "Expectations and the Cross-Section of Stock Returns." *The Journal of Finance,* 51 (1996): 1715-42.
Kallapur, S., and Eldenburg, L. "Uncertainty, Real Options, and Cost Behavior: Evidence from Washington State Hospitals." *Journal of Accounting Research,* 43 (2005): 735–752.
Kama, I. and Weiss, D. "Do Earnings Targets and Managerial Incentives Affect Sticky Costs?" *Journal of Accounting Research* 51(2013): 201–224.
Kim, M., and Prather-Kinsey, J. "An Additional Source of Financial Analysts' Earnings Forecast Errors: Imperfect Adjustments for Cost Behavior." *Journal of Accounting, Auditing & Finance* 25 (2010): 27-51.
Mikhail, M., Walther, B. and Willis, R. "The Effect of Experience on Security Analyst Underreaction." *Journal of Accounting and Economics*, 35 (2003): 101-116.
Noreen, E. and Soderstrom, N. "The Accuracy of Proportional Cost Models: Evidence from Hospital Service Departments." *Review of Accounting Studies*, 2 (1997): 89-114.
Penman, S. "*Financial statement analysis and security valuation*." Fourth Ed. McGraw-Hill/Irwin, 2009.
Petersen, M.A. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies,* 22 (2009): 435–480.
Sinha, P., Brown, L.D. and Das, S. "A Re-Examination of Financial Analysts' Differential Earnings Forecast Accuracy." *Contemporary Accounting Research*, 14 (1997): 1-42.
Sloan, R. and Lundholm, R.. "*Equity valuation and analysis w/ eVal*." Second Ed. McGraw-Hill/Irwin, 2006.
Stickel, S. "Reputation and Performance among Security Analysts." *Journal of Finance*, 47 (1992): 1811-1836.
Subramaniam, C. and Weidenmier, M.. "Additional Evidence on the Behavior of Sticky Costs." Working paper, Texas Christian University, 2003.
Subramanyam, K.R. and Wild, J. "*Financial statement analysis*." 10th Ed. McGraw-Hill/Irwin, 2008.
Tan, H., Wang, S. and Welker, M. "Analyst Following and Forecast Accuracy after Mandated IFRS Adoptions." *Journal of Accounting Research*, 49(2011): 1307–1357

Weiss, D. "Cost behavior and Analysts' Earnings Forecasts." *The Accounting Review,* 85 (2010): 1441-1471.

Wu, J.S. "Financial Analysts' Understanding of the Seasonal Pattern in Quarterly Earnings and Its Implications for Market Efficiency." Ph.D. Dissertation, Tulane University, 1999.

