Analyst forecasts: sales and profit margins

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Abstract
Sales and profit margins are two popular earnings components discussed in the media. We study properties of one-year-ahead analyst forecasts of these two components. As sales are in dollar amounts and profit margin is a ratio, we propose robust statistical methods to assess and contrast their forecast properties. We find that four performance properties associated with earnings forecasts—optimism, relative accuracy with respect to benchmark model forecasts, forecast suboptimality, and serial correlation of forecast errors—apply to both sales and profit margins. Sales forecasts, in general, perform better than profit margin forecasts. Further evidence also shows that sales forecasts perform better than profit margin forecasts in terms of how their forecast errors explain earnings forecast errors and how realized surprises affect adjustments of the respective forecasts. We also find that a better information environment, surrogated by size, improves sales forecasts more than profit margin forecasts. All of these findings suggest that forecasting profit margins is inherently more difficult than forecasting sales.

Note: This data is mandatory.

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1 Introduction

This paper investigates whether previously documented performance properties of analyst forecasts of earnings apply to both sales and profit margin and whether these properties differ with respect to the two multiplicative earnings components.[1] We study four popular forecast properties: optimism, relative accuracy with respect to benchmark model forecasts, forecast suboptimality, and serial correlation of forecast errors. We also conduct two

[1]Profit margin is a ratio of earnings to sales, defined as earnings/sales. Therefore earnings = sales* profit margin. We use IBES data to generate earnings (=shares outstanding*EPS).

additional analyses to contrast forecasts of sales and profit margin: (1) their contributions to the forecast errors of earnings and (2) financial analysts' forecast adjustments as a result of new information contained in sales and profit margin. These additional analyses can bring insights into the information usefulness of sales and profit margin forecasts. Furthermore, we study whether a better information environment, surrogated by size, affects the performance of forecasts of sales and profit margin differently.

We focus on sales and profit margin due to the real-world attention paid to them.[2] Although studies exist evaluating how sales and expenses differ in their usefulness in the capital market context (e.g., Ertimur et al. 2003), evidence on profit margin is lacking. Profit margin is influenced by expenses scaled by sales, and findings on expenses may not be strictly carried over to profit margin. We focus on directly evaluating the forecast performance properties of sales and profit margin forecasts, rather than the capital market effects of these forecasts. We suggest novel methods to contrast the information properties of sales and profit margin. We consider this paper's approach to be fundamental and important.

We examine four forecast properties that are widely accepted for analyst forecasts of earnings. As summarized in Bradshaw (2011), findings for four performance properties stand out as being generally accepted.[3] First, analyst forecasts tend to be too optimistic; that is, realized earnings tend to be lower than analyst forecasts (optimism). Second, benchmark forecasting models tend to forecast less accurately than analyst forecasts (relative forecast accuracy). Third, research suggests that analyst forecasts of earnings can be improved by considering predictions from statistical models (suboptimality). Fourth, positive or negative earnings forecast errors tend to be followed by similarly signed errors—a small but identifiable positive serial correlation (positive errors serial correlation).

Our main research question is whether these four performance properties of analyst earnings forecasts apply to *both* sales and profit margin and whether sales forecasts will perform better or worse than profit margin forecasts. We italicize the word "both" because earnings forecast properties can hold for either sales or profit margin, but it is not clear that this will be the case for both of them. Even if it is likely that the properties can hold for both, it will also be interesting to document which forecast performs better. On prior ground, the two components differ sufficiently: one is a dollar amount (sales) and the other one is a ratio (profit margin with sales as the scaler). If sales contributes to the main variability in earnings, then a scaled number, such as profit margin, will not capture the variability in earnings; sales forecasts should then constitute the main element driving the forecasting properties for earnings. On the other hand, if sales is predictable and expense is difficult to predict, then analyst forecasts of profit margin will drive the forecasting properties for earnings. A priori, it is likely that expense is

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[2] Even a cursory review of financial media clearly suggests that the analysis of firms' performance centers on sales and profit margin, and these two metrics provide the standard breakdown of earnings. For example, a *Wall Street Journal* article on Oct. 28, 2016, titled "AB InBev Cuts Revenue Forecast," reported that "Anheuser-Busch InBev NV cut its revenue forecast for the year after the world's largest brewer reported weak third-quarter results. …" Another *Wall Street Journal* article on Oct. 11, 2015, titled "The Number to Watch This Earnings Season," reported that "As third-quarter U.S. corporate results roll out this week, many investors are putting an increased focus on profit margins as a sign of companies' ability to propel earnings higher. …"

[3] These properties are widely accepted under broad circumstances, which rules out conditioning variables, such as analysts' independence and capability, firm size, earnings risk, etc. This paper focuses on broad circumstances.

more uncertain than sales for reasons that we will discuss later. However, financial analysts may expend extra effort and extract better and insightful information for hard-to-predict expenses. This effort may be especially worthwhile for firms with better information environments; hence this may lead to similar forecast performance for sales and profit margin, even if one is more difficult to predict than the other. We use firm size as a surrogate for the information environment and analyze whether firm size has an effect and if the effect differs with respect to sales and profit margin.

In addition to bringing evidence that provides new insights, our paper contributes to the literature by suggesting novel methods to the analyst forecast literature. Specifically, we develop robust research methodology to evaluate the performance properties of analyst forecasts of sales and profit margin throughout. In general, we adopt a simple count metric, based on relative scores by comparing two numbers (e.g., assign 1 or 0, according to whether one number is greater or smaller than the other number). We then generate the percentage of observations in a sample that has the score of 1. We term this as the relative accuracy score (RAS). As sales is a dollar amount and profit margin is a ratio, such a comparison fits especially well for our analyses. Moreover, this methodology is robust to outliers and scaling effects.

We propose a few models, which are not typically used in prior research, to analyze the analyst forecasts. Specifically, we develop benchmark forecasting models for sales and profit margin differently. We reason that future sales should be affected by sales growth, while profit margin should follow a mean-reverting process. Hence we incorporate growth into the benchmark model for sales but not for profit margin. We propose an error analysis method to analyze the earnings forecast errors to be explained by sales versus by profit margin. We also propose an adaptive expectation model to assess the effect of realized information about sales and profit margin on analysts' forecast adjustments for sales and profit margin, respectively.

Our sample consists of 25,230 observations from I/B/E/S over 15 years from 2002 to 2016. We assign them into five size groups, based on a firm's market value at the time of analyst forecasts.[4] We develop test scores for each of the 75 size-year groups and then conduct various statistical analyses, based on these test scores. Since our paper uses research methodologies that are not typically adopted by papers in the analyst forecast literature, to improve readability, we first summarize our methodology and findings below.

1.1 Optimism

We develop two test scores: relative accuracy score (RAS) and a factor K. RAS is measured as the percentage that an analyst forecast is less than the realization for each size-year group for sales and profit margin, respectively.[5] Optimism exists if the

[4] Our definition of size group is based on the annual average market value of *all* NYSE, AMEX, and NASDAQ firms in CRSP. In other words, we will not have the same number of observations in each size group. However, we also conduct robustness checks using the same number of observations for each size group.

[5] In a strict sense, the RAS for optimism focuses on the ratio that an analyst forecast is lower than the realization, i.e., less optimal, rather than the accuracy. The smaller the RAS, more observations are optimal, implying higher optimism. For easy reference, we use the term RAS when discussing our first three performance properties. For the analysis of analyst forecast optimism, if RAS is higher than 50%, then analyst forecast conservatism exists. As it is considered that conservatism is better than optimism, a higher RAS implies better performance.

percentage is less than 50%, and the lower the RAS, the more upward biases exist. Factor K is developed to measure the degree of upward biases. We employ an iterative method to find a constant factor K (we term this "haircut adjustment") to adjust the analyst forecasts so that they are equal to the realizations. If K is smaller than 1, then more optimism exists (since this means that the forecast has to be reduced to a smaller number to become closer to the actual value).

1.2 Relative accuracy

We rely on the RAS, measured by the percentage that analyst forecasts are more accurate than forecasts from a benchmark model. As discussed earlier, we design the benchmark models differently for sales and profit margin. Specifically, we consider sales growth for sales, but for PM, we follow the random walk model.

1.3 Suboptimality

We rely on the RAS measured by the percentage that analyst forecasts are less accurate when they are modified by benchmark model forecasts. In other words, if the analyst forecasts can be improved by taking model forecasts into account, then suboptimality exists. Specifically, we modify the forecasts by adjusting the analyst forecasts with model forecasts. We first allocate a small weight (5%) to the benchmark model forecasts. Since we are using relative scores, as long as benchmark model forecasts help, the magnitude of the weight should not matter. We also use a robust regression method (Theil-Sen method, following Ohlson and Kim 2015) to find optimal weights.[6]

1.4 Errors serial correlation

We rely on the relative scores based on the percentage that the consecutive analyst forecast errors have the same sign (i.e., both upticks or both downticks across two periods).

We find that all four performance properties apply to sales and profit margin forecasts; however, there are different degrees of the effects of size. We find that, on average, sales forecasts perform better than profit margin forecasts.[7] However, we often see no differences when firms are small and more differences when they are larger. Consequently, we argue that the size effect (i.e., improving analyst forecasts) is, on average, larger for sales forecasts than for profit margin forecasts, implying that a better information environment assists analysts in forecasting sales more than in forecasting profit margin.

[6] Our approach discards OLS because of the pervasive presence of data outliers and heteroscedasticity. These dysfunctional data attributes are as true for profit margin as for sales and related forecasts. Instead, we apply the Theil-Sen method of estimation (Wilcox 2012, p. 484). This method is insensitive to outliers, eliminating any need for trimming or winsorization. No less important, coefficient estimates are independent of any scaling of both sides of the equation estimated. The Theil-Sen method adds the advantage of being more efficient than OLS in capital market settings, as Ohlson and Kim (2015) report.

[7] By performing better, we mean less optimism, higher accuracy relative to our selected benchmark model, and less suboptimality. Analyst forecasts of sales and profit margin bear similar levels of serial correlations.

As sales forecasts perform better than profit margin forecasts, it is likely that the former will be more useful than the latter. To bring insights into the information usefulness in contrasting the two, we pose two questions. First, are analyst earnings forecast errors explained more by profit-margin than by sales forecast errors? Second, is the degree of analyst forecast adjustments in response to the realizations stronger in the sales forecasting process than in the profit margin forecasting process? For the first question, we attribute earnings forecast errors to sales and profit margin using a variance analysis framework; for the second question, we analyze the forecasting adjustments in response to realizations of sales versus profit margin using an adaptive expectation concept. We summarize our analyses below.

