

The Relative Accuracy of Analyst and Time-Series Disaggregated Forecasts

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Abstract

This study addresses three research questions: (1) Are analyst earnings forecasts that are accompanied by disaggregated forecasts relatively more accurate than those for which disaggregated forecasts are not provided?, (2) conditional on providing disaggregated forecasts, which forecasted components of earnings do analysts provide the most incremental accuracy over random walk (RW) forecasts?, and (3) what factors are associated with analyst superiority over RW forecasts? We find that both analyst and RW forecasts of earnings are less accurate when analysts provide disaggregated forecasts relative to when they do not. We also find, however, that analyst earnings forecasts yield greater superiority over RW forecasts, when disaggregated forecasts are provided. Furthermore, when analysts provide disaggregated forecasts, their forecasts of operating expenses provide the most incremental accuracy over RW forecasts; however, superior analyst forecasts of sales and operating expenses do not translate into superior forecasts of operating profits. Analyst forecasts of non-operating expenses lead to the greatest improvement in earnings forecasts over RW forecasts. We also find that the analyst forecast improvement over RW models increases with the inaccuracy of the RW forecasts, extreme growth, and firm size and that longer-run analyst operating profit forecasts are superior to RW forecasts only for firms in the highest historical sales growth tercile and the largest size tercile.

Keywords: analyst forecasts, disaggregated forecasts; RW; analysts' superiority

JEL Code: G17, M40, M41

The Relative Superiority of Analyst and Time-Series Disaggregated Forecasts

A long stream of academic research has examined sell-side analysts' forecasts of accounting earnings.¹ A widely-held view about these forecasts is that they are more accurate than forecasts based on time-series models (Fried and Givoly 1982). However, several recent studies re-characterize this view as an overgeneralization and document that analysts' superiority over even simple time-series forecasts is limited (e.g., Allee 2010; Gao and Wu 2010; Jung et al. 2011; Bradshaw et al. 2013). Time-series forecasts are relatively costless to implement, so the effort devoted by analysts to forecasting earnings suggests that analysts must provide some value through their research activities. In this study, we provide insight into when and how analysts' costly research efforts enhance market efficiency through more accurate expectations of future earnings. We address this issue by examining analysts' disaggregated earnings component forecasts.

Prior research documents that analysts' superiority over time-series forecasts is due to both a timing advantage and an information advantage (Brown et al. 1987). Analysts have a timing advantage because the information in time-series forecasts is restricted to the period ended with the most recent earnings report, whereas analysts enjoy the advantage of a reduced forecast horizon with each day beyond the date of the most recent earnings report.² Analysts have an information advantage because the information set available to them includes everything impounded in the historical earnings series, plus other information yet to be reflected in earnings.

We focus on the *process* by which analysts derive earnings forecasts and investigate the

¹ See reviews of this literature by Givoly and Lakonishok (1984), Schipper (1991), Brown (1993) – including discussions by O'Hanlon (1993), Thomas (1993), and Zmijewski (1993) - and Ramnath et al. (2008).

² We attempt to minimize the timing advantage by comparing analysts' forecasts released contemporaneously with the announcement of earnings (i.e., the random walk forecast).

contribution of analyst forecasts of disaggregated earnings components - sales, operating expenses, and nonoperating expenses – to the accuracy of the earnings (EPS) forecasts. We examine three questions. First, is the provision of disaggregated component forecasts by analysts associated with more accurate EPS forecasts? Financial statement analysis texts typically describe the earnings forecast process as beginning with sales forecasts, followed by expense forecasts that algebraically yield an earnings forecast (e.g., Lundholm and Sloan, 2007; Penman 2009; Wahlen et al. 2011). Call et al. (2009) suggest that a structured approach to forecasting that includes an analysis of individual earnings components could lead analysts to better understand the earnings generation process and, therefore, to more accurate EPS forecasts. We provide insight into this by examining whether analyst EPS forecasts accompanied by disaggregated components are more accurate than forecasts that are not.

Second, conditional on providing disaggregated forecasts, we examine which forecasted components of earnings analysts provide the most incremental accuracy over random walk (hereafter, RW) forecasts. Algebraically, an error in the forecast of any component directly impacts bottom-line EPS forecasts. However, operating expenses are frequently driven by the level of sales, which implies that an inaccurate forecast of sales might trigger errors in expense forecasts. In addition, prior research suggests that analysts do not fully consider differential cost behaviors when forecasting expenses (Kim and Prather-Kinsey 2010; Weiss 2010; Baumgarten et al. 2011). This suggests that analysts' improvement in EPS forecast accuracy over RW forecasts is likely more attributable to their sales forecasts than to their expense forecasts. We examine the improvement in accuracy of analyst forecasts over RW forecasts for sales, operating expenses, and non-operating expenses to provide insight into the components for which analysts provide the greatest forecasting contribution over RW forecasts.

Finally, we examine which factors are associated with analyst superiority over RW forecasts. Bradshaw et al. (2013) find that RW EPS forecasts outperform analysts' EPS forecasts over longer horizons and for firms that are smaller, younger, and when analysts forecast negative or large changes in earnings. Similarly, we examine the association between analysts' superiority over RW EPS forecasts and factors such as RW forecast accuracy, size, growth, and analyst following.

Academic research has attempted to delve into the 'black box' in which analysts derive their EPS forecasts. However, empirical archival approaches to understanding the forecasting process are generally limited to examining correlations between hypothesized inputs into the forecasting exercise (e.g., information in past earnings, prices, and other information) and the outputs of that process (i.e., the EPS forecast and subsequent realized earnings). We are similarly limited in our ability to peer inside analysts' actual thought processes and activities. However, our examination of analysts' disaggregated forecasts provides some insight into the actual process through which analysts' derive bottom-line EPS forecasts. By analyzing such disaggregated forecasts, we can observe, albeit indirectly, how analysts use internally generated inputs to produce an ultimate EPS forecast.

We examine disaggregated forecast accuracy for both analyst and RW forecasts. Our analyses include forecasts made across various horizons, including the current year (FY_{t+1}) and the following two years (FY_{t+2} and FY_{t+3}). Consistent with prior research, we compute signed forecast errors as the difference between the actual disaggregated component and the corresponding analyst (or RW) forecast of that component. Although we provide some descriptive evidence on signed forecast errors, our primary analyses are based on analyst and RW forecast accuracy, which is captured by the absolute forecast error. We quantify analysts'

forecast superiority (*AFS*) for each disaggregated component and for total earnings by computing the difference in the accuracy of analyst and RW forecasts. *AFS* is a direct measure of the forecast improvement, and hence analyst superiority, for each disaggregated item relative to a simple RW extrapolation.