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

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

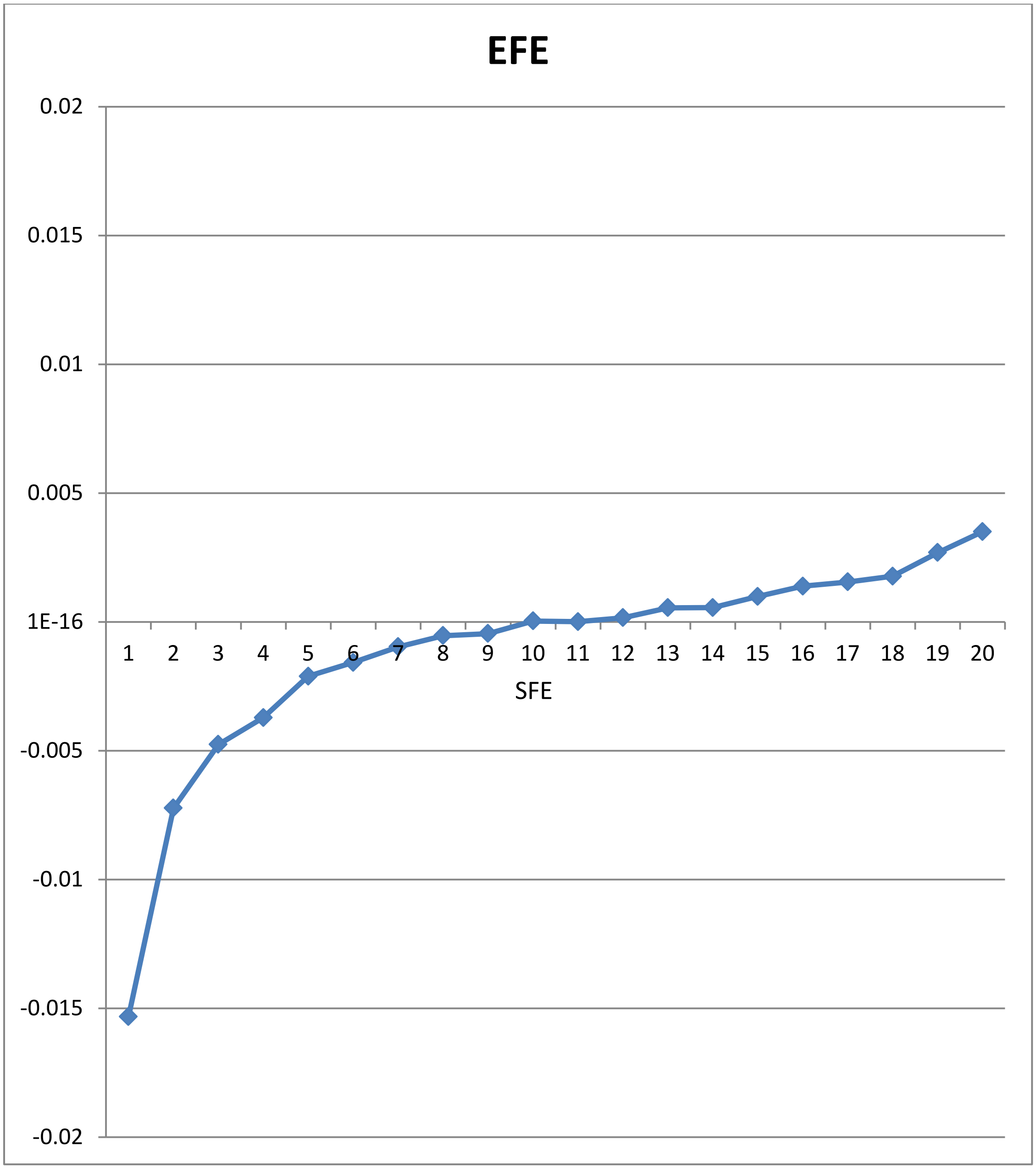

Table 1
Descriptive Statistics

Panel A: Deflated Forecast Errors

	P10	Q1	MEAN	MEDIAN	Q3	P90	STD	t-stat
EFE	-0.0074	-0.0014	-0.0012	0.0002	0.0019	0.0058	0.0176	-21.74***
SFE	-0.0189	-0.0043	0.0004	0.0008	0.0066	0.0204	0.0406	3.04***
XFE	-0.0170	-0.0043	0.0016	0.0006	0.0065	0.0214	0.0406	12.48***
EFE/SFE	-0.8488	-0.0505	0.2388	0.1029	0.5098	1.5457	1.1680	67.07***

Panel B: Undeflated Forecast Errors

	P10	Q1	MEAN	MEDIAN	Q3	P90	STD	t-stat
EFE	-0.1000	-0.0200	-0.0051	0.0100	0.0400	0.0900	0.1509	-11.00***
SFE	-0.3095	-0.0742	0.0467	0.0139	0.1329	0.4245	0.6382	23.98***
XFE	-0.2806	-0.0718	0.0517	0.0103	0.1290	0.4186	0.6260	27.10***

Panel C: Other Variables

	P10	Q1	MEAN	MEDIAN	Q3	P90	STD	t-stat
MARGIN	0.1333	0.2481	0.4276	0.4058	0.6060	0.7634	0.2359	593.00***
STICKY	-1.3031	-0.4483	-0.0111	-0.0205	0.4078	1.3195	1.3068	-2.15**
NEG	0.0000	0.0000	0.4363	0.0000	1.0000	1.0000	0.4959	288.53***

*, **, *** 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 1998-2011. There are 107,577 firm-quarter observations in the sample that have data in Compustat CRSP Merged Files 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 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. MARGIN is operating leverage, which is computed as sales (SALEQ) minus cost of goods sold (COGSQ) divided by sales (Weiss [2010]). MARGIN is winsorized to be between one and zero. NEG is an indicator variable which equals 1 if SFE<0 and 0, otherwise.