1.5 Attribution of earnings forecast errors

Following the cost variance analysis for attributing the differences between actual and standard costs to the two multiplicative components of costs (costs = unit cost*quantity), we develop an error analysis for attributing earnings forecasts to the two multiplicative components: sales and profit margin (earnings = sales* profit margin). Specifically, earnings forecast errors are equal to the weighted sum of sales forecast errors and profit margin forecast errors plus a small amount. We first apply a robust regression method (the Theil-Sen method) to verify the validity of the model. We then rely on the relative accuracy score, based on the percentage that profit margin forecast errors explain earnings forecast errors more than sales forecast errors do. We find that the percentages are much larger (and significant) than 50% for all size groups (but monotonically decrease across size groups), suggesting that the earnings forecast errors are more due to profit margin forecasts than sales forecasts and that a better information environment can reduce these differences.

1.6 Analysts' forecast adjustments in response to realizations

We assess whether analysts adjust their forecasts once they learn about the current realizations of sales and profit margin, respectively. We apply the adaptive expectation concept and develop analyst forecast adjustment models for predicting sales and profit margin of period $t + 1$ when sales and profit margin are known in period t. The model adjusts the original analyst forecasts (i.e., for period t) with the weighted new information, that is, the forecast error (= realization – forecasts). The adjustment model predicts that analyst forecasts of period $t + 1$ will be equal to the analyst forecasts of period t plus the product of a weight, $(1 + v)$, times the forecast error.[8] Since sales involves growth, but profit margin does not, the adjustment model for the former differs from that for the latter. The weight should be greater than 1 (i.e., $v > 0$) for sales to capture the extrapolation of growth to the future. However, as profit margin follows a mean-reverting process, the weight should be less than 1 (i.e., $v < 0$). To validate our adoption model, we apply the Theil-Sen method by regressing analyst forecasts of period $t + 1$ on the realization in period t and analyst forecasts of period t for sales and profit margin, respectively. We find that the coefficient on realized sales from the sales

[8] A simple form: $AF(t + 1) = AF(t) + (1 + v)*AFE(t)$, where AF represents the analyst forecasts and AFE represents the analyst forecast errors.

regression model is much larger than the coefficient on realized profit margin from the profit margin regression model, indicating that analysts rely on sales more than on profit margin realizations in adjusting their forecasts for sales and profit margin, respectively.

These two additional analyses provide more insights into the importance of sales versus profit margin forecasts with respect to improving earnings forecasts, as well as the information content of sales versus profit margin realization. They also support our findings based on the four performance properties: analyst forecasts of sales perform better than those of profit margin.

In evaluating how information can improve analyst forecasts, we use firm size as a surrogate for information richness. We focus on size for the following reasons. The analyst forecast literature underscores that most conclusions related to analyst forecasts of earnings depend on various conditions, such as firm size, analyst following, extent of analysts' independence, analysts' characteristics, incentives and their capability, accounting conservatism, firm profitability, information uncertainty, the macroeconomic environment, regulatory environment, etc. Such conditioning increases the chances that one can identify differences between sales forecasts and profit margin forecasts. It is also noteworthy that, because a conclusion related to the earnings forecast itself may depend on the conditioning variables, the same could be true for either sales or profit margin forecasts, potentially in a similar manner. To keep the current research manageable, we consider only one conditioning factor, namely, firm size measured by market capitalization at the time of the forecasts. Size can capture the depth of the information environment as well as stability of the firm. Moreover, analysts also generally pay much more attention to large, stable, and profitable firms.

In sum, our study extends past research on earnings forecasts to earnings components: sales and profit margin. We acknowledge that research exists focusing on earnings components.[9] Our study and previous studies share the common belief that earnings components do provide incremental information rather than by earnings alone. However, compared to prior works, we consider profit margin, a less studied component, instead of expenses. For practitioners, profit margin often appears in the financial media (see footnote 1). It is also a ratio that behaves more like a random walk, whereas expenses are in dollar amounts and build in growth. We also investigate how a firm's information environment affects the results of analyst forecast performance on sales versus on profit margin. Our findings that many of the analyst forecast inefficiencies disappear for large firms suggest that analyst forecast research should be conducted separately for large versus small firms.[10] Moreover, the finding that size improves analyst forecasts of sales more than analyst forecasts of profit margin provides new evidence, which deserves further research.

In addition to the new empirical findings, our paper also contributes by designing robust methods for analyst forecasts research. We use robust methods based on the relative score that is unaffected by different measuring units or by outliers. We also

[9] For example, Ertimur et al. (2003) investigate the differential market reactions to revenue and expense surprises around earnings announcement dates. Rees and Sivaramakrishnan (2007) examine the value implications of joint analyst forecast errors of revenue and earnings. Keung (2010) finds that the market responds more vigorously to analysts' earnings forecast revisions when sales forecasts are also provided.

[10] For example, we find that both analyst forecasts of sales and profit margin are optimistically biased mainly in the three smallest firm size groups.

introduce different benchmark models for sales and profit margin, where the former reflects a growth forecast while the latter does not. Furthermore, our analyses of attributions of earnings forecast errors to earnings' multiplicative components and how their realization affects the next period's analyst forecasts provide innovative applications for the analyst forecast literature. These methodologies can be readily applied to analyst forecasts of other accounting numbers, for example, forecasts of operating cash flows or return on assets.[11]

The remainder of this paper proceeds as follows. Section 2 reviews research related to our topic. Section 3 describes the sample data. Sections 4 and 5 provide analyses for the four performance properties and additional analyses, respectively. Section 6 concludes and suggests directions for future work.

2 Literature

While the literature on analyst forecasts addresses a great variety of questions, core issues and findings tend to be agreed upon. Bradshaw (2011) appraises "what-we-have-learned," with an emphasis on one-year-ahead forecasts—the only setting evaluated herein. Relying on Bradshaw's work as a primary source in our literature survey, four performance properties stand out. First, analysts' earnings forecasts tend to be too optimistic. Second, with respect to relative forecasting accuracy, it is generally agreed that analyst forecasts beat benchmark models, such as the random walk models. The word "generally" is needed here because researchers have recognized that, under more confined circumstances (e.g., excluding losses or considering two fiscal years' horizons), the random walk model will not be easily beaten (Bradshaw et al. 2012). The third property relates closely to the second, but the emphasis shifts to the extent of suboptimality of analyst forecasts. Research examines the extent to which more sophisticated forecasting models can do better than analyst forecasts. A primary focus of this research evaluates statistical methods, such as time-series models of earnings and adding predictive information to which analysts may not pay adequate attention (e.g., accruals). As noted by Bradshaw (2011), results have been mixed. Fourth, in the analysis of analyst forecast errors, it is accepted that the serial correlation is consistently positive. In other words, optimism or pessimism has a tendency to persist over periods. We next discuss the literature with respect to these four properties in turn.

Research on analyst forecast optimism traces back to the research of Fried and Givoly (1982) and O'Brien (1988). Numerous papers afterwards hypothesize various reasons for optimism. Elgers and Lo (1994), Easterwood and Nutt (1999), and Hwang et al. (1996) focus on firms with poor performance and provide evidence that this performance correlates with excess optimism. Others have focused on analysts' incentives to please management (Das et al. 1998; Francis and Philbrick 1993; Dugar and Nathan 1995; Dechow et al. 2000; Lim 2001; Cowen et al. 2006; Bradshaw et al. 2006). Furthermore, McNichols and O'Brien (1997) note that the apparent analyst optimism is partially due to self-selection bias; that is, out-of-favor stocks tend to be

[11] For example, DuPont formula: ROA = profit margin*asset turnover. Financial analysts often provide forecasts of ROA.

dropped by analysts. Due to scope limitations, this paper does not consider whether these hypotheses bear on sales and profit margin similarly or differentially.

Regarding the relative accuracy of analyst forecasts, a large body of literature (mostly published in the 1980s and 1990s) introduces benchmark forecasting models, whose accuracy can be compared to analysts' forecasts of earnings. These models are in the spirit of random walks or, more generally, various time-series dynamics of earnings. In general, it can be concluded that these benchmarks do not dominate analyst forecasts, although there can, of course, be some exceptions, depending on a firm's circumstances. Not all of the papers simply compare the relative predictive power of analyst forecasts to benchmark models; some focus on developing models for the best measurement of unexpected earnings in earnings-returns settings. A few representative studies include those by Collins and Hopwood (1980), Fried and Givoly (1982), Conroy and Harris (1987), Brown et al. (1987), O'Brien (1988), Swaminathan and Weintrop (1991), Elgers and Murray (1992), and Lobo (1992).

A decent benchmark model can never be pure random walks. Forecasting models for earnings must confront growth, implicitly if not explicitly. Initially, one can argue that future earnings growth can be connected to its recent growth. It then follows that any forecasting using a random walk model without drift or growth will be too pessimistic (Bradshaw et al. 2012). One can either neglect growth because it can be viewed as sufficiently unimportant and deal with it in an ad hoc fashion or employ more sophisticated statistical techniques (by early work, such as by Granger and Ramanathan (1984) and Guerard (1989)). Our paper deals with the earnings growth issue in a way that is hard to argue against: earnings *trend* growth should be attributed solely to the trend growth of sales but not that of profit margin.

Analyst forecast research has also considered the possibility of combining analyst forecasts of earnings with statistical models to improve analyst forecasts (analyst forecast suboptimality). Given the vast number of possibilities of expanding on analyst forecasts, it is inevitable that findings have generally been mixed. Superior forecasting methods tend to be circumstantial, depending on, for example, firm size, firm age, the forecast horizon, analyst following, and (the change in) profitability. The issue is also confounded with analyst forecast optimism, which provides a relatively straightforward opportunity for improvement of analyst forecasts. Indeed, Han et al. (2001) provide modeling and evidence to that effect. Some studies do find improvements, although not without qualifications, such as size (Conroy and Harris 1987; Granger and Ramanathan 1984; Guerard 1989; Lobo and Nair 1990; Newbold et al. 1987; Lobo 1992; Bradshaw et al. 2012). An extended strand of the forecasting literature expands on the above by adding information hypothetically helpful in the forecasting of earnings. Elgers and Lo (1994) and Hughes et al. (2008) provide such analyses.[12] So (2013) evaluates the predictive power of information, such as accruals, cash flows, and dividends, again suggesting forecasting accuracy improvements. Overall, however, for one year's horizon and large firms, the evidence clearly suggests that no simple schemes dominate analyst forecasts. Our analysis accordingly assesses the analyst forecasts of sales and profit margin from this perspective: can one combine simple benchmark forecasts with analyst forecasts to improve analyst forecasts? Our main interest pertains to whether the

[12] It would, of course, be interesting to determine if the results in these papers extend to S and PM individually, but such an inquiry is way beyond the scope of the current paper.

findings will apply to analyst forecasts of sales and profit margin, more so than how to best improve the analyst forecasts.