We find significantly larger median analyst EPS forecast errors when analysts provide disaggregated forecasts relative to when analysts do not provide them. However, we find that median *RW* forecasts are also less accurate when analysts provide disaggregated forecasts, suggesting that analysts provide disaggregated forecasts for firm/years in which forecasting is more difficult. We also find that our measure of analyst EPS forecast superiority (*AFS*) is significantly greater when disaggregated forecasts are provided than when they are not, suggesting that the provision of disaggregated forecasts leads to greater improvement in accuracy, when benchmarked by *RW* forecasts. When analysts provide disaggregated forecasts, we find that analyst forecasts of sales, operating expenses, and non-operating expenses are superior to the related *RW* forecasts and that analyst forecast errors increase across forecast horizons across all the disaggregated components. We also find that analyst forecast superiority increases across the forecast horizons for sales and operating expenses but decreases across horizons for operating profit and net income.

Some prior research assumes that analysts are superior in forecasting sales but fail to accurately consider the differential cost behaviors (Kim and Prather-Kinsey, 2010; Weiss, 2010; Baumgarten et al. 2011); however, we find the greatest analyst forecast superiority over *RW* forecasts for operating expenses. In addition, while we document that analyst sales and operating expense forecasts are superior to *RW* forecasts for each of the three forecast horizons, we find that analyst operating profit forecasts (the net of sales less operating expense forecasts) are *not*

superior to RW forecasts for two- and three-year ahead forecast horizons. Finally, we find that analysts' non-operating expense forecasts are more accurate than their forecasts of operating profit across all three horizons.

These results provide insight into the relative forecast accuracy of analyst and RW forecasts of earnings components and into the source of analyst forecast superiority for forecasting bottom-line earnings. Our results suggest that analysts provide disaggregated forecasts when forecasting is more difficult and that analysts provide the greatest relative improvement over RW forecasts for operating expense forecasts. The results also suggest, however, that these superior operating expense forecasts do not translate into superior operating profit forecasts. Finally, non-operating expense forecasts contribute the greatest to the superiority of analyst forecasts over RW forecasts of earnings. Our study contributes to research on analyst forecasting by demonstrating how the differential accuracy of disaggregated forecasts is related to earnings forecast accuracy, which enhances our understanding of how analysts contribute value through their costly forecasting activities.

The study proceeds as follows. The next section reviews relevant prior literature. We describe our data and formalize hypotheses in section 3. Primary tests appear in section 4, and section 5 concludes.

2 Prior research and contribution

Early academic research on forecasting earnings provides evidence that annual earnings approximate a simple RW process (e.g., Little 1962; Ball and Watts 1972; Brown 1993). Early research also documents that analyst earnings forecasts are more accurate than RW forecasts (e.g. Brown et al. 1987a; Brown et al. 1987b). Subsequent research explores the explanation for

analyst forecasting superiority over time-series models and concludes that analyst forecasts should be superior to time-series forecasts because analysts have access to a broader information set.

Brown et al. (1987a) classify analysts' advantage into two sources: an information advantage and a timing advantage. O'Brien (1988) argues that analysts' forecasting superiority is explained by analysts' use of time-series models and a broader information base, including information about industry and firm sales and production, general macroeconomic information, and other analysts' forecasts. Consistent with the information environment argument, Kross et al. (1990) document a positive association between analysts' superiority and firm coverage in the *Wall Street Journal*. The timing advantage reflects the notion that analysts utilize information acquired between the date on which the RW forecast is made and the date on which the analysts' forecast is made. Consistent with this argument, research finds that analyst forecast accuracy is negatively associated with forecast horizon (Lys and Soo 1995; Kross et al. 1990).

More recent research, however, (e.g. Bradshaw et al. 2013) employs a much broader sample of firms than typically included in the prior studies and considers varying forecast horizons. The authors document that, contrary to the broadly held belief that analysts have superior ability to forecast earnings over time-series models, a RW model dominates analysts' forecasts of earnings over longer horizons and for certain types of firms. This recent evidence motivates a deeper understanding of how analysts improve upon baseline forecasts as cheaply available as random walk forecasts.

Banker and Chen (2006) examine time-series models for forecasting year-ahead return on equity. The authors examine models which include: (1) aggregate earnings, (2) earnings disaggregated into operating income and non-operating income, (3) earnings disaggregated into

accruals and cash flows, and (4) earnings disaggregated into components that reflect the variability of costs with sales revenue and the stickiness of costs with sales declines. Although they find that forecasts based on each of the time-series models are less accurate than analyst forecasts, they report that their “cost stickiness” model is the most accurate time-series model and that it bridges over 30 percent of the information advantage financial analysts possess over the aggregate time-series model. This suggests that cost behavior explains a significant portion of analysts’ advantage over time-series models.

Nonetheless, more recent research suggests that analysts do not fully consider cost behavior when forecasting. Specifically, Weiss (2010) examines bottom-line analyst EPS forecasts for industrial firms and finds that analyst forecasts are less accurate when prior quarter expenses reflect more sticky cost behavior. Baumgarten et al. (2011) examine analyst forecasts of bottom-line earnings and actual cost structures and find that analyst forecasts appear to disregard actual cost stickiness. This research suggests that sticky cost behavior reduces the accuracy of analysts’ consensus EPS forecasts, suggesting that analysts do not consider the notion that costs decrease less with sales declines than they increase with sales growth.

In related research, Kim and Prather-Kinsey (2010) suggest that analyst EPS forecasts make very basic assumptions about growth rates for sales and expenses. They examine a sample of analyst EPS forecasts for which sales forecast errors are zero and find that analyst forecast errors are positively associated with expected sales growth. The authors suggest that analyst forecast accuracy is reduced because analysts assume equal growth rates for expenses and sales, thus not considering fixed costs.

This stream of research has attempted to provide insight into the superiority of analyst forecasts over RW forecasts. We contribute to this literature by examining analysts’ explicit

forecasts of sales, operating expenses, and non-operating expenses. Specifically, we examine whether analysts provide superior forecasts over RW forecasts of sales, operating expenses, operating profit, and non-operating expenses for one-year, two-year, and three-year ahead forecasts. This examination provides insight into when and how analysts provide improvements in accuracy over time-series models. By examining forecasts of earnings components directly, we enhance our understanding of the components by which analysts provide the greatest improvement over RW forecasts.

Another stream of research examines analyst forecasts of disaggregated components. Ertimur et al. (2011) study the role of reputation in explaining analysts' decisions to *provide* revenue and expense forecasts to I/B/E/S.³ The authors argue that, while all analysts privately produce these forecasts, not all of them make those forecasts available to I/B/E/S. Thus, the presence of these forecasts might be explained by analysts' incentives.