Table 2
Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – Portfolio Analyses

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 first and second columns titled Analysts Forecasts show the mean sales (SFE) and earnings (EFE) forecasts. The right column shows the mean value of EFE/SFE ratios.

Portfolio	N	Ranges of Sales Forecast Errors Portfolios (SFE)	Analysts Forecasts		
			Mean Forecast Errors		Mean Ratio For EFE/SFE
			Sales Error (SFE)	Earnings Error (EFE)	
1 – low	10,251	<-0.020	-0.0523	-0.0099	0.2018
2	2,804	[-0.020,-0.015)	-0.0174	-0.0043	0.2160
3	4,333	[-0.015,-0.010)	-0.0123	-0.0035	0.2451
4	7,926	[-0.010,-0.005)	-0.0072	-0.0023	0.2383
5	21,618	[-0.005,0)	-0.0020	-0.0007	0.0677
6	29,305	(0,+0.005]	0.0020	0.0005	0.4376
7	10,948	(+0.005,+0.010]	0.0072	0.0009	0.1740
8	5,799	(+0.010,+0.015]	0.0123	0.0014	0.1352
9	3,587	(+0.015,+0.020]	0.0174	0.0016	0.1055
10 – high	11,006	>+0.020	0.0512	0.0026	0.0716
Asymmetry Tests [a]					
abs(5) – abs(6)			-0.00005	0.00017	-0.2989
			(-2.57)***	(1.18)	(-11.10)***
abs(4) – abs(7)			0.00000	0.0011	0.0588
			(0.11)	(5.06)***	(2.48)**
abs(3) – abs(8)			0.00002	0.0018	0.0982
			(0.46)	(5.50)***	(4.69)***
abs(2) – abs(9)			0.00004	0.0024	0.1028
			(0.87)	(5.04)***	(4.67)***
abs(1) – abs(10)			0.00106	0.0069	0.1252
			(0.35)	(9.72)***	(10.00)***

*, **, *** 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 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.

Table 3
Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – Regression Models

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it}*NEG_{it} + e_{it} \qquad (17)$$

Variables	Deflated variables		Undeflated variables	
	I	II	III	IV
Intercept	-0.0007	0.0019	-0.0115	0.0209
	(-1.17)	(3.47)***	(-1.90)*	(3.33)***
NEG		-0.0020		-0.0406
		(-8.69)***		(-26.79)***
SFE	0.0905	0.0101	0.0441	0.0129
	(6.98)***	(2.43)**	(8.37)***	(4.92)***
SFE* NEG		0.1834		0.0669
		(11.01)***		(10.98)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0598	0.0997	0.0662	0.0987
N	107,577	107,577	107,577	107,577

*, **, *** 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

Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – Loss and Profit Observations

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it}*NEG_{it} + e_{it} \quad (17)$$

Panel A: Loss Observations

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	0.0013 (0.63)	0.0064 (2.30)**	-0.0119 (- 0.60)***	0.0248 (1.08)
NEG		-0.0061 (-7.90)***		-0.0448 (-11.97)***
SFE	0.0957 (3.36)***	0.0080 (1.17)	0.0302 (2.90)***	-0.0014 (-0.63)
SFE* NEG		0.2306 (6.23)***		0.1460 (5.99)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0708	0.1109	0.0541	0.1003
N	17,284	17,284	17,284	17,284