The literature that bears on the serial correlation in analyst forecast errors is more limited but with reasonably unambiguous findings. Focusing on quarterly earnings, Mendenhall (1991) and Abarbanell and Bernard (1992) find positive serial correlations, as do Ali et al. (1992) for annual analyst forecasts of earnings and subsequent papers by Brown et al. (1996) and Nutt et al. (1999). Markov and Tamayo (2006), who address quarterly earnings, also identify a positive serial correlation. To explain the findings, they raise the issue of whether irrationality constitutes the underlying cause and suggest not. Instead, they argue in favor of a broad learning hypothesis. Gong et al. (2011) switch the focus away from analyst forecasts to management forecasts and conclude the same: the positive serial correlation still applies. Although it is perhaps less than clear why there is a positive correlation, the evidence supports its existence, and this motivates the question of whether positive correlations exist among analyst forecasts of sales and profit margin similarly.

A number of studies have considered the incremental information content of unexpected sales, given unexpected earnings, using return studies, including Swaminathan and Weintrop (1991), Ertimur et al. (2003), Rees and Sivaramakrishnan (2007), and Keung (2010). In general, for a variety of reasons put forward, results show that sales add to the information content beyond that of earnings.[13,14] Different from these previous studies, we focus on profit margin rather than expenses; in addition, we do not rely on efficient market responses but focus on the behavior of analyst forecasts of sales and profit margin themselves.

The literature observes that analyst forecasts are at their comparative best whenever the information environment is deep, especially when firms are large or followed by many analysts (Brown et al. 1987; Wiedman 1996; Fan et al. 2006). Following this stream of the literature, we condition our analyses on firm size. Again, the most important aspect pertains to the comparative analysis, sales versus profit margin. Specifically, while size may be relevant to understanding the properties of analyst forecasts, it may or may not be the case that the effect of size on sales is the same as that on profit margin.

[13] Ertimur et al. (2003) suggest that one of the drivers for the differential market responses to sales and expense surprises is the relative persistence between sales and expenses. Their findings imply that the sales number is more reliable than expenses. Because sales is affected by growth, if growth is very uncertain, it may not be more persistent than profit margin (behaving more or less like a random walk). Hence Ertimur et al.'s findings may not be strictly applied to sales versus profit margin. Moreover, they are silent on the size effect. Rees and Sivaramakrishnan (2007) examine the value implications of joint analyst forecast errors of revenue and earnings and document a significant increase (reduction) in the market premium to meeting earnings forecasts when the revenue forecast is also met (not met). Keung (2010) finds that the market responds more vigorously to analysts' earnings forecast revisions when sales forecasts are also provided. These two studies suggest that sales provides information beyond earnings. Profit margin may also provide more information beyond earnings; however, this cannot be concluded without empirical analysis.

[14] Other studies relate to the forecasting of sales or cost components of earnings. For example, Curtis et al. (2014) forecast the sales of the retail industry by modeling the growth rates of branch stores and sales generated by each store. Myungsun and Prather-Kinsey (2010) show that analysts incorrectly anticipate the growth rate of expenses by using the growth rate of sales when making expenses forecasts (and hence the earnings forecast errors are positively associated with the growth rate of sales). Ertimur et al. (2011) suggest that less renowned analysts are more likely than reputable analysts to issue disaggregated earnings forecasts.

3 Data and basic descriptive statistics

We obtain from the I/B/E/S detailed files of forecasts and actual values for annual sales (the "SAL" variable; FPI = 1) and EPS for nonfinancial firms (SIC codes are <6000 or > 6999) from 2002 to 2016 (a total of 15 years).[15] We also obtain shares outstanding to generate total earnings. We retain only individual forecasts that have both sales and EPS by the same analysts and derive the profit margin forecasts as (shares outstanding)*(EPS forecasts)/(sales forecasts). We select the forecasts for each firm-year by the median of the latest individual forecasts made between the 12th and ninth months prior to the forecast-period end date (FPEDATS). We use these earlier earnings forecasts to avoid potential walk-down by management (Richardson et al. 2004). A firm size measure should reflect the firm's information environment (e.g., Frankel and Li 2004), and more information should facilitate forecasting. We measure firm size by the market value when financial analysts provide the forecasts. As individual analysts provide forecasts on different dates, we use the average of the market values at the individual analysts' forecasting dates.[16] Our final sample comprises 25,230 observations.

To evaluate the size effect, we focus on size groups rather than the exact size measure. We allocate our sample into five groups by the pre-set size break points identified in each year based on the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NADAQ-listed firms; size groups run from group 1 (the smallest firms) to group 5 (the largest firms).[17] Panel A of Table 1 summarizes the final sample across size groups. The majority of firms fall into two groups of large firms, groups 5 and 4, accounting for 33.0% and 29.1%, respectively; only 2.8% of firms fall into group 1. This distribution appears because financial analysts tend to follow large firms.

Panel B of Table 1 provides summary statistics for sales and profit margin with respect to both forecasts and realizations. Because a cross-sectional distribution of sales has no economic meaning, the sales tabulation instead considers sales growth: analyst forecasts of sales for period t + 1 divided by the current reported sales. Based on the full sample across 15 years, the median of the analyst forecasts of sales growth equals 7.5%, and the interquartile equals 13.9% (= 16.0% – 2.1%). Switching the statistics to realizations, the median of sales growth (7.2%) is similar to the analyst forecasts, with the analyst forecasts exhibiting an upward bias. Regarding the forecasts of profit margin, the median equals 5.6%, and the interquartile range equals 8.0% (= 10.1% – 2.1%). The median of profit margin (5.3%) is similar to the analyst forecasts, with the analyst forecasts exhibiting an upward bias.

Panel C of Table 1 provides the Spearman rank correlations between analyst forecasts and realizations with respect to each group. For group 5, the rank correlations of analyst forecasts and realizations equal 0.78 for sales growth and 0.94 for profit

[15] Years 2002 to 2016 are defined as the forecasting years, so the dataset includes the actual values up to year 2017. We start at 2002 because, prior to 2002, sales forecast data are rare, especially for smaller firms.

[16] We also use the consensus measure of analyst forecasts, which is provided by I/B/E/S every month, and the market value on the day when I/B/E/S provides the summary statistics. Our results are qualitatively similar.

[17] We define size break points using all listed firms, so that readers can obtain a clear sense of what we mean by large or small firms in the actual capital market. For robustness checks, we also set the break points evenly on the final sample, such that each size group has equal observations. The findings are qualitatively similar, but the size effect becomes less obvious, as expected. The untabulated results are available upon request.

Table 1 Sample data and descriptive statistics

Panel A: Summary of the sample firms across five size groups

Size group	No. of observations	% of Total	Market cap (mean/median, in million)
1	705	2.8	58/53
2	3154	12.5	159/143
3	5692	22.6	418/364
4	7343	29.1	1240/1066
5	8336	33.0	16,901/5736
Total	**25,230**		

Panel B: Analyst forecasts and realizations of sales growth and profit margin (in %)

Variable	25th Pctl	Median	75th Pctl	Interquartile
AF(SG, t + 1)	2.1	7.5	16.0	13.9
SG(t + 1)	−1.3	7.2	18.4	19.7
AF(PM, t + 1)	2.1	5.6	10.1	8.0
PM(t + 1)	1.5	5.3	10.1	8.6

Panel C: Spearman correlation coefficients between analyst forecasts and realizations of sales growth and profit margin

Size group	AF(SG, t + 1) with SG(t + 1)	AF(PM, t + 1) with PM(t + 1)
1	0.58	0.74
2	0.67	0.812
3	0.76	0.84
4	0.78	0.89
5	0.78	0.94

Panel D: Analyst forecast errors of sales and profit margin (in %)

Size group	|AFE(S)/S(t + 1)|	|AFE(PM)|	|AFE(PM)|/PM(t + 1)
1	12.3	5.9	n.a.
2	7.8	3.1	n.a.
3	6.1	1.7	55.2
4	4.8	1.0	18.8
5	3.8	0.7	8.1

This table presents the descriptive statistics for the sample from 2002 to 2016 (15 years). Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *Market Cap* is firms' market value. *AF*(.) represents analyst forecasts, measured as the median of the latest forecasts by individual analysts between the 12th and ninth months prior to the forecast period end date. *S* represents actual sales. *SG(t + 1)* is sales growth, defined as *S(t + 1)/S(t)* – 1. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. |*AFE(.)*| represents the absolute value of the analyst forecast errors, defined as the differences between the realization and the forecasts. Panel A reports the sample distribution and market cap. Panel B reports forecasts and realizations for sales growth and profit margin across the whole sample. Panel C reports Spearman rank correlations between analyst forecasts and realizations based on the pooled data per size group. Panel D reports the averaged yearly median of sales forecast errors scaled by realization (the first column) and profit margin forecast errors without scaling (the second column) for each size group. The rightmost column is the averaged yearly median of analyst forecast errors of profit margin scaled by the averaged yearly median of realized profit margin

margin. These correlations increase somewhat with size monotonically for both sales growth and profit margin. This sets the stage for our prediction that the performance of analyst forecasts may improve with size, although, of course, it cannot constitute a foregone conclusion, since the level of intrinsic forecasting difficulty may increase with firm size.