Other research examines the accuracy of forecasts when analysts provide disaggregated forecasts for cash flows and accruals. Call et al. (2009) find that analysts' earnings forecasts issued with cash flow forecasts are more accurate than those issued without cash flow forecasts. They argue that the increased earnings accuracy for analysts that issue cash flow forecasts is likely due to their structured forecasting process and their better understanding of the time-series properties of the earnings process. However, Givoly et al. (2009) examine analyst cash flow forecasts and find that their cash flow forecasts are less accurate than their earnings forecasts. The authors conclude that analyst cash flow forecasts appear to be a naïve extension of their earnings forecasts. Thus, it is unclear whether analysts that provide disaggregated forecasts yield

³ Another stream of research examines factors associated with the issuance of *management* disaggregated forecasts (e.g., Hirst et al. 2007; Elliott et al. 2011; Landsford et al. 2011). While these studies are related to our study, our initial focus is on analysts disaggregated forecasts without consideration of management forecasts.

more accurate forecasts of the components and bottom-line earnings.

We contribute to this stream of research by specifically examining whether analyst EPS forecasts that are accompanied by disaggregated component forecasts are more accurate relative to RW forecasts than those that are not accompanied by disaggregated forecasts. We also contribute to the literature by examining the analyst forecast accuracy for each component of earnings and by assessing the incremental improvement of the analyst forecast over the RW forecast for each component. This provides insight into whether and how disaggregated component forecasts contribute to analyst forecast accuracy.

3 Data and sample

Our sample construction begins with the universe of I/B/E/S disaggregated annual forecasts for the years 2003 through 2009, including realizations of each item.⁴ We begin with 2003, as this is the first year in which disaggregated forecasts are available in large numbers. We examine three annual forecast horizons, FY_{t+1} , FY_{t+2} , and FY_{t+3} . For each disaggregated forecast, we retain the consensus I/B/E/S forecast and the corresponding actual value to compute analyst forecast errors. To avoid the influence of outliers, we eliminate the top and bottom one percent of RW and analyst earnings forecast errors. These procedures result in 13,332, 10,500, and 5,103 firm-year observations for the FY_{t+1} , FY_{t+2} , and FY_{t+3} forecast horizon, respectively.

We calculate RW and analyst forecasts errors as the actual realization less the forecast, and scale forecast errors by lagged total assets.

$$RWFE_{DI_{t+1}} = \text{CompustatActual}_{t+1} - \text{CompustatActual}_t (\text{Forecast}) \quad (1)$$

$$AFE_{DI_{t+1}} = \text{I/B/E/S Actual}_{t+1} - \text{I/B/E/S Forecast}_{t+1} \quad (2)$$

⁴ Prior research (e.g. Abarbanell and Lehavy, 2003) finds that the best match for calculating I/B/E/S analysts' earnings forecast errors is the actual value reported by I/B/E/S. As with earnings forecasts, I/B/E/S reports actual values for the disaggregated forecasts, which we use to calculate the analyst forecast errors.

Thus, positive (negative) forecast errors mean the forecasts underestimate (overestimate) the actual value. *RWFE* refers to the RW forecast error, and *AFE* refers to the analyst forecast error. *DI* represents the three disaggregated forecasts provided by I/B/E/S – sales (*SALE*), operating profit (*OPPROF*), and net income (*NI*) forecasts. All forecast errors are scaled by lagged total assets. Note that RW forecast errors use the most recent realization as the forecast, whereas the I/B/E/S forecast reflects the consensus from I/B/E/S. Forecast errors for forecast horizons $t+2$ and $t+3$ are computed similarly, with the exception that the RW forecasts use the most recent actual values as the forecast for all three horizons (i.e., Actual_{*t*}).⁵

In addition to these explicit forecasts, we generate implicit forecasts for operating expenses (*OPEXP*), defined as $SALE - OPPROF$, and non-operating expenses (*NONOP*), defined as $OPPROF - NI$. *OPEXP* and *NONOP* are comparable to the (total) *EXPENSES* variable employed in Ertimur et al. (2003), who employ analysts' revenue forecasts and calculate *EXPENSES* as the difference between the revenue and net income forecasts. Including *OPEXP* and *NONOP* allows us to parse the analysts' forecasts of *NI* into three distinct items – sales, operating expenses and non-operating expenses.

Consistent with prior literature, positive (negative) forecast errors indicate that the forecast underestimates (overestimates) the actual value. Our primary focus in this study is accuracy, however, calculated as the absolute value of the forecast error. Moreover, we quantify the relative forecast accuracy of analysts' and RW forecasts as analyst forecast superiority (*AFS*). *AFS* is the difference between the absolute value of the RW forecast accuracy and the analyst forecast accuracy. Thus, positive (negative) values of *AFS* indicate that the analyst forecast is more (less) accurate than the RW forecast.

⁵ For FY_{t+2} (FY_{t+3}), the RW forecast is the realized value (e.g. sales) two (three) years prior to the targeted forecast year. Thus, the RW forecast error is the change in sales over the forecasted year(s).

4 Results

4.1 Descriptive statistics

Table 1 provides descriptive statistics for our sample. Panel A presents the number of firm-year observations for our primary sample of firm-years for which we have all three disaggregated analyst forecasts (*SALE*, *OPPROF*, *NI*) by year and forecast horizon. There is a general increase in the number of firm-years over the sample period. In addition, there are more FY_{t+1} forecasts than FY_{t+2} , and more FY_{t+2} forecasts than FY_{t+3} forecasts each year, consistent with prior findings on the lower availability of longer horizon forecasts. Panel B presents descriptive statistics on the firm-year characteristics of our sample, benchmarked against the I/B/E/S population. Firm-years for which disaggregated analysts' forecasts are available reflect smaller firms (in terms of total assets) but higher sales and greater net income. The results in panel B also reveal that the firm-years with disaggregated analyst forecasts have higher sales and profits scaled by total assets than the I/B/E/S population. They also have higher levels of operating and non-operating expenses scaled by total assets than the I/B/E/S population. These relations hold in general across all forecast horizons.

[Please place Table 1 here]

4.2 Comparative accuracy of aggregated and disaggregated forecasts

Our first research question is whether the existence of disaggregated forecasts results in bottom-line EPS analyst forecasts that are relatively more accurate. Table 2 includes results that address this question by documenting whether analyst and RW forecast accuracy for firm/year observations with a full complement of disaggregated forecasts differ from the accuracy for

firm/year observations for which the disaggregated forecasts are not available. In Panel A we present mean and median absolute values of the analysts and RW EPS forecasts errors and of the RW disaggregated forecasts for FY_{t+1} , FY_{t+2} , and FY_{t+3} . We also present t-statistics and Wilcoxon two-sample test statistics to provide evidence of differences between the two samples.