Panel B: Profit Observations

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0010 (-1.86)*	0.0010 (2.08)**	-0.0115 (-1.84)*	0.0194 (3.09)***
NEG		-0.0014 (-7.05)***		-0.0378 (-21.81)***
SFE	0.0855 (7.64)***	0.0124 (2.53)***	0.0466 (7.87)***	0.0158 (4.52)***
SFE* NEG		0.1487 (9.17)***		0.0612 (9.47)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0753	0.1158	0.0751	0.1061
N	90,293	90,293	90,293	90,293

*, **, *** 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 observations. 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

Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – High and Low Growth (BM)

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it}*NEG_{it} + e_{it} \quad (17)$$

Panel A: High Growth

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0008 (-1.60)	0.0010 (2.04)**	-0.0059 (-0.87)	0.0198 (2.82)***
NEG		-0.0017 (-8.34)***		-0.0385 (-24.93)***
SFE	0.0636 (2.78)***	0.0105 (1.04)	0.0326 (4.35)***	0.0121 (3.23)***
SFE* NEG		0.1720 (6.71)***		0.0613 (9.21)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0372	0.0874	0.0562	0.1072
N	52,509	52,509	52,509	52,509

Panel B: Low Growth

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0003 (-0.34)	0.0028 (2.85)***	-0.0150 (-1.52)	0.0207 (2.01)**
NEG		-0.0023 (-6.23)***		-0.0427 (-18.96)***
SFE	0.0918 (6.28)***	0.0086 (2.11)**	0.0516 (12.23)***	0.0143 (4.56)***
SFE* NEG		0.1782 (9.01)***		0.0595 (7.84)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0719	0.1053	0.0818	0.1022
N	52,538	52,538	52,538	52,538

*, **, *** 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 high and low growth firms. Firm-quarter observations are separated into two groups (high and low) based on book-to-market ratio at the beginning of the quarter. High (low) growth firms are those with book to market ratio below (above) median. We delete observations with negative book value of equity. 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 6
Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – High and Low Analyst Following

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it}*NEG_{it} + e_{it} \quad (17)$$

Panel A: High Analyst Following (above or equal to median)

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0007 (-1.59)	0.0006 (1.38)	-0.0105 (-1.28)	0.0211 (2.35)**
NEG		-0.0013 (-5.71)***		-0.0419 (-18.38)***
SFE	0.1051 (8.83)***	0.0274 (4.43)***	0.0429 (5.25)***	0.0129 (3.40)***
SFE* NEG		0.1250 (5.36)***		0.0718 (8.60)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0688	0.0853	0.0772	0.1142
N	55,430	55,430	55,430	55,430

Panel B: Low Analyst Following (below median)

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0006 (-0.58)	0.0029 (2.92)***	-0.0127 (-1.34)	0.0206 (2.24)**
NEG		-0.0027 (-7.57)***		-0.0395 (-19.69)***
SFE	0.0880 (5.25)***	0.0086 (1.69)*	0.0468 (9.09)***	0.0130 (3.75)***
SFE* NEG		0.1924 (8.84)***		0.0626 (7.08)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0598	0.1025	0.0541	0.0856
N	52,147	52,147	52,147	52,147

*, **, *** 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 high and low analyst following firms. Firm-quarter observations are separated into two subsamples (high and low) based on number of analysts following the firm in quarter t-1. 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 7
Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – High and Low SG&A Cost Intensity

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it}*NEG_{it} + e_{it} \quad (17)$$

Panel A: High SG&A Intensity

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	0.0012 (1.62)*	0.0042 (3.90)***	0.0055 (0.80)	0.0415 (4.81)***
NEG		-0.0022 (-5.57)***		-0.0354 (-21.04)***
SFE	0.1176 (3.48)***	0.0087 (1.56)	0.0467 (3.09)***	0.0053 (1.58)
SFE* NEG		0.3031 (9.15)***		0.1742 (15.13)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0717	0.1468	0.0579	0.1410
N	45,347	45,347	45,347	45,347