Finally, Panel D of Table 1 provides the descriptive statistics of the normalized absolute analyst forecast errors. First, we discuss analyst forecast errors for sales. We define the analyst forecast errors as the difference between the realization and the forecasts: $|AFE(S)| = |S(t+1) - AF(S, t+1)|$, where AFE represents analyst forecast errors and AF represents analyst forecasts. For sales, we scale the forecast errors by the realization. For each size-year group, we first derive the median and then report the average of the 15 medians for each size group. As firm size increases, the $|AFE(S)/(S,t+1)|$ decreases monotonically from 12.3% for small firms to 3.8% for large firms. Turning to analyst forecast errors of profit margin: $|AFE(PM)| = |PM(t+1) - AF(PM, t+1)|$. Note that we do not normalize analyst forecast errors of profit margin, since it is a ratio and normalization may induce severe outlier problems. However, for comparison to $|AFE(S)/(S,t+1)|$, which is scaled by realizations, we also scale the average of yearly median of $|AFE(PM)|$ by the average of yearly median of profit margin$(t+1)$. Similar to the sales case, as firm size increases, the median of $|AFE(PM)|$ decreases from 5.9% to 0.7% from groups 1 to 5. Because the averaged yearly medians of profit margin$(t+1)$ for firms in groups 1 and 2 are negative, we do not have the scaled $|AFE(PM)|$ in the right-most column of the panel. Excluding these two groups, however, the magnitude of $|AFE(PM)|/PM(t+1)$ also decreases monotonically from 55.2% for group 3 to 8.1% for group 5. Furthermore, they are all larger than those of sales. This comparison sets the tone for our future analyses.

4 Results: Four performance properties of analyst forecasts of sales and profit margin

This section presents analyses related to the four performance properties that are popular in analyst forecasts of earnings. We examine the extent to which these performance properties extend to the sales and profit margin forecasts, respectively. We further investigate whether firm size will improve the performance properties, as larger firms have better information environments. We do not have an a priori stance on the *differential* size effects on both forecasts; how the forecasts behave under an improving information environment is an empirical question.

4.1 Optimism

To assess analyst forecast optimism, we use two tests. The first one evaluates the relative accuracy score (RAS), based on the percentage of times that analyst forecasts are less than the realizations for each size-year group.[18] Overall, the

[18] In a strict sense, the RAS for analyst forecast optimism is not for accuracy assessment but rather for relative optimism comparison. For easy reference, we simply use the term “RAS” across all our relative score measures.

smaller is the RAS, the greater is the optimism. Because the first test using RAS focuses on counts that cannot indicate the magnitude of optimism, we develop an adjustment method that quantifies the bias, as measured by haircuts of analyst forecasts to attain unbiased estimates. Specifically, we assign a weight (the adjustment factor K) to adjust analyst forecasts to be closer to the realizations, so that the percentage of the forecasts that are greater than the realizations is approximately 50%: $K^*AF(X, t+1) > X(t+1) \approx 50\%$ in each size-year group.[19] Different from counts that lead to the RAS, the weight, that is, factor K, can provide the extent of optimism: the further the adjustment factor K is less than 1, the more optimistic are the forecasts.[20]

Panel A of Appendix Table A1 provides the detailed RAS for each of the 75 size-year groups, including the binomial tests.[21] Here, we focus on reporting average results. Panel A of Table 2 reports the mean statistics for sales and profit margin optimism for each size group: the average of the yearly RAS and the t-test results on whether the RAS is less than 50%. We find that the optimistic bias exists in both forecasts in the three smallest size groups. Specifically, the test results show that the RAS is significantly less than 50 for both sales and profit margin forecasts for size groups 1, 2, and 3 but not for groups 4 and 5. The evidence that upward bias diminishes as firm size increases suggests that the literature on analyst forecast optimism should analyze large firms separately from smaller firms. We also contrast sales and profit margin forecasts by subtracting the RAS for profit margin forecasts from the RAS for sales forecasts for each size-year group. The differences in RAS are all positive (see the row labeled [RAS(S) – RAS(PM)]), suggesting that sales forecasts are less optimistic than profit margin forecasts. However, based on simple t-tests of the differences between 15 yearly scores, we do not find that the differences are significant, except for the largest size group.[22] As the RAS is based on a simple comparison, that is, larger or smaller, the test scores may lack power. Our next test will consider the degree of differences.

Panel B of Table 2 reports the results for the second test. For each size-year group, we report the averages of factor K that are used to adjust the forecasts to be equal (or close) to the realizations for half of the time in each year. For sales, the averages of factor K range from 0.93 to 0.99 for groups 1 to 3 and essentially equal 1 for the two largest groups. For profit margin, the averages of K range from 0.65 to 0.90 for groups 1 to 3 and are close to 1 for the two largest groups. Simple t-tests show that Ks are significantly different from the null of 1 (i.e., analyst forecasts are unbiased, as no haircut is needed to remove the bias) for groups 1 to 3, for both sales and profit margin. We also contrast the averages of K between sales and profit margin. For groups 1 to 3,

[19] We use an iterative method to identify a factor K for each size-year group, such that the absolute value of (yearly RAS – 50) is minimized. We also calculate K for each observation, i.e., $K^*AF(X,t+1) = X(t+1)$. The median Ks are very similar for the forecasts of sales; however, because profit margin is sometimes negative, this method is not applicable.

[20] Alternatively, if analyst forecasts are higher than the realizations (i.e., optimistic), a K that is smaller than 1 will bring down the higher forecasts to the realizations.

[21] We provide details in the appendix for several analyses. Details of other analyses are available upon request.

[22] Note that, for the largest group, the RAS is higher than 50, implying conservative estimation or conservatism. The significant difference in RAS of 1.6 for the largest group thus implies that sales forecasts are more conservative than the profit margin forecasts.

Table 2 Optimism – analyst forecasts of sales and profit margin

Panel A. Percentages that analyst forecasts are less than the realizations

	% of AF(S, t + 1) < S(t + 1)					% of AF(PM, t + 1) < PM(t + 1)				
	Size group					*Size group*				
	1	2	3	4	5	1	2	3	4	5
Average	29.1***	37.1***	43.3***	50.0	53.3	27.3***	36.5***	42.7***	48.7	51.7
t-value	(−5.74)	(−6.44)	(−2.90)	(−0.01)	(0.99)	(−9.32)	(−8.75)	(−4.48)	(−0.61)	(0.79)
						Comparison between S and PM				
						Size group				
						1	2	3	4	5
[RAS(S) – RAS(PM)]						1.8	0.6	0.6	1.3	1.6***
t-value						(0.58)	(0.54)	(0.33)	(0.48)	(2.43)

Panel B: Simple haircut adjustment for bias by a constant adjustment factor, K

	K(S)					K(PM)				
	Size group					*Size group*				
	1	2	3	4	5	1	2	3	4	5
Average	0.93***	0.97***	0.99***	1.00	1.00	0.65***	0.63***	0.90***	0.99	1.01
t-value	(−4.32)	(−5.96)	(−2.44)	(−0.09)	(1.20)	(−6.83)	(−7.53)	(−2.66)	(−0.63)	(0.92)
						Comparison between S and PM				
						Size group				
						1	2	3	4	5
[K(S) – K(PM)]						0.28***	0.34***	0.09***	0.01	−0.01
t-value						(4.75)	(6.93)	(2.58)	(0.68)	(−0.21)

This table analyzes the optimism of analyst forecasts of sales and profit margin. Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *AF*(.) represents analyst forecasts, measured as the median of the latest forecasts by individual analysts between the 12th and ninth months prior to the forecast period end date. *S* represents actual sales. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. For $X = \{S, PM\}$, K is the adjustment factor generated by an iterative method, such that $K{*}AF(X, t+1) > X(t+1) \approx 50\%$ in each size-group year, i.e., a K leading to the absolute value of (adjusted RAS – 50) is minimized. Panel A presents the relative accuracy score (*RAS*), based on the percentages that analyst forecasts are less than the realizations, i.e., the *RAS* that $AF(X, t+1) < X(t+1)$, where $X = \{S, PM\}$. The lesser the RAS is, the more optimistic the analyst forecasts are. Panel B reports the adjustment factor *K*'s for sales and profit margin; the smaller *K* relative to 1 reflects more optimism. *Average* represents the means of the yearly RAS (Panel A) and K (Panel B). Specifically, RAS or K is first derived for each size-year, and then we report the mean with a simple t-test statistic to test the mean. *t-value* reports the t-statistics for testing whether the mean is significantly different from 50 (panel A) or 1 (panel B). The differences in RAS and K between sales and profit margin forecasts are reported in the last row of each panel; the t-value is for testing whether the mean is significantly different from 0

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

Ks of sales are significantly larger than those of profit margin. In other words, sales forecasts for groups 1 to 3 are less upward-biased than profit margin forecasts, as smaller K's are needed to bring down the latter forecasts.

Results from both tests provide similar conclusions that for both sales and profit margin, forecast optimism exists only in the three smallest groups. Concerning the differences in the two types of forecasts, in general, sales performs better (i.e., less optimistic bias). However, the significant differences mainly exist in the smaller size groups, according to the factor K analysis, which shows significant differences for the three smallest group.[23]

4.2 Relative forecast accuracy

To assess the analyst forecasts' relative forecast accuracy, we compare analyst forecasts to benchmark models. We develop benchmark models for sales and profit margin separately, as future sales should involve growth and future profit margin is likely to be mean-reverting and may just follow a random walk model.[24]

Let BM(X, t + 1), where X = {S, PM}, S stands for sales, PM stands for profit margin and BM stands for "benchmark models"; t + 1 denotes the forthcoming reporting date and the prior date t is the date of forecast. We state the benchmark models formally below.

$$BM(PM, t+1) = PM(t) \tag{1}$$

Sales forecasts modify the random walk by adding growth, and g(t) = projected sales growth for the forthcoming year:

$$BM(S, t+1) = [1 + g(t)]^*S(t) \tag{2}$$

For our main reports, we arbitrarily design g(t) = [40% of most recent median sales growth for firms in the same size group] + [60% of the firm's recent sales growth]. Our results by varying weights show robustness. We also consider using the industry growth rate. Results are qualitatively similar.[25]

The RAS now refers to the percentage of times that sales forecasts win over the benchmark forecasts. Panel B of Appendix Table A1 provides the detailed RAS for each size-year group and binominal tests. Table 3 presents the results based on the averages. The superiority of analyst forecasts is apparent for both sales and profit margin. The RAS averages for sales range from 52.7 to 68.6, and those for profit margin range from 58.7 to 65.4. They are all significantly greater than 50. Moreover,

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[23] It makes sense that the factor K analysis shows significant results, due to the fact that factor K considers the extent of optimism rather than the RAS, which only considers whether optimism exists. The formal test should have more power.