We begin by considering differences in accuracy between EPS forecasts for analyst and RW forecasts, included in Panel A. We document that both analyst (*AAFE_EPS*) and RW (*RWFE_EPS*) EPS forecast errors are larger for the set of firm/years where disaggregated analysts forecasts are provided, with the results concentrated in the medians. We also document greater analyst forecast superiority (*AFS*) for the set of firm/years where disaggregated forecasts are provided. The results are inconsistent with those reported in Call et al. (2009), who find that analysts EPS forecasts issued in conjunction with cash flow forecasts are more accurate than forecasts issued without.

We are, however, interested in more than just the relative accuracy of the EPS forecasts. To provide evidence beyond EPS forecasts, we examine the relative accuracy of the RW disaggregated forecasts (*SALE*, *OPEXP*, *OPPROFIT*, *NONOP*, and *NI*) across the two subsamples. The findings with respect to the relative accuracy of the RW components forecasts are consistent with the EPS forecasts; in short, the RW disaggregated forecasts are less accurate for the set of firm/years where disaggregated forecasts are provided. These findings are consistent with analysts choosing to provide disaggregated forecasts when they are most informative – when RW forecasts are less accurate.

While our primary interest is in forecast accuracy, we also examine differences in bias across the two sets of firms. These results are provided in Panel B. Consistent with prior research, we find that analysts over-estimate EPS, across all three forecast horizons. In contrast,

RW forecasts underestimate EPS as well as the disaggregated components of earnings. In terms of differences across the two samples, however, we find that RW forecasts for the set of firms that do provide all three disaggregated forecasts are significantly more biased than forecasts for the set of firms that do not provide the disaggregated forecasts.

The overall takeaway from Table 2 is that analysts provide greater improvement over RW forecasts when they provide disaggregated forecasts even though the earnings and components of earnings appear to be more difficult to forecast using a RW model.

[Please place Table 2 here]

4.3 Analyst forecast superiority across income components

We next provide insight into our second research question. Conditional on analysts providing disaggregated forecasts, we examine the superiority of the analyst forecast relative to the RW forecast for each income component. Table 3 reports the forecast accuracy (Panel A) and bias (Panel B) of the RW and analyst forecasts for those firm/years in which analysts provide disaggregated forecasts for each component of forecasted income.

Panel A documents that analyst forecasts of each component for FY_{t+1} are significantly more accurate than the analogous RW forecasts. Interestingly, analysts appear to more accurately forecast operating expenses than sales and to have the greatest superiority over RW forecasts when forecasting operating expenses. However, while analysts provide the greatest forecast superiority for sales and operating expenses, they provide the least superiority over RW forecasts with respect to operating profit. This is consistent with analysts providing value in forecasting sales and operating expenses but perhaps not fully understanding the interrelation between sales and operating expenses to translate those component forecasts into more accurate forecasts of

operating profit. Analyst superiority at forecasting net income for FY_{t+1} appears to be driven by their superiority in forecasting non-operating expenses and not by their superiority in forecasting operating profit.

Analyst forecasts of sales, operating expenses, non-operating expenses, and net income for FY_{t+2} and FY_{t+3} are also generally superior to RW forecasts. In addition, the analyst forecast superiority for sales and operating expenses appears to increase over the longer horizons.

However, we find that analyst forecasts of operating profit for FY_{t+2} and FY_{t+3} are significantly *less* accurate than RW forecasts at the mean and are not different from RW forecasts for FY_{t+3} at the median. This is consistent with the results for FY_{t+1} , and suggests that while analysts are more accurate at forecasting sales and operating expenses two- and three-years ahead, they are not more accurate at forecasting the difference between sales and expenses (operating profit).

To provide some insight into the accuracy differences in Panel A, Panel B of Table 3 reports the RW and analyst forecast bias for each of the income components. Analyst forecast superiority could be driven by less optimistically biased analysts' forecasts and/or pessimistically biased RW forecasts, or some other combination. Given that the RW forecasts include no growth component, it is not surprising that the RW forecasts consistently underestimate each component of income. The results for analyst forecasts yield some insight into the accuracy results in Panel A. Specifically, for FY_{t+1} , analyst forecasts of sales are unbiased; however, analysts appear to underestimate operating expenses leading to optimistically biased forecasts of operating profit. This is consistent with analysts not fully considering the effect of sales forecasts on the variable and fixed components of operating expenses. For FY_{t+2} and FY_{t+3} , analysts appear to overestimate sales and underestimate operating expenses (only at the median for FY_{t+2}). This suggests that, for longer horizon forecasts, analysts appear to exhibit an optimistic bias for sales

forecasts but continue to underestimate operating expenses. Again, this is consistent with analysts not fully incorporating cost structures into their forecasts. These results are consistent with evidence in Kim and Prather-Kinsey (2010), Weiss (2010), and Baumgarten et al. (2011), although we are able to examine operating expense forecasts directly and our results suggest that analyst forecast errors are not solely due to errors in operating expense forecasts. Analysts appear to provide the greatest value in terms of forecast accuracy over RW forecasts with regards to either sales or operating expenses. However, analysts do not appear to translate these superior forecasts into superior forecasts of operating profit. The results in Panel B also suggest that analysts tend to overestimate non-operating expenses across all forecast horizons.

[Please place Table 3 here]

To simultaneously examine the association between various disaggregated component forecasts and bottom-line forecast accuracy, Table 4 presents the results of multivariate regression analyses. The dependent variable is analyst forecast superiority over the RW forecasts of net income (*AFS_NI*). We regress the *AFS_NI* on the rank of the analyst forecast superiority for each individual component of net income. We calculate the scaled decile rank for each of our disaggregated components for use in our analysis, similar to Abarbanell and Bushee (1998). Specifically, we rank the values of the variables into deciles (0,9) each year and divide the decile number by nine so that each variable observation takes on a value between zero and one. This ranking process allows us to compare across the coefficients within a model.

Model 1 includes all components of income. However, because *AFS_SALE* is highly correlated with *AFS_OPEXP* (0.84 for FY_{t+1}, 0.91 for FY_{t+2}, and 0.91 for FY_{t+3}, untabulated), we also report the results of Model 2, which excludes *AFS_OPEXP* from the regression. The resulting ranked variables are indicated with an “R” prefix on the associated variable name. If the

improvement in accuracy obtained from a disaggregated analyst forecast is related to an increase in the analysts' superiority in forecasting net income, relative to a random walk forecast, we expect a positive coefficient on the disaggregated forecast variable.