Panel B: Low SG&A Intensity

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0019 (-2.14)**	0.0001 (0.07)	-0.0220 (-2.18)**	0.0071 (0.66)
NEG		-0.0017 (-5.75)***		-0.0377 (-13.48)***
SFE	0.0631 (5.72)***	0.0107 (1.58)	0.0441 (7.00)***	0.0175 (3.65)***
SFE* NEG		0.1062 (5.79)***		0.0416 (5.43)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0539	0.0779	0.0791	0.0985
N	45,318	45,318	45,318	45,318

*, **, *** 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 high and low SG&A firms. Firm-quarter observations are separated into two subsamples (high and low) based on SG&A intensity (SG&A costs to sales ratio) in quarter t-1. <u>We exclude firm-quarter observations with negative SG&A.</u> 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 8

Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – Individual Analysts

$$IEFE_{ijt} = \lambda_0 + \lambda_1 INEG_{ijt} + \lambda_2\ ISFE_{ijt} + \lambda_3 ISFE_{ijt}{*}INEG_{ijt} + e_{ijt} \qquad (17a)$$

Panel A: Analysts with perfect earnings forecast of firm i on quarter t-1 (earnings forecast error = 0).

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	0.0003 (1.58)	0.0011 (5.38)***	0.0096 (3.75)***	0.0241 (9.01)***
NEG		-0.0011 (-6.46)***		-0.0234 (-13.14)***
SFE	0.1156 (12.03)***	0.0580 (6.27)***	0.0765 (14.69)***	0.0390 (8.57)***
SFE* NEG		0.0778 (3.45)***		0.0447 (3.45)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0758	0.0847	0.0982	0.1161
N	33,507	33,507	33,507	33,507

Panel B: Analysts with imperfect earnings forecast of firm i on quarter t-1 (earnings forecast error ≠ 0).

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	0.0004 (2.82)***	0.0015 (11.36)***	0.0174 (6.50)***	0.0360 (14.49)***
NEG		-0.0014 (-12.04)***		-0.0308 (-13.29)***
SFE	0.1268 (21.77)***	0.0523 (7.57)***	0.0979 (19.47)***	0.0629 (11.16)***
SFE* NEG		0.1091 (7.98)***		0.0424 (3.87)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0737	0.0832	0.1104	0.1200
N	312,446	312,446	312,446	312,446

*, **, *** 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 zero error and error analysts. Analyst-firm-quarter observations are separated into two groups (zero error and error) based latest analyst forecast error in quarter t-1. Zero error analysts are those with zero error in earnings forecast. Error analysts are those with nonzero error in earnings forecast. IEFE is earliest individual analyst earnings forecast in *I/B/E/S* Detail Files minus actual earnings deflated by lagged price. ISFE is individual analyst sales per share forecast minus actual sales per share. Sales per share is generated by dividing the sales per share with number of share outstanding (CSHOQ from Compustat). INEG is a dummy variable which equals 1 if individual sales forecast error is negative, 0 otherwise. 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 9

Analysts' Earnings Forecast Errors Conditioned on Favorable and Unfavorable Sales Surprises of Equivalent Amounts – Latest Consensus Forecasts

$$EFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2 SFE_{it} + \lambda_3 SFE_{it}{*}NEG_{it} + e_{it} \quad (17)$$

Variables	Deflated variables		Undeflated variables	
	I	II	I	II
Intercept	-0.0007 (-1.24)	0.0013 (2.41)**	-0.0057 (-1.37)	0.0160 (3.73)***
NEG		-0.0019 (-11.18)***		-0.0318 (-28.11)***
SFE	0.0639 (6.87)***	0.0116 (3.19)***	0.0327 (8.99)***	0.0129 (5.69)***
SFE* NEG		0.1294 (9.98)***		0.0359 (6.95)***
Clustering	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Adjusted - R^2	0.0357	0.0569	0.0409	0.0602
N	124,346	124,346	124,346	124,346

*, **, *** 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. We use the latest consensus sales and earnings forecast available from *I/B/E/S* Summary Files. 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 10
Specification Validity – Placebo Test