[24] Random walk models have long played an important role in the EPS forecasting literature, starting out with the work of Ball and Watts (1972) as well as that of Fried and Givoly (1982). The murky issue of the need to adjust for (secular) growth, due to earnings retention, has also existed. To the best of our knowledge, the literature does not seem to have arrived at a consensus regarding recognition of the problem and the best way to deal with it. Part of the problem has been the offsetting effect due to the forecast optimism. Indeed, Bradshaw et al. (2012) show that random walk forecasts are more accurate than analyst forecasts for long horizons under the circumstances that the forecasts are likely to be more optimistic than usual.

[25] The modeling of positive sales growth rate—as opposed to one with a zero rate—is critical for all size groups, except the two smallest ones. Untabulated RAS tests, BM(S, t + 1) versus a random walk model, show that BM(S, t + 1) is more accurate for groups 3 through 5. Group 2 is a draw, and group 1 is in favor of the random walk model. Group 1 thus reflects that sales growth is more of a dubious empirical fact. Using an inferior benchmark model to assess relative accuracy may bias upward the relative accuracy performance of analyst forecasts. Keeping this in mind in evaluating our findings, we do not find that analyst forecasts of sales perform with extra accuracy for groups 1 and 2; hence we conclude that the potential bias is not much of a problem.

the superiority increases monotonically as size increases, indicating that the information environment improves for both types of forecasts. Comparing sales and profit margin, the scores for the former are significantly larger than those for the latter, except for group 1 (see the row labeled [RAS(S) – RAS(PM)]). Overall, Table 3 indicates that sales forecasts are, in general, more accurate than profit margin forecasts and that, in general, size improves sales forecasts more than profit margin forecasts, which is consistent with the notion that profit margin is a harder variable to forecast than sales. However, when firms are very small, analysts' forecasts of sales do not necessarily perform better than those of profit margin.

Note that our conclusions are restricted by the benchmark models that can generally be improved by common sense economics and accounting modifications. For example, the sales model could be improved if one were to reduce extreme changes in sales that are most likely due to transitory acquisitions or divestitures. Concerning the profit margin benchmark, it most likely performs very poorly when profit margin is negative (current year is a loss year) or when it deviates strongly from an average of the two (or three) previous years, especially if profit margin mean-reverts. Since "reasonable guess adjustments" can be implemented to handle the matters, one can try out more sensible competitive benchmark schemes (some of these may seriously challenge analyst forecasts). Although such analyses may be quite interesting, we will not follow this potential line of empirical inquiry, as it would necessitate extensive work beyond the scope of this paper. Moreover, whatever we can improve in the design of our benchmark models may not change the fundamental conclusions that are of interest in this paper. However, we do understand that our conclusion on the relative accuracy should be confined to our model design.

4.3 Suboptimality

We now examine whether analyst forecasts can be improved by considering the benchmark forecasts, using a scheme that combines the weighted average of benchmark and analyst forecasts. We refer to this as a mixed model (MM). Formally, let w denote the weight put on the benchmark model forecasts (BM) and (1-w) will be the weight put on the analyst forecasts (AF):

$$MM(X, w, t+1) = w{*}BM(X, t+1) + (1–w){*}AF(X, t+1) \tag{3}$$

where X = {S, PM}.

The mixed model approach to forecasting has a modest objective, that is, to pick a weight w such that the model performs better than the analyst forecasts. As we use relative comparison, a small w suffices to show the analyst forecast suboptimality. This methodology incorporates the idea that, while analyst forecasts provide an effective starting point, these forecasts can be slightly modified because analysts do not adequately appreciate the information inherent in the benchmark model forecasts. In the empirical section, we present results for w = 5%. As a second test, we identify empirically the optimal weights on the benchmark model and the analyst forecasts. However, we caution that the ex post findings may not imply the optimal weight for the out-of-sample prediction.

Table 3 Relative accuracy by analyst forecasts of sales and profit margin to their benchmark models

Percentages that analyst forecasts are more accurate than the benchmark models										
	(1) % of AF(S, t + 1) win					(2) % of AF(PM, t + 1) win				
	Size group					*Size group*				
	1	2	3	4	5	1	2	3	4	5
Average	52.7	63.5***	66.6***	68.5***	68.6***	58.7***	59.5***	62.5***	63.7***	65.4***
t-value	(0.82)	(10.51)	(13.07)	(16.22)	(12.56)	(2.99)	(6.71)	(17.89)	(13.70)	(19.68)
						Comparison between S and PM				
						Size group				
						1	2	3	4	5
[RAS(S) – RAS(PM)]						−6.0***	4.0***	4.1***	4.8***	3.2*
t-value						(−2.53)	(4.19)	(3.29)	(3.37)	(1.88)

This table presents the relative accuracy score (*RAS*), based on the percentages that analyst forecasts are more accurate than the benchmark models. Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *AF(.)* represents analyst forecasts, measured as the median of the latest forecasts by individual analysts between the 12th and ninth months prior to the forecast period end date. *S* represents actual sales. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. *BM(.)* represents benchmark models. For sales, $BM(S, t+1) = [1 + g(t)]*S(t)$, where $g(t)$ is the implied growth rate (= 0.4*recent growth in the firm's sales +0.6*recent growth in the size group (the median value) to which the firm belongs). For profit margin, $BM(PM, t+1) = PM(t)$, i.e., a random walk. The left panel reports the *RAS* that $|AF(S, t+1) - S(t+1)| < |BM(S, t+1) - S(t+1)|$, and the right panel reports the *RAS* that $|AF(PM, t+1) - PM(t+1)| < |BM(PM, t+1) - PM(t+1)|$. The higher the *RAS* is, the more accurate the analyst forecasts are, compared to the benchmarks. *Average* represents the means of the yearly RAS. Specifically, RAS is first derived for each size-year, and then we report the mean with a simple t-test statistic to test the mean. *t-value* reports the t-statistics for testing whether the mean is significantly different from 50. The differences in *RAS* between S and PM forecasts are reported in the last row of the panel. The t-value is for testing whether the means are significantly different from 0. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

We define the RAS as the percentage of times that mixed model forecasts win over analyst forecasts. Panel C of Appendix Table A1 provides the detailed RAS and binomial tests for each size group. Panel A of Table 4 provides the average RAS for both sales and profit margin. We find that, for sales, mixed model forecasts win over analyst forecasts only for the smallest group. Specifically, the RAS is 60, which is significantly larger than 50 at the 1% level. For profit margin, we find that mixed model forecasts win over analyst forecasts significantly for the three smaller groups. Specifically, the scores are 60.4, 56.3, and 51.9 for the three smallest groups, respectively. They are all significantly different from 50 at the 1% and 10% levels. Turning to the comparison, the differences are all negative (see the row labeled [RAS(S) – RAS(PM)]), implying that it is harder for mixed model to win over the analyst forecasts for sales than for profit margin. Simple t-tests reveal that differences are significant (at the 1% level) for only groups 2 and 3. To sum up, the findings suggest that suboptimality exists mainly for smaller firms and more for profit margin forecasts than for sales forecasts.

To assess the extent of suboptimality, we search for the optimal weights, k(1) and k(2), placed on the benchmark model and analyst forecasts in the following linear forecasting model:

$$X(\mathrm{t}+1) = k(1)^{*}BM(X,t+1) + k(2)^{*}AF(X,t+1) + noise(t+1) \tag{4}$$

where X = {S, PM}.

We hypothesize that the benchmark model contains extra information to improve analyst forecasts, and thus the weight on BM, k(1), should be bigger than zero. The weight on AF, k(2), should be less than one if analyst forecasts are upward-biased. Panel B of Table 4 reports the mean estimates of k(1) and k(2), using the Theil-Sen method for each size-year group. For sales, only group 1 (the smallest size) has a significantly positive weight on the benchmark model (k(1) = 0.15; t-value = 3.14, significant at the 1% level); consistently, the weight on analyst forecasts is significantly less than 1 (k(2) = 0.77; t-value = −3.87, significant at the 1% level). Similar to the result in Panel A for group 1, this result also suggests that sales forecasts miss information in the benchmark model. For other groups, analyst forecasts have weights that are approximately 1, which is again consistent with Panel A's results that the mixed model approach does not win over analyst forecasts for groups 2 to 5 with respect to forecasting sales. For forecasting profit margin, the weight on the benchmark model, k(1), is significantly positive, and similarly k(2) is significantly less than one for the three smaller groups (k(1) = 0.43, 0.20, and 0.08, respectively, significantly greater than 0 at the 1% level; and k(2) = 0.65, 0.71, and 0.87, respectively, significantly less than 1 at the 1% level). Again, these results are in accordance with the results in Panel A that mixed model forecasts of profit margin win over analyst forecasts of profit margin for the three smaller groups.

Overall, in Panel B, the large magnitudes of k(1) suggest that analyst forecasts can be improved by including part of the information from the benchmark model. Our findings suggest that the improvement for sales only exists in group 1, but the improvement for profit margin exists in groups 1, 2, and 3. The factor k(2), being less than one, reflects the fact that analyst forecasts are generally upward (optimistically) -biased. Note that weights k(2) of profit margin are less than those of sales for all groups, consistent with earlier findings that profit margin forecasts are more upward-biased than sales forecasts. The size effect is in a robust monotonic fashion—k(1) is decreasing while k(2) is increasing as firm size increases, suggesting that analyst forecasts are becoming more accurate, and the benchmark model does not help much to improve when the information environment improves.

4.4 Errors serial correlation

We evaluate the serial correlation in analyst forecast errors (AFE = Actual – Analyst Forecasts) using a robust approach. Specifically, we group the observations of consecutive-period uptick (+ve) and/or downtick (−ve) analyst forecast errors into a 2 × 2 matrix. We then count for each matrix cell the frequency of observations out of the total. If the consecutive-period analyst forecast errors are positively (negatively) correlated, we should intuitively see larger (smaller) than 50 the sum of the concordant pairs (i.e., the diagonal cells containing either both upticks or both downticks of analyst forecast errors for periods t and t + 1).