We fail to document a significant association between the rank of the superiority of analysts' sales or operating expense forecasts and analysts' superiority of net income forecasts across any forecast horizon. In fact, the coefficients on *RAFS_SALE* and *RAFS_OPEXP* are either insignificant or significantly *negative* in each of the regressions. This suggests that, while analyst forecast superiority over RW forecasts is highest for sales and non-operating expenses (as evidenced in Table 3), the superiority of these line item forecasts does not translate into analyst net income forecast superiority. In contrast, we document a consistently positive association between analysts' superiority in forecasting operating profit and their superiority at forecasting net income. In short, analyst forecasts of net income are only superior to RW forecasts of net income when analysts are able to combine the accurate forecasts of sales and operating expenses into a superior forecast of operating profit. In fact, the results suggest that providing superior forecasts of sales leads to significantly *less* superior forecasts of net income, after controlling for improved operating profit forecasts. Therefore, while much focus and effort has been on forecasting sales, the results suggest that translating superior sales forecasts into superior forecasts of operating profit is of great importance. Superior forecasts of operating profit, not superior forecasts of sales, drive analyst forecast superiority in forecasting net income.

The results also suggest that the superiority of analysts' FY_{t+1} forecasts of net income over RW forecasts is driven by analysts' non-operating expense forecasts. Specifically, the coefficient on *RAFS_NONOP* (0.0852) is greater than the coefficient on *RAFS_OPPROF* (0.0514). For FY_{t+2} and FY_{t+3} , however, analyst net income forecast superiority is driven by their

ability to forecast operating profit (coefficient estimates of 0.1023 and 0.1352) rather than non-operating expenses (coefficient estimates of 0.0603 and 0.0670).

[Please place Table 4 here]

4.4 Analyst forecast superiority by firm/year characteristics

In this section, we address our third research question, which is whether various firm characteristics are associated with analysts' superiority over RW forecasts. We examine analyst disaggregated forecast superiority over RW forecasts across three firm-year characteristics: (1) the accuracy of the RW benchmarks, (2) historical sales growth, and (3) firm size. We argue that these three characteristics are related to the underlying difficulty of forecasting across firms. Table 5 provides the results of the analysis.

Panel A of Table 5 presents the results based on RW EPS forecast accuracy. We argue that firm/years in which RW forecasts are more accurate are less difficult to forecast than firm/years in which RW forecasts are less accurate. As expected, for FY_{t+1} , analyst forecast superiority increases for each of the disaggregated components as the RW EPS forecast accuracy decreases. This same general pattern holds for FY_{t+2} and FY_{t+3} . However, we note that analyst operating profit forecasts are no more accurate (significantly less accurate) than the RW forecasts in FY_{t+2} (FY_{t+3}), even when the RW forecasts are least accurate. Again, the results suggest little superiority of analyst operating profit forecasts over RW forecasts, even when RW EPS forecasts are the least accurate and when analysts' sales and operating expenses forecast superiority is the greatest.

Panel B of Table 5 presents analyst forecast superiority across historical sales growth terciles. We argue that firm/years with moderate sales growth are inherently more stable than

firm/years with greater sales growth. Thus, we expect analyst forecast superiority to be greatest when there is more extreme historical sales growth. Consistent with our expectations and RW forecasts' failure to incorporate growth, we document that the analyst disaggregated forecast superiority generally increases across all the sales growth terciles for all components.

Specifically, the monotonic increase in analyst superiority across the growth terciles is observed for each component of income, including net income, for FY_{t+2} and FY_{t+3} . However, this monotonic increase in analyst forecast superiority across terciles fails to hold for FY_{t+1} net income forecasts. In addition, we find significant analyst superiority for forecasting operating profit in FY_{t+2} and FY_{t+3} only in the highest tercile of sales growth.

Panel C presents analyst forecast superiority across firm size terciles. In general, we find no consistent relation between analysts' disaggregated forecast superiority and firm size for FY_{t+1} . For FY_{t+2} and FY_{t+3} , we find some evidence of an increase in analyst forecast superiority from the smallest size tercile to the middle size tercile for sales, operating expenses, operating profit, and net income. There does not appear to be an increase in analyst forecast superiority from the middle to the highest size tercile for the income components. In contrast, there is a significant increase in analyst forecast superiority across the size terciles for forecasts of operating profit, and the analyst superiority is significant only in the highest size tercile for FY_{t+1} and FY_{t+2} .

In summary, we find significant analyst forecast superiority for operating profit forecasts at the FY_{t+1} forecast horizon for all growth and size terciles and for the two lowest RW EPS accuracy terciles. For FY_{t+2} and FY_{t+3} , there is no significant analyst forecast superiority for operating profit among any of the RW accuracy terciles. We document significant operating profit analyst forecast superiority only for the highest growth tercile and the largest firm size

tercile. Therefore, while there is no significant operating profit analyst forecast superiority at FY_{t+2} or FY_{t+3} horizons overall, we find evidence of analyst forecast superiority for large and high growth firms. In contrast, we find significant net income analyst forecast superiority for each tercile of RW forecast accuracy, historical growth, and size.

[Please place Table 5 here]

To allow for simultaneous controls for individual firm characteristics, we perform multivariate regression analyses in Table 6. As with the regressions in Table 4, the dependent variable in the regressions is *AFS_NI*. In Table 6, however, we include explanatory variables that capture the firm characteristics examined in Table 5. Specifically, we include indicator variables for (1) the least and most accurate EPS RW forecast terciles (*RWBad* and *RWGood*), (2) the highest and lowest (sometimes negative) sales growth terciles (*HighGR* and *LowGR*), (3) and the largest and smallest firm size terciles (*Large* and *Small*). We also include an explanatory variable to capture variation in the number of analysts that provide *SALES* forecasts, scaled by the number of analysts that provide *EPS* forecasts (*Ratio_SE*) *Ratio_SE* is included to provide insight into whether the superiority of analyst forecasts over RW forecasts increases as the number of analysts providing disaggregated forecasts increases.

For FY_{t+1} , we find that analysts' net income forecast superiority is significantly greater (less) for less (more) accurate RW forecasts. Analysts' net income forecast superiority is also significantly greater for firm/years with both higher and lower sales growth. This suggests that analysts provide the most benefit in forecasting net income for companies experiencing either very high or very low growth, consistent with RW forecasts not capturing growth. Analysts' net income forecast superiority is also positively associated with firm size; *AFS_NI* is greater for larger firms and less for smaller firms. Finally, we find that analyst forecast superiority increases

with the number of analysts providing disaggregated (sales) forecasts. Overall, analysts' net income forecast superiority appears to be most highly associated with inaccurate RW forecasts (*RWBad*).

For FY_{t+2} and FY_{t+3} we find, consistent with the results for FY_{t+1} , that analyst net income forecast superiority is significantly greater for inaccurate EPS RW forecasts, high growth and large firms, and significantly lower for accurate EPS RW forecasts and small firms. However, for FY_{t+2} and FY_{t+3} , we find that analyst net income forecast superiority is significantly less for low growth firms as well. In addition, we find no relation between analyst forecast superiority and the number of analysts that provide disaggregated (sales) forecasts in the longer term.