Portfolio	Ranges of Analysts Sales Forecast Errors Portfolios (SFE)	Time-series Forecasts: Mean ratio for EFE/SFE
1 – low	<-0.020	0.0505
2	[-0.020,-0.015)	0.0412
3	[-0.015,-0.010)	0.0183
4	[-0.010,-0.005)	-0.0064
5	[-0.005,0)	-0.0295
6	(0,+0.005]	-0.0568
7	(+0.005,+0.010]	-0.0574
8	(+0.010,+0.015]	-0.0436
9	(+0.015,+0.020]	0.0253
10 – high	>+0.020	0.0221
Asymmetry Tests [a]		
abs(5) – abs(6)		-0.0061
		(0.80)
abs(4) – abs(7)		-0.0056
		(-0.52)
abs(3) – abs(8)		-0.0153
		(-0.77)
abs(2) – abs(9)		-0.0717
		(-1.43)
abs(1) – abs(10)		0.0123
		(1.10)

*, **, *** 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 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.

Notes:
The table presents results from performing the portfolio analysis described in Table 2 using simulated time-series forecasts as in Banker and Chen [2006]. Specifically, rather than utilizing analysts' earnings forecasts, we simulate a standard seasonal random walk (SRW) model for estimating sales forecasts, and compute earnings forecasts using the CVCS model employed by Banker and Chen [2006]. The CVCS model incorporates cost variability and cost stickiness into earnings predictions. The right column reports the mean simulated ratio EFE/SFE. To allow comparability of the reported figures, the portfolios are sorted using the same ranges of sales forecast errors used in Table 2.

Table 11
Simulation Results - Multiple Scenarios

Variables	CASE I Perfect recognition of both cost stickiness and cost variability	CASE II Ignore sticky costs and perfectly recognize cost variability	CASE III Ignore sticky costs and erroneously over-estimate cost variability
Intercept	0.68 (0.26)	-100.01*** (-40.63)	+100.02*** (37.43)
NEG	1.15 (0.31)	4.81 (1.36)	3.74 (1.01)
SFE	0.51*** (18.78)	0.50*** (17.73)	0.51*** (16.42)
SFE* NEG	0.03 (0.81)	0.11*** (2.89)	0.09*** (2.25)

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

Notes:
The table presents results from estimating regression model (17) using simulated data. The simulation follows the example in footnote 3. Forecasting sales, we assume sales on prior period is S_{t-1}=1000. We use a four-scenario sales distribution on period t. A random number evenly distributed between 0 and 100, *R*, is used for generating sales on period t: $S_{t-1}-2R$, $S_{t-1}-R$, $S_{t-1}+R$, and $S_{t-1}+2R$. The analyst perfectly predicts sales on each of the four scenarios. Forecasting costs on each of the four scenarios, we assume cost variability is v=0.5 and cost stickiness is β=-0.2. Therefore, total cost in each scenario is $C_t = 100 + 0.5*S_t – 0.2*(S_t – S_{t-1})$, where $S_t \in \{S_{t-1}-2R, S_{t-1}-R, S_{t-1}+R$, and $S_{t-1}+2R\}$. Earnings in each scenario are predicted as $X_t = S_t – C_t$.
Both sales and earnings forecasts are predicted as means assuming equal probability for each scenario. The forecast errors are: SFE = S_t – sales forecast, and EFE = X_t – earnings forecast. NEG_t = 1 if $S_t < S_{t-1}$ and zero otherwise.
We simulate sales and earnings forecasts for 100 firms (100 iterations) and then estimate regression model (17) in three cases with equal probability for each of the four scenarios:
Case I - The analyst perfectly recognizes both cost stickiness and cost variability (β=-0.2 and v=0.5). Accordingly, costs on each scenario are predicted to be $C_t = 100 + 0.5*S_t – 0.2*(S_t – S_{t-1})$.
Case II - The analyst ignores cost stickiness and perfectly recognizes cost variability (β=0 and v=0.5). Costs on each scenario are predicted to be $C_t = 100 + 0.5*S_t$.
Case III - The analyst ignores sticky costs (β=0) and erroneously predicts high cost variability (v=0.7). Costs on each scenario are predicted to be $C_t = 100 + 0.7*S_t$.