Table 5 shows the 2 × 2 matrix of the average (across 15 sample years) frequency (%) of upticks and downticks by consecutive-period analyst forecast errors. Across the

Table 4 Suboptimality of analyst forecasts of sales and profit margin

Panel A: Percentages that analyst forecasts are more accurate than the mixed models										
	(1) % of MM(S, 5%, t+1) win					(2) % of MM(PM, 5%, t+1) win				
	Size group					*Size group*				
	1	2	3	4	5	1	2	3	4	5
Average	60.0***	51.8	48.4	47.6*	48.2	60.4***	56.3***	51.9*	49.4	49.4
t-value	(4.44)	(1.08)	(−1.02)	(−1.89)	(−1.20)	(2.73)	(4.93)	(1.94)	(−0.58)	(−0.58)
						Comparison between S and PM				
						Size group				
						1	2	3	4	5
[RAS(S) – RAS(PM)]						−0.4	−4.5***	−3.5***	−1.8	−1.2
t-value						(−0.16)	(−3.36)	(−3.13)	(−1.30)	(−0.67)
Panel B. The Theil-Sen estimators, k(1) and k(2), of the two linear models for sales and profit margin:										
*Sales: S(t+1) = k(1)*BM(S, t+1) + k(2)*AF(S, t+1) + noise(t+1) PM: PM(t+1) = k(1)*BM(PM, t+1) + k(2)*AF(PM, t+1) + noise(t+1)*										
	S					PM				
	Size group					*Size group*				
	1	2	3	4	5	1	2	3	4	5
k(1)	0.15***	0.01	0.00	−0.03*	−0.03	0.43***	0.20***	0.08***	0.02	−0.02
t-value	(3.14)	(0.32)	(0.09)	(−1.65)	(−1.49)	(3.47)	(6.16)	(3.78)	(0.88)	(−1.01)
k(2)	0.77***	0.96	0.98	1.03	1.04	0.65***	0.71***	0.87***	0.97	1.03
t-value	(−3.87)	(−1.77)	(−0.77)	(1.46)	(1.74)	(−2.40)	(−4.54)	(−4.69)	(−1.13)	(1.49)
k(1) + k(2)	0.92***	0.97***	0.98***	1.00	1.00	1.07	0.91***	0.95***	0.99	1.01
t-value	(−3.80)	(−5.17)	(−2.27)	(−0.66)	(0.82)	(0.53)	(−12.55)	(−12.99)	(−10.77)	(1.18)

This table analyzes the suboptimality of analyst forecasts. Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *Average* represents the means of the yearly RAS. Specifically, RAS is first derived for each size-year, and then we report the mean with a simple t-test statistic to test the mean. *AF(.)* represents analyst forecasts, measured as the median of the latest forecasts by individual analysts between the 12th and ninth months prior to the forecast period end date. *S* represents actual sales. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. *MM(.)* represents the mixed models. For *X* = {*S*, *PM*}, *MM(.)* = (1-*w*)**AF(X, t+1)* + *w*BM(X, t+1)*, where *BM(.)* is the benchmark model and *w* is the weight placed on the benchmark model forecasts. It is set to 5% to show that adding only a small amount of information from the benchmark can already beat the analyst forecasts. Panel A reports the relative accuracy score (*RAS*), based on the percentages that analyst forecasts are more accurate than the mixed models, i.e., the *RAS* that |*AF(X, t+1) – X(t+1)*| < |*MM(X, 5%, t+1) – X(t+1)*|, where *X* = {*S*, *PM*}. The lower the *RAS* is, the more accurate the analyst forecasts are, compared to the mixed models. *t-value* reports the t-statistics for testing if the mean is significantly different from 50. The differences in *RAS* between sales and profit margin forecasts are reported in the last row of the panel. The t-value is for testing if the mean is significantly different from 0. Panel B reports the optimal weights placed on the benchmark and analyst forecasts for forming the mixed models for *S* and *PM*. The linear models are estimated by the Theil-Sen method in cross-sections each year. The figures represent the mean of the 15 yearly k(1) and k(2) for sales and profit margin. *t-value* reports the t-statistics for testing whether the mean is significantly different from 0 and 1, respectively, and whether their sums are significantly different from 1. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

five size groups, the sums of the concordant pairs are larger than 50. For example, for sales, the sums are 72.7, 57.3, 55.4, 56.0, and 57.8 for size groups 1 to 5, respectively; for profit margin, the sums are 70.1, 61.0, 56.0, 58.1, and 54.4 for size groups 1 to 5,

Table 5 Serial correlations of analyst forecast errors of sales and profit margin

			AFE(S, t + 1)					AFE(PM, t + 1)			
	Size group		**+ve**	**-ve**	**Sum of diagonal**			**+ve**	**-ve**	**Sum of diagonal**	**(S-PM)**
AFE(S, t)	1	+ve	*9.7*	10.6		**AFE(PM, t)**	+ve	*6.5*	10.5		
		-ve	16.7	*63.0*	***72.7****		-ve	19.5	*63.5*	***70.1****	***2.6***
	2	+ve	*13.7*	20.0			+ve	*15.1*	17.7		
		-ve	22.6	*43.6*	***57.3****		-ve	21.3	*46.0*	***61.0****	***−3.7****
	3	+ve	*19.5*	22.2			+ve	*19.7*	21.2		
		-ve	22.3	*35.9*	***55.4****		-ve	22.8	*36.3*	***56.0****	***−0.7***
	4	+ve	*27.5*	22.6			+ve	*27.6*	21.5		
		-ve	21.4	*28.5*	***56.0****		-ve	20.5	*30.4*	***58.1****	***−2.1****
	5	+ve	*32.4*	21.8			+ve	*30.7*	21.9		
		-ve	20.4	*25.4*	***57.8****		-ve	20.7	*26.7*	***57.4****	***0.4***

This table presents the 2 × 2 matrix of the time-series means of the 15 yearly percentages of upticks (+ve) and downticks (−ve) by consecutive-period analyst forecast errors of sales and profit margin, where +ve (−ve) means that the forecast errors are larger (less) than 0. Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *S* represents actual sales. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. *AFE(.)* represents analyst forecast errors, defined as the differences between the realization and the forecasts. For consecutive periods t and $t+1$ and $X = \{S, PM\}$, $AFE(X, t) = X(t) - AF(X, t)$ and $AFE(X, t+1) = X(t) - AF(X, t)$. The sum of the diagonal represents the means of the yearly sum of the two diagonal cells in the matrix. Simple t-tests are then performed to determine whether the means are significantly different from 50 (i.e., analyst forecast errors are not serially correlated). The mean differences in the sum of diagonals between sales and profit margin forecasts are reported in the last column of the right panel. Simple t-tests are then performed to compare whether the means are significantly different from 0. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

Percentages of upticks (+ve) and downticks (−ve) by consecutive-period analyst forecast errors of sales and profit margin

respectively. They are all significantly greater than 50, indicating the presence of nontrivial serial correlation in both sales and profit margin forecast errors.[26]

Comparing sales and profit margin forecasts, on average, the sums for the former forecasts are lower (i.e., less serial correlation); for example, the averages across five groups are 59.74 and 60.52, respectively. However, the difference of −0.68 is not significant. Examining individual size groups, we find that there exist some significant differences for sales forecasts outperforming profit margin forecasts (for groups 2 and 4). We conclude that our evidence weakly supports that sales forecasts perform better than profit margin forecasts with respect to the error serial correlations.

For the size effect, the serial correlations (sums of the concordant pairs) reduce from 72.7 to 57.8 for S (a spread of 14.9) and from 70.1 to 57.4 (a spread of 12.7) for profit

[26] Simple t-tests and binomial tests are performed for each size group on whether the 15 yearly sums of diagonal are significantly different from the null of 50. Both tests reach the same conclusions for significance. Detailed results are available upon request.

margin. The trend is strictly monotonic from group 1 to group 3 and stops at group 4. These results are consistent with the previous finding that forecast performance generally improves as the information environment improves.

5 Additional analyses

Up to now, we have found that sales forecasts are generally superior to profit margin forecasts and that firm size improves both forecasts and the improvement is largely stronger for sales than for profit margin.[27] In this section, we perform two additional analyses: how analyst forecast errors of sales and profit margin contribute to the analyst forecast errors of earnings and the effects of realization of sales and profit margin on analyst forecast adjustments. These additional analyses can further enhance understanding of the role of sales and profit margin in forecasting earnings and the information content of sales and profit margin for analyst forecast adjustments. Based on the findings of the four performance properties that sales performs better than profit margin, we may easily predict that the earnings forecast errors should be explained more by profit margin forecast errors than by sales forecast errors, and that the analyst forecasts of sales (profit margin) should respond more (less) to the sales (profit margin) realizations. However, we take the position that illustration of these methodologies is important, as they provide convincing evidence of the usefulness of sales and profit margin forecasts; moreover, the methodologies developed in this section can be applied to other component analyses.

5.1 Attributions of earnings forecast errors

We attribute analyst forecast errors (AFE) in forecasting earnings to analyst errors in forecasting sales and profit margins using a framework that is similar to the variance analysis for a standard cost system (e.g., Datar and Rajan 2018). To simplify the notation, we ignore the time indicator and define AFE(X) = X − AF(X), where X represents earnings, sales, or profit margin, and AF indicates analyst forecasts. Then the forecast errors of earnings can be decomposed as below[28]:

$$AFE(Earnings) = AFE(S)*AF(PM) + AFE(PM)*AF(S) + AFE(S)*AFE(PM) \qquad (5)$$

[27] To demonstrate the firm size effects on analyst forecasts, we perform the following tests. We contrast by simple t-tests the 15 yearly RAS of group 5 with RAS of groups 4, 3, 2, and 1 per sales and profit margin in Tables 2, 3, and 4. If there is a size effect, we should observe increasing differences for the four group pairs {(5–4), (5–3), (5–2), (5–1)}. For Table 2, the *p*-values for the differences are (0.453, 0.021, 0.000, 0.000) for sales and (0.328, 0.002, 0.000, 0.000) for profit margin. For Table 3, the p-values are (0.944, 0.316, 0.016, 0.000) for sales and (0.195, 0.012, 0.001, 0.102) for profit margin. For Table 4, the p-values are (0.760, 0.899, 0.118, 0.000) for sales and (0.977, 0.085, 0.000, 0.013) for profit margin. Results show that the differences are most significant for the (5–2) and (5–1) pairs, indicating the presence of a size effect when the size differences are large.