[Please place Table 6 here]

5. Conclusion

We provide insight into the value that analysts provide to the forecasting process relative to RW forecasts. We examine three research questions. First, we examine whether the reporting of disaggregated forecasts improves the analysts' accuracy in forecasting bottom-line earnings. Second, conditional on analysts providing disaggregated forecasts, we examine which disaggregated forecasts contribute most to analyst net income forecast superiority. Finally, we examine what cross-sectional characteristics are associated with greater analyst forecast superiority over RW forecasts.

There are several caveats to our analysis. First, we ignore well-documented cross-sectional variation in analysts' incentives to provide accurate forecasts and to provide disaggregated forecasts (Ertimur et al. 2011). Although most research on analysts' incentives focuses on individual analysts (e.g., O'Brien; McNichols and Hsiou-Wei 2005), our analyses

utilize the consensus forecast, which filters some of the cross-sectional variation in individual analyst incentives, although incentives driven by firm-level factors (like growth and external financing) remain. We attempt to control for these in multivariate analyses. Second, we intentionally restrict our analysis to earnings forecasts, and are aware that analysts serve many roles. In addition to earnings forecasts, analysts provide price targets and stock recommendations, coordinate conferences that network institutional investors and managers, and provide numerous other client-related services. We believe that a better understanding of the overall value provided by analysts is rooted in the fundamental role of earnings forecasting, but acknowledge that other factors may be more important and may interact with output of the forecasting activities we examine.

Overall, we document that analysts provide disaggregated forecasts both when RW and analyst forecasts are less accurate. However, we also document that analyst forecasts are significantly more accurate than RW forecasts when disaggregated forecasts are provided relative to when analyst forecasts are issued without disaggregated forecasts. These results are consistent with analysts using a more structured approach to forecasting when earnings are more difficult to forecast and with greater accuracy relative to RW forecasts when they do provide disaggregated forecasts. These results contribute to the literature on when analysts provide disaggregated forecasts (Ertimur et al. 2011) and whether analysts' provision of disaggregated forecasts yield more accurate EPS forecasts (Call et al. 2009; Givoly et al. 2009).

Second, not surprisingly, we find that the analysts' contribution to the forecasting process appears to lie in their superior ability to forecast sales, operating expenses, and non-operating items. However, we find that analyst sales and operating expense forecast superiority do not, on average, translate into operating profit forecast superiority. This suggests that, while

analysts are able to provide superior sales and operating expense forecasts, they do not appear to consistently translate these forecasts into superior operating profit forecasts. The superiority of analyst net income forecasts is, therefore, driven by their superior ability to forecast non-operating expenses.

We also find that analyst superiority in forecasting net income is positively associated with analyst operating profit forecast superiority but negatively associated with analyst sales and operating expense forecast superiority. This suggests that analyst net income forecast superiority might improve if analysts focused less on sales forecast accuracy or operating expense forecast accuracy and instead focused more on understanding the relation between the sales forecast and the operating expense forecast. We also document that longer-run analyst forecasts of operating profit are superior to RW forecasts only for large firms and firms with high sales growth.

Our results are consistent with those in Baumgarten et al. (2011), Kim and Prather-Kinsey (2010), and Weiss (2010) that analysts do not fully incorporate the cost behaviors in their forecasts. This does not suggest, however, that analyst superiority is primarily driven by their sales forecasts. Instead, our results suggest that analyst operating expense forecasts, and not sales forecasts, yield the greatest superiority over RW forecasts. Our results do suggest, however, that analysts do not consider the interrelation between accurate sales forecasts and operating expense forecasts when forecasting operating profit.

Appendix A
Variable definitions.

RWFE (AFE) indicates the variable is the RW (analyst) forecast error.

ARWFE (AAFE) indicates the variable is the absolute value of the RW (analyst) forecast error.

Random walk (RW) variables:

Random walk forecasts and forecast errors are based on Compustat data:

Analysts (A) variables:

Analysts' variables are based on the median of the first analysts (annual) consensus forecasts made after the annual earnings announcement less the I/B/E/S reported actual.

An additional *A* at the beginning of a variable indicates that the variable is the absolute value of the calculated variables.

Variable Name	Compustat Variable	Variable Description
RWFE or ARWFE	SALE OPPROF NI OPEXP NONOP	REVT OIADP NI REVT - OIADP OPPROF - NI
		Revenues – net sales. Operating income after depreciation. Net income/loss. Operating expenses Non-operating expenses.
RWFE or ARWFE	SALE OPPROF NI OPEXP NONOP	SALE - OPPROF OPPROF - NI
		Median consensus I/B/E/S sales forecast. Median consensus I/B/E/S operating profit forecast Median consensus I/B/E/S net income forecast
AFS	Analysts' forecast superiority	ARWFE – AAFE = the difference in accuracy between the RW forecast error and the A forecast error.

Table 1 Descriptive statistics and distribution of disaggregated forecasts by year*Panel A: Restricted sample by year*

	2003	2004	2005	2006	2007	2008	2009	All Years
FY t+1	984	1156	2070	2317	2259	2267	2279	13332
FY t+2		741	1699	1995	1888	2057	2127	10500
FY t+3			763	967	982	1144	1247	5103

Panel B: Descriptive statistics

	FY_{t+1}			FY_{t+2}			FY_{t+3}		
	All IBES	Restricted	<i>Stat.</i>	All IBES	Restricted	<i>Stat.</i>	All IBES	Restricted	<i>Stat.</i>
<i>Sales (unscaled)</i>									
Mean	4437.0	4484.9	0.25	4970.4	4896.6	-0.33	6576.7	6005.0	-1.51
Median	618.1	725.2	6.21	719.6	822.2	4.75	1009.45	984.8	-1.45
<i>Total Assets</i>									
Mean	11832.9	6646.9	-7.83	13424.2	7186.7	-7.47	17238.6	7750.8	-7.48
Median	959.6	834.8	-5.40	1099.1	949.3	-6.27	1500.7	1113.0	-8.32
<i>NI (unscaled)</i>									
Mean	306.5	308.9	0.11	342.2	331.9	-0.50	458.8	398.4	-1.71
Median	31.4	34.5	3.07	37.1	39.8	-1.89	51.75	45.7	-2.44
<i>Sales/TA</i>									
Mean	0.987	1.073	9.44	0.964	1.070	10.31	0.951	1.048	7.19
Median	0.791	0.906	12.74	0.780	0.897	16.39	0.771	0.883	11.31
<i>OPEXP/TA</i>									
Mean	0.907	0.983	8.76	0.885	0.981	9.63	0.870	0.959	6.89
Median	0.715	0.810	11.62	0.701	0.800	15.87	0.690	0.783	11.36
<i>OPPROF/TA</i>									
Mean	0.080	0.090	6.16	0.079	0.089	6.66	0.081	0.089	3.51
Median	0.074	0.090	13.72	0.074	0.087	10.73	0.077	0.090	6.09
<i>NONOP/TA</i>									
Mean	0.047	0.048	1.75	0.045	0.048	2.88	0.047	0.050	1.98
Median	0.037	0.042	9.45	0.037	0.042	7.11	0.039	0.045	5.14
<i>NI/TA</i>									
Mean	0.033	0.042	5.95	0.033	0.041	5.35	0.034	0.039	2.50