In each case, we estimate the regression model using the simulated forecast errors. The table presents mean coefficients and t-values.

Table 12

The Effects of Cost Variability and Sticky Costs on EFE/SFE Ratio - 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 quarterly means over 1998-2011. The t-statistics are computed based on the Fama and MacBeth [1973] procedure.

Panel A: Cost Variability Effect

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

	High Cost Variability (MARGIN below median)		Low Cost Variability (MARGIN above median)		Difference (High-Low)	Difference (High-Low)
(1)	(2)	(3)	(4)	(5)	(6)=(2)-(4)	(7)=(3)-(5)
	Mean	Median	Mean	Median	Mean	Median
Unfavorable sales surprises (NEG=1)	0.1901	0.0548	0.1101	0.0549		
Favorable sales surprises (NEG=0)	0.1358	0.0616	0.4020	0.2277		
Difference (1-0) [a]	0.0543 (2.36)***	-0.0068 (-0.67)	-0.2919 (-9.81)***	-0.1728 (-9.35)***	0.3462 (14.70)***	0.1660 (12.60)***

Panel B: Sticky Costs Effect

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

	Sticky Costs		Anti-Sticky Costs		Difference (sticky – anti-sticky)	Difference (sticky – anti-sticky)
(1)	(2)	(3)	(4)	(5)	(6)=(2)-(4)	(7)=(3)-(5)
	Mean	Median	Mean	Median	Mean	Median
Unfavorable sales surprises (NEG=1)	0.2657	0.1337	-0.0677	-0.0041		
Favorable sales surprises (NEG=0)	0.0830	0.0593	0.3480	0.1557		
Difference (1-0) [a]	0.1826 (8.05)***	0.0744 (6.81)***	-0.4157 (-14.84)***	-0.1599 (-9.86)***	0.5983 (20.79)***	0.2342 (15.22)***

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

Table 13

The Effects of Cost Variability and Sticky Costs on EFE/SFE Ratio – Regression Models

$$EFE_{it} / SFE_{it} = \lambda_0 + \lambda_1 NEG_{it} + \lambda_2\, DMARGIN_{it} + \lambda_3\, DSTICKY_{it} + \lambda_4\, NEG_{it} * DMARGIN_{it} + \lambda_5 NEG_{it} * DSTICKY_{it} + \lambda_6\, MV_{it} + \lambda_7\, BM_{it} + \lambda_8\, LFLLW_{it} + \lambda_9\, LOSS_{it} + \lambda_{10}\, DISP_{it} + \lambda_{\backslash 11}\, CV_{it} + \lambda_{12} INDROE_{it} + \lambda_{13}\, SUE1_{it} + \lambda_{14}\, SUE2_{it} + \lambda_{15}\, LTV_{it} + e_{it} \quad (18)$$

	I	II
Intercept	0.5453 (5.66)***	0.5809 (5.89)***
NEG	-0.6232 (-29.88)***	-0.6249 (-30.01)***
DMARGIN	-0.2258 (-16.44)***	-0.2288 (-16.49)***
DSTICKY	-0.2725 (-22.82)***	-0.2740 (-22.85)***
NEG*DMARGIN	0.2711 (11.88)***	0.2673 (11.74)***
NEG*DSTICKY	0.6412 (33.13)***	0.6370 (32.82)***
MV		-0.0268 (-5.27)***
BM		0.0013 (0.08)
LFLLW		0.0132 (1.54)
LOSS		0.0513 (2.28)**
DISP		3.0966 (2.68)***
CV		0.0011 (1.01)
INDROE		-0.0716 (-0.89)
SUE1		-0.0542 (-0.45)
SUE2		0.2310 (2.10)**
LTV		0.0198 (3.85)***
Clustering	Yes	Yes
Quarter Dummies	Yes	Yes
Adjusted - R^2	0.0426	0.0452
N	49,091	49,091

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

Table 13 - Continued

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 Table 1. DMARGIN is an indicator variable which equals 1 if the firm has high cost variability (below median 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 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].