[28] We show the derivation as follows: AFE(Earnings) = S*PM – AF(S)*AF(PM) = [S-AF(S) + AF(S)]*[PM – AF(PM) + AF(PM)] – AF(S)*AF(PM) = [AFE(S) + AF(S)]*[AFE(PM) + AF(PM)] – AF(S)*AF(PM). The first term can be expanded to four elements, with the last element being cancelled out with the second term (i.e., AF(S)*AF(PM)): AFE(Earnings) = AFE(S)*AFE(PM) + AFE(S)*AF(PM) + AF(S)*AFE(PM). Rearranging the expression leads to Equation (5).

As the third term AFE(S)*AFE(PM) tends to be very small, in empirical form, we express the above equation as follows:

$$AFE(Earnings, t+1) = k(1)*AFEA(S, t+1) + k(2)*AFEA(PM, t+1) + noise(t+1) \quad (6)$$

where AFEA(S, t + 1) = AFE(S, t + 1)*AF(PM, t + 1) and AFEA(PM, t + 1) = AFE(PM, t + 1)*AF(S, t + 1), which stand for analyst forecast errors of earnings error attribution (A) to analyst forecast errors of sales and analyst forecast errors of profit margin, respectively.

We first estimate Eq. (6) to ensure that it makes empirical sense; that is, the coefficients on the two right-hand side terms are approximately equal to one. Applying the Theil-Sen estimation to each size-year group, Panel A of Table 6 shows that, for each size group, both k(1) and k(2) are close to 1 in a practical sense, even though some of the cases show significant differences from 1.

To evaluate the relative contributions by both forecast errors to the forecast errors of earnings, we compare the magnitude of the absolute values of both terms by counting the percentage of times that |AFEA(S, t + 1)| < |AFEA(PM, t + 1)|. We presume that the term with a larger absolute magnitude contributes more to the earnings forecast errors. Panel B shows that profit margin contributes to earnings forecast errors more than sales by a margin of way above 50%. Results hold across all size groups with a wide margin ranging from 91.2% for group 1 to 71.6% for group 5.[29]

5.2 Analysts' forecasts adjustments in response to realizations

This section concerns the updating of analyst forecasts, that is, the change from AF(X, t) to AF(X, t + 1), due to the realization of the variable previously forecasted (sales or profit margin). The framework applied here is often referred to as "adaptive expectations" modeling.[30] It compares responses by putting forecasts of the next period, AF(X, t + 1), on the left-hand side and previous forecasts of current period, AF(X, t), and forecast errors, AFE(X, t) = X(t) – AF(X, t), on the right-hand side of the equation. AFE(X, t) is the new information. It is expected that the financial analysts will consider this new information when they adjust their forecasts from period t to period t + 1. The growth factor should be considered for forecasting sales but not profit margin. We use a general equation below to describe the analyst forecast adjustments:

$$AF(X, t+1) = (1+g)*\{AF(X, t) + (1+v)*[X(t) – AF(X, t)]\} \quad (7)$$

[29] Binomial tests are performed for each size group on whether the percentages of times that |AFEA(S, t + 1)| < |AFEA(PM, t + 1)| are significantly different from the null of 50. The tests are all significant. Details are available upon request.

[30] Ali et al. (1992) apply adaptive expectations modeling to EPS. Our approach is essentially the same in an empirical sense, except that we examine both sales and profit margin, which has a significant impact on what one should expect to find on the basis of prior reasoning. For an extension of this paper to allow for a nonlinear setting, see Mest and Plummer (2000).

Table 6 Attribution of analyst forecast errors of earnings to sales and profit margin forecast errors

Panel A. k(1) and k(2) are the Theil-Sen estimators for the linear model: AFE (Earnings, t + 1) = k(1)*AFEA(S, t + 1) + k(2)*AFEA(PM, t + 1) + error

	The Theil-Sen estimators, k(1) and k(2)				
	Size group				
	1	2	3	4	5
k(1), expect =1	0.97	0.96***	0.98***	0.99	1.00
t-value	(−0.87)	(−3.71)	(−2.83)	(−1.67)	(0.84)
k(2), expect = 1	0.93***	0.97***	0.99***	0.99	1.00
t-value	(−4.42)	(−8.75)	(−3.69)	(−1.94)	(−0.48)

Panel B. attribution errors by sales versus profit margin

% of |AFEA(S, t + 1)| < |AFEA(PM, t + 1)|

Size group				
1	2	3	4	5
91.2***	88.5***	84.7***	79.5***	71.6***

This table analyzes attribution of the earnings forecast errors to those of sales and profit margin. Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *AF(.)* represents analyst forecasts, measured as the median of the latest forecasts by individual analysts between the 12th and ninth months prior to the forecast period end date. *S* represents actual sales. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. *AFE(.)* represents analyst forecast errors, defined as the differences between the realization and the forecasts. Specifically, for *X* = {*Earnings*, *S*, *PM*}, *AFE(X, t+ 1) = X(t+ 1) − AF(X, t+ 1)*. *AFEA(.)* represents the attribution of earnings forecast errors, that is, *AFEA(S, t+ 1) = AFE(S, t+ 1)*AF(PM, t+ 1)* and *AFEA(PM, t+ 1) = AFE(S, t+ 1)*AF(PM, t+ 1)*. Panel A reports the estimation results of Eq. (6), as provided above, by the Theil-Sen method in cross-sections each year. The figures represent the mean of the 15 yearly k(1) and k(2) for sales and profit margin. *t-value* reports the t-statistics for testing whether the mean is significantly different from 1. Panel B reports the percentages that the sales forecast errors are smaller than the profit margin forecast errors, i.e., |*AFEA(S, t+ 1)*| < |*AFEA(PM, t+ 1)*|, for each size group. Binomial tests are performed for each size group to determine whether the percentages are significantly different from 50. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

Note that [X(t) – AF(X, t)] identifies the new (or unexpected) information at period t; g is the growth factor; and v is the adjustment factor for the new information. The 1 in coefficient (1 + v) reflects that AF(X, t) can be first adjusted by the forecast error to reach to X(t), the realization, then the X(t) will be adjusted by a factor v times the forecast error. If it so happens that the forecast in period t-1 for period t (i.e., AF(X, t)) is 100% correct (i.e., no forecast errors), then the recent realization of X(t) provides the expected forecast only via an adjustment for growth, if any. If there is a forecast error, then an analyst forecast adjustment should incorporate the forecast error in a logical manner. For sales, v should be mostly positive (i.e., v > 0), as the forecast error is due to the unexpected growth that will extrapolate into the future. However, for profit margin, as it is mean-reverting, on average, the response to the error term should be lower than or equal to zero (i.e., v < =0). The prediction that v is likely to be positive for sales and v is likely to be negative for profit margin implies that sales is more important than profit margin in affecting the analysts' forecast adjustments. We shall prove this empirically.

To estimate Eq. (7a) empirically, we transform the equation into the following linear model:

$$AF(X, t+1) = k(1)^{*}X(\mathrm{t}) + k(2)^{*}AF(X, t) + noise(t+1) \tag{8}$$

where the coefficients k(1) = (1 + g)(1 + v) and k(2) = −(1 + g)*v. If there are no bias and serial correlations, k(1) + k(2) ≈ 1 + g.

The coefficient v illustrates the importance of the realization of X; similarly, the coefficient on X(t), that is, k(1), can also indicate the importance of the realization of X. For sales, typically g > 0 and (1 + v) > 1; hence it is expected that k(1) > =1 (and k(2) < =0). For profit margin, typically g = 0 and (1 + v) < 1; hence it is expected that k(1) < = 1 (and k(2) > = 0). Accordingly, our model predicts that k(1) (and v) for sales is greater than k(1) (and v) for profit margin; that is, the importance of the realization of sales is greater than that of profit margin. As the information environment improves, we also predict that k(1) (and v) improves (i.e., increases) when firms get larger.

We use the Theil-Sen method to estimate Eq. (7) for each size-year group. Table 7 reports the results.[31] We first report coefficients of k(1) and k(2), followed by k(1) + k(2) and *fitted* v derived from either of the equations: v = k(1)/(k(1) + k(2)) – 1, or v = −k(2)/(k(1) + k(2)). The estimated coefficients of k(1) and k(2) are in accordance with our predictions; that is, k(1) > 1 (and k(2) < 0) for S; k(1) < 1 (and k(2) > 0) for PM, suggesting that the realization of sales is more important than the realization of profit margin in financial analysts forecasts. For the significance test, only when the size group is the smallest (size group = 1) and only for sales, we find that the differences (i.e., k(1) > 1 and k(2) < 0) are not significant. Importantly, we find that coefficient k(1) increases (mostly) monotonically in size for both sales and profit margin, which is in accordance with our suggestion that information environment improves the importance of the realization for financial analysts adjustments.

If X has no bias and no serial correlation, then k(1) + k(2) = 1 + g. In generating the fitted value v, we assume that k(1) + k(2) = 1 + g, and we do not restrict g = 0 for profit margin (the model assumption). We now evaluate this assumption. For sales, k(1) + k(2) are significantly greater than 1; they are 1.03, 1.08, 1.09, 1.09, and 1.07 for size groups 1 to 5, respectively. For profit margin, k(1) + k(2) are significantly less than 1 for size groups 1 to 3; they are 0.75, 0.82, 0.94, 0.99, and 1.03 for size groups 1 to 5, respectively. The fitted v for sales and profit margin are consistent with our prediction; that is, v is positive for sales (0.003, 0.077, 0,222, 0.330, and 0.319 for size groups 1 to 5, respectively; similar to k(1), v is not significantly greater than 0 for size group 1) and negative for profit margin (−0.414, −0.418,-0.285, −0.191, and − 0.107 for size group 1 to 5, respectively, all significantly less than 0), and the coefficient value increases in size.

To verify whether the conclusions about k(1) and v remain robust when the assumption of k(1) + k(2) = 1 + g is violated, we preset g rather than using k(1) + k(2)

[31] 2002 and 2003 are excluded from the estimation of k(1) and k(2) for group 1 because these two years contains an insufficient number of firm-year observations for the Theil-Sen estimation, but inference results are similar if these two years are included. To conserve space, we do not report the yearly coefficients, but they are available upon request.