Median	0.039	0.051	13.49	0/039	0.051	9.35	0.042	0.051	4.85
<i>N</i>	20840	13332		15560	10500		8272	5103	

Panel A details the number of observations in the restricted samples. Panel B provides descriptive statistics for the “All I/B/E/S” firms and our “Restricted” sample. The “All I/B/E/S” sample includes firms with available Compustat data to compute RW EPS forecasts and forecast errors and I/B/E/S data to compute analysts’ EPS forecast errors. The “Restricted” sample includes firms with the same data availability as the first group along with available Compustat data to compute RW forecasts and forecast errors and I/B/E/S data to compute analysts’ forecast errors for *SALES*, *OPPROF*, and *NI*. The FY_{t+1} (FY_{t+2} , FY_{t+3}) sample includes firm/year observations for which there are I/B/E/S FY_{t+1} (FY_{t+2} , FY_{t+3}) data.

Table 2 Non-disaggregated and disaggregated samples: RW disaggregated forecasts, RW EPS forecasts, and analyst EPS forecasts.

Panel A: RW absolute forecast errors (ARWFE), analyst absolute forecast errors (AAFE), and analyst forecast superiority (AFS)

	FY _{t+1}			FY _{t+2}			FY _{t+3}		
	<u>NOT DISAGG</u>	<u>DISAGG</u>	<u>Stats</u>	<u>NOT DISAGG</u>	<u>DISAGG</u>	<u>Stats</u>	<u>NOT DISAGG</u>	<u>DISAGG</u>	<u>Stats</u>
AAFE_EPS									
Mean	0.00089	0.00088	0.02	0.00135	0.00141	-0.95	0.00101	0.00153	-7.63
Median	0.00014	0.00020	-9.29	0.00023	0.00035	-9.94	0.00020	0.00041	-13.05
ARWFE_EPS									
Mean	0.00145	0.00148	-0.93	0.00160	0.00172	-2.25	0.00120	0.00170	-8.05
Median	0.00031	0.00047	-10.64	0.00037	0.00057	-9.87	0.00028	0.00060	-14.65
AFS_EPS									
Mean	0.00056	0.00060	-0.79	0.00025	0.00030	-0.95	0.00019	0.00017	0.34
Median	0.00006	0.00012	-5.70	0.00003	0.00006	-0.96	0.00002	0.00005	-3.55
ARWFE_SALE									
Mean	0.163	0.157	1.66	0.226	0.264	-6.32	0.273	0.340	-8.01
Median	0.046	0.103	-28.52	0.066	0.182	-29.57	0.124	0.245	-19.33
ARWFE_OPEXP									
Mean	0.181	0.174	1.82	0.231	0.271	-6.95	0.279	0.343	-8.02
Median	0.067	0.127	-26.58	0.086	0.196	-28.17	0.142	0.256	-19.01
ARWFE_OP PROF									
Mean	0.036	0.042	-9.73	0.045	0.059	-12.67	0.051	0.069	-12.01
Median	0.016	0.027	-21.92	0.022	0.040	-22.27	0.028	0.049	-16.54
ARWFE_NONOP									
Mean	0.045	0.040	4.19	0.038	0.042	-3.38	0.037	0.048	-7.39
Median	0.011	0.018	-18.00	0.013	0.022	-18.23	0.017	0.026	-14.53
ARWFE_NI									
Mean	0.057	0.055	1.40	0.058	0.065	-4.97	0.057	0.075	-8.93
Median	0.016	0.028	-22.60	0.021	0.038	-20.53	0.026	0.045	-16.34
N	7195	13323		4867	10500		3076	5103	

Panel B: RW and analyst forecast bias

	FY _{t+1}			FY _{t+2}			FY _{t+3}		
	<u>NOT DISAGG</u>	<u>DISAGG</u>	<u>Stats</u>	<u>NOT DISAGG</u>	<u>DISAGG</u>	<u>Stats</u>	<u>NOT DISAGG</u>	<u>DISAGG</u>	<u>Stats</u>
<i>AFE_EPS</i>									
Mean	-0.00042	-0.00041	-0.23	-0.00083	-0.00097	2.16	-0.00071	-0.00118	6.62
Median	-0.00001	-0.00000	-4.17	-0.00004	-0.00008	4.21	-0.00004	-0.00012	6.33
<i>RWFE_EPS</i>									
Mean	0.00006	0.00002 [^]	1.43	0.00016	0.00016	0.06	-0.00011	0.00016	-3.76
Median	0.00000	0.00000	-3.83	0.00000	0.00004	-4.39	0.00001 [^]	0.00006	-6.73
<i>RWFE_SALE</i>									
Mean	0.073	0.100	-9.08	0.154	0.196	-6.32	0.199	0.271	-7.59
Median	0.022	0.072	-17.10	0.037	0.150	-20.58	0.083	0.220	-15.67
<i>RWFE_OPEXP</i>									
Mean	0.127	0.136	-2.18	0.174	0.223	-7.71	0.222	0.293	-7.94
Median	0.047	0.111	-20.99	0.062	0.177	-23.36	0.115	0.240	-16.97
<i>RWFE_OPPROF</i>									
Mean	0.013	0.013	0.25	0.018	0.021	-1.99	0.020	0.028	-3.90
Median	0.005	0.010	-4.81	0.007	0.018	-6.99	0.011	0.026	-6.82
<i>RWFE_NONOP</i>									
Mean	0.001 [^]	0.002	-0.84	0.004	0.009	-3.71	0.009	0.011	-1.15
Median	0.002	0.004	-0.59	0.003	0.008	-5.59	0.005	0.011	-3.58
<i>RWFE_NI</i>									
Mean	0.010	0.010	-0.12	0.013	0.012	0.79	0.009	0.017	-3.19
Median	0.002	0.008	-4.48	0.003	0.011	-5.12	0.006	0.018	-6.19
<i>N</i>	7195	13323		4867	10500		3076	5103	

This table provides mean (median) values and t-statistics (Wilcoxon two-sample test) of a difference in mean (median) values of the analysts and RW EPS forecast errors and the RW disaggregated-component forecast errors between NOT DISAGG firm/years (with I/B/E/S EPS forecasts but not *SALE*, *OPPROF*, and *NI* forecasts) and DISAGG firm/years (with I/B/E/S EPS, *SALE*, *OPPROF*, and *NI* forecasts). Panel A focuses on differences in forecast accuracy (based on absolute forecasts errors) while Panel B focuses on differences in forecast bias. Variable definitions are detailed in Appendix A.