Table 7 Analyst forecast adjustments in response to the realizations of sales and profit margin, respectively *k(1) and k(2) are the Theil-Senestimators for the linear model:* ***Sales****: AF(S, t + 1) = k(1)*S(t) + k(2)*AF(S, t) + noise(t + 1)* ***PM****: AF(PM, t + 1) = k(1)*PM(t) + k(2)*AF(PM, t) + noise(t + 1) Theatrical Prediction: k(1) = (1 + g)(1 + v) and k(2) = −(1 + g)*v; k(1) + k(2) = (1 + g) fitted v: v = k(1)/(k(1) + k(2))-1, or v = −k(2)/(k(1) + k(2)).*

	S					PM				
	Size group					*Size group*				
	1	2	3	4	5	1	2	3	4	5
k(1)	1.05	1.16***	1.33***	1.45***	1.41***	0.45***	0.47***	0.66***	0.80***	0.92***
t-value	(0.53)	(6.27)	(9.82)	(20.95)	(10.79)	(8.36)	(18.21)	(26.79)	(27.68)	(54.24)
k(2)	−0.02	−0.08***	−0.24***	−0.36***	−0.34***	0.31***	0.35***	0.27***	0.19***	0.11***
t-value	(−0.23)	(−3.42)	(−7.45)	(−15.00)	(−9.63)	(8.51)	(11.30)	(9.95)	(7.03)	(5.77)
k(1) + k(2)	1.03**	1.08***	1.09***	1.09***	1.07***	0.75***	0.82***	0.94**	0.99	1.03
t-value	(1.78)	(8.03)	(9.97)	(11.61)	(9.76)	(−5.36)	(−4.39)	(−2.48)	(−0.34)	(3.45)
Fitted v	0.003	0.077***	0.222***	0.330***	0.319***	−0.414***	−0.418***	−0.285***	−0.191***	−0.107***
t-value	(0.03)	(3.34)	(7.41)	(14.39)	(9.50)	(−8.70)	(−12.72)	(−10.24)	(−7.01)	(−5.64)
(1 + g)	1.02	1.04***	1.07	1.09	1.07	1.00***	1.00***	1.00***	1.00	1.00
k(1) + k(2) vs. (1 + g): t-value	(1.13)	(2.64)	(1.17)	(0.25)	(−0.34)	(−5.36)	(−4.39)	(−2.48)	(−0.34)	(3.45)
v(k(1))	0.036	0.116***	0.246***	0.336***	0.316***	−0.550***	−0.529***	−0.335***	−0.196***	−0.083***
t-value	(0.37)	(4.22)	(7.30)	(12.24)	(8.43)	(−10.23)	(−20.45)	(−13.52)	(−6.74)	(−4.89)
v(k(2))	0.013	0.080***	0.225***	0.331***	0.319***	−0.305***	−0.352***	−0.271***	−0.190***	−0.111***
t-value	(0.16)	(3.41)	(7.52)	(14.14)	(9.60)	(−8.51)	(−11.30)	(−9.95)	(−7.03)	(−5.77)

This table analyzes how analyst forecasts adjust to the realizations of sales and profit margin, respectively. Firms are categorized into five size groups (1-smallest to 5-biggest), defined according to pre-set size break points calculated (in each year) by the monthly average market capitalization (from CRSP) of *all* NYSE-, AMEX-, and NASDAQ-listed firms. *AF(.)* represents analyst forecasts, measured as the median of the latest forecasts by individual analysts between the 12th and ninth months prior to the forecast period end date. *S* represents actual sales. *PM* is profit margin, defined as earnings/sales where earnings = (shares outstanding)*EPS. Profit margin forecasts are derived from earnings forecasts divided by sales forecasts for each analyst. The table reports the estimation results of Eq. (7), as listed above, by the Theil-Sen method for each size-year group. (Note that 2002 and 2003 are excluded from the estimation of $k(1)$ and $k(2)$ for group 1 because these two years contain insufficient firm-year observations for the estimation.) We report yearly averaged values of the coefficients per size group. For sales, *t-value* reports the t-statistics for testing whether $k(1)$ is bigger than 1, $k(2)$ is less than 0, and their sum is greater than 1. For profit margin, *t-value* reports the t-statistics for testing whether $k(1)$ and $k(2)$ are both positive and the sum equals 1. Based on the theoretical prediction, $k(1) = (1 + g)(1 + v)$, $k(2) = -(1 + g)*v$, hence, $k(1) + k(2) = (1 + g)$, where g is the growth factor, and v is the adjustment factor for new information. *Fitted v* reports the averaged yearly v values by imposing $k(1) + k(2) = 1 + g$ (and g is not restricted to 0 for profit margin). *t-value* reports the t-statistics for testing whether fitted v is bigger than 0. *(1 + g)* reports the averaged yearly median of individual firm's sales growth (= *S(t)/S(t-1)*); for profit margin, *(1 + g)* are set to 1 by model assumption for all years and all size groups. *k(1) + k(2)* vs. *(1 + g): t-value* reports the t-statistics for testing whether $[k(1) + k(2)]$ and $(1 + g)$ are significantly different from each other. *v(k(1))* reports the averaged yearly $v(k(1)) = k(1)/(1 + g) - 1$; *v(k(2))* reports the averaged yearly $v(k(2)) = -k(2)/(1 + g)$, where $(1 + g)$ is set to the realized growth for sales (= median of individual firm's sales growth) and 1 for profit margin. *t-value* reports the t-statistics for testing whether the two vs calculated from $k(1)$ and $k(2)$ are significantly different from 0, respectively. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level to derive v. For each size-year group, we use the median of firms' actual sales growth (i.e., S(t)/S(t-1)) as $1 + g$ for sales and set $g = 0$ for profit margin (i.e., no growth in profit margin) and then derive v based on either $v = k(1)/(1 + g) - 1$, or $v = -k(2)/(1 + g)$, termed as v(k(1)) and v(k(2), respectively). Note that v(k(1)) and v(k(2)) will differ from each other. In Table 7, we first compare $(1 + g)$ with $k(1) + k(2)$. We find that, for sales, $(1 + g)$ is very similar to $k(1) + k(2)$ and $(1 + g)$ is only significantly different from $k(1) + k(2)$ for size group 2 (where $k(1) + k(2) = 1.08$, but $1 + g = 1.04$). For PM, $k(1) + k(2)$ are significantly less than 1 for size groups 1 to 3, suggesting that the assumption of $k(1) + k(2) = 1 + (g = 0)$ is violated. These findings are consistent with our previous findings that profit margin is more biased and serially correlated for the smaller groups. Turning to v, we find that our conclusion does not change, in the sense that v(k(1)) and v(k(2)) are both positive for sales and both negative for profit margin, consistent with the signs and size trends of the fitted v values.

To conclude, sales informs more than profit margin does in the context of analyst forecast revisions.

6 Conclusion

Why attach significance to the two components of earnings or EPS—as opposed to the hypothesis that earnings by itself suffices for all practical purposes? The most apparent answer points toward the financial media, which generally refer to sales no less than earnings when they report the news. Cases abound when sales and its growth (or the lack thereof) make the headlines. For profit margin, it also takes on a prominent role in discussions about corporate performance. Indeed, profit margin appears more often than expenses because the former is a ratio, which is easier for comparison among firms than the latter, which is in dollar amounts. This observation suggests that, from a broad information perspective, sales is central and profit margin acts as a complement. It further indicates that earnings cannot act as a sufficient statistic. In other words, significant information is lost if one bypasses the component's information by taking the product. There is no lack of stylized facts supporting the questions addressed in the paper: analysts' forecasts and related forecast errors of the two components are of considerable interest in the investment community.

A stylized setting helps to understand why analysts are keenly aware of the earnings decomposition. Consider two companies, A and B, that both have increased earnings by 10%, and that the 10% realization conforms perfectly to the earnings forecasts. Further assume that the two firms differ in terms of how the 10% improvement was achieved. Assume in the case of A that sales increased by 10% while profit margin remained flat; in contrast, B's profit margin increased by 10% while sales remained flat. Do the companies convey the same news as the earnings numbers suggest? Or did one of the companies report better news? Most people would probably argue in favor of firm A, insofar as sales growth typically begets more sales growth in the future, and thus sales growth adds considerable value incrementally. The profit margin increase, by contrast, is worth something, but it does not allow for any extrapolation; that is, it adds less value. If one grants this scenario, it makes sense that analysts forecast/monitor sales and profit margin separately. This stylized example should suggest that it makes sense to study analyst forecasts of the two components separately.

The paper provides empirical evidence that the performance properties found for forecasting earnings apply to both sales and profit margin. In sum, optimism, the superiority of analyst forecasts versus benchmarks, the suboptimality of analyst forecasts versus the mixed models, and the positive error serial correlations all apply to both sales and profit margin. Largely, analyst forecasts of sales perform better than analyst forecasts of profit margin. Intuition supports this evidence insofar as investors tend to consider profit margin as a more arcane variable, due to the complexities inherent in accounting for expenses. Moreover, we find that earnings forecast errors are due to profit margin forecast errors more than to sales forecast errors. In addition, there is less to be learned from reported profit margin than from reported sales in the revision of analyst forecasts. It is as if the reported profit margin must be taken with a grain of salt, consistent with the idea that profit margin includes invisible transitory elements that can only be guessed at.

This study also investigates the firm size effect. Larger firms have better information environments, which should facilitate analysts' forecasting. We observe that size improves the performance of analyst forecasts to an extent that some of the performance properties, such as upward bias, do not exist for the largest firms. We also find that the size trend effect is generally stronger for analyst forecasts of sales than for those of profit margin —an effect that is not predicable a priori. One can argue that a better information environment facilitates more forecasts of above-the-line variables, such as sales, but one can also contend that the marginal improvement for profit margin with a better information environment is bigger since profit margin intrinsically embeds the more uncertain information. Our findings thus illuminate the understanding of how the information environment affects the forecasts of accounting variables of different nature.

Finally, our paper bears on practice and future research. First, we provide good reasons for why both variables should be of interest and cannot be overlooked. Second, our findings do suggest that it is not easy to beat the accuracy of analysts' sales forecasts, using statistical models, especially in the case of large firms. Subsequent research needs to recognize this aspect. For example, claims that analyst forecasts (only one-year-ahead, to be sure) can be improved would need to show that it can also be true for (relatively) large firms and sales forecasts. The issue of size effect is subtle, and there are no convincing reasons to believe that standard financial statement analysis or statistical modeling can do better than analysts who also pay attention to management, markets, and the state of the industry. Third, our paper uses innovative and robust methods, which can be applied to analyst forecasts and other research studies.

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