Table 3 Summary statistics - disaggregated forecast errors.*Panel A: RW and analyst absolute forecast errors and analyst forecast superiority (AFS)*

ABSOLUTE FORECAST ERRORS				
FY_{t+1}	RW	Analysts	AFS	t-test/sign test
SALES				
Mean	0.157	0.080	0.078	60.17
Median	0.103	0.045	0.047	3381.5
OPEXP				
Mean	0.175	0.069	0.106	81.88
Median	0.127	0.039	0.079	4289.5
OPPROF				
Mean	0.043	0.035	0.008	17.92
Median	0.027	0.019	0.006	2414.0
NONOP				
Mean	0.040	0.016	0.024	41.96
Median	0.018	0.009	0.007	1346.5
NI				
Mean	0.055	0.027	0.028	44.80
Median	0.029	0.013	0.011	2748.0
FY_{t+2}	RW	Analysts	AFS	t-test/sign test
SALES				
Mean	0.264	0.174	0.090	35.47
Median	0.182	0.105	0.070	2066.5
OPEXP				
Mean	0.272	0.144	0.128	54.74
Median	0.196	0.083	0.104	2888.5
OPPROF				
Mean	0.061	0.061	-0.002	-2.44
Median	0.036	0.036	0.003	270.5
NONOP				
Mean	0.042	0.023	0.019	30.66
Median	0.019	0.015	0.006	1242.5
NI				
Mean	0.066	0.047	0.019	24.19
Median	0.038	0.025	0.009	1277.5
FY_{t+3}	RW	Analysts	AFS	t-test/sign test
SALES				
Mean	0.340	0.219	0.121	27.53
Median	0.245	0.135	0.103	1092.5
OPEXP				
Mean	0.343	0.177	0.166	42.27
Median	0.256	0.107	0.141	1537.5
OPPROF				
Mean	0.069	0.078	-0.008	-6.45
Median	0.049	0.047	0.001 [^]	55.5
NONOP				

Mean	0.048	0.028	0.020	20.18
Median	0.026	0.018	0.007	634.5
NI				
Mean	0.075	0.059	0.016	12.65
Median	0.046	0.033	0.010	523.5

Panel B: RW and analyst forecast bias

FORECAST BIAS				
FY_{t+1}	RW	Analysts	t-test/sign test	
SALES				
Mean	0.100	-0.002 [^]		60.17
Median	0.072	0.000 [^]		3381.5
OPEXP				
Mean	0.135	0.010		81.88
Median	0.111	0.006		4289.5
OPPROF				
Mean	0.012	-0.012		17.92
Median	0.010	-0.004		1346.5
NONOP				
Mean	0.002	-0.004		41.96
Median	0.004	-0.002		2414.0
NI				
Mean	0.010	-0.009		44.80
Median	0.008	-0.001		2748.0
FY_{t+2}	RW	Analysts	t-test/sign test	
SALES				
Mean	0.196	-0.030		5.88
Median	0.149	-0.006		1641.5
OPEXP				
Mean	0.223	0.004 [^]		24.57
Median	0.177	0.011		2490.5
OPPROF				
Mean	0.021	-0.035		33.92
Median	0.018	-0.017		471.5
NONOP				
Mean	0.009	-0.008		17.87
Median	0.008	-0.005		791.5
NI				
Mean	0.011	-0.026		27.83
Median	0.011	-0.010		450.5
FY_{t+3}	RW	Analysts	t-test/sign test	
SALES				
Mean	0.271	-0.038		64.95
Median	0.220	-0.008		2272.5
OPEXP				
Mean	0.293	0.010		60.39
Median	0.240	0.020		2203.5

<i>OPPROF</i>			
Mean	0.028	-0.048	64.69
Median	0.026	-0.025	2208.5
<i>NONOP</i>			
Mean	0.011	-0.011	11.36
Median	0.011	-0.007	1062.5
<i>NI</i>			
Mean	0.017	-0.037	50.97
Median	0.018	-0.016	2116.5

Panel A reports mean and median values of the RW and analyst disaggregated absolute forecast errors (accuracy), analyst forecast superiority (*AFS*), and statistical tests of the difference in mean and median values. *AFS* = the absolute value of RW forecast error minus the absolute value of the analysts' forecast error for each firm/year. Positive (negative) values of *AFS* indicate that analyst forecasts are superior (inferior) to RW forecasts. Panel B reports mean and median values of the RW and analyst disaggregated forecast bias and statistical tests of the difference in those values. All values are scaled by lagged total assets.

Table 4: Multivariate analysis of the relative importance of the analysts' forecast superiority of the disaggregated components in explaining the net income analysts' forecast superiority. Table values are parameter estimates with t-statistics in below.

$$AFS_NI = \alpha + \beta_1 RAFS_SALE + \beta_2 RAFS_OPEXP + \beta_3 RAFS_OPPROF + \beta_4 RAFS_NONOP + \varepsilon$$

	FY_{t+1}							
	Intercept	<i>RAFS_SALE</i>	<i>RAFS_OPEXP</i>	<i>RAFS_OPPROF</i>	<i>RAFS_NONOP</i>	F-STAT	R^2	
Model 1	-0.0385 -27.87	-0.00672 -2.48	0.0035 1.35	0.0517 26.25	0.0852 46.77	1025.3	23.5	
Model 2	-0.0380 -28.42	-0.0041 -2.17		0.0514 26.27	0.0854 47.07	1366.35	23.5	
	FY_{t+2}							
	Intercept	<i>RAFS_SALE</i>	<i>RAFS_OPEXP</i>	<i>RAFS_OPPROF</i>	<i>RAFS_NONOP</i>	F-STAT	R^2	
Model 1	-0.0539 -32.76	-0.0004 -0.010	-0.0152 -4.06	0.1000 40.19	0.0612 27.39	979.55	27.1	
Model 2	-0.0552 -34.74	-0.0137 -5.95		0.1023 42.11	0.0603 27.09	1298.6	27.0	
	FY_{t+3}							
	Intercept	<i>RAFS_SALE</i>	<i>RAFS_OPEXP</i>	<i>RAFS_OPPROF</i>	<i>RAFS_NONOP</i>	F-STAT	R^2	
Model 1	-0.0689 -26.00	-0.00930 1.34	-0.03586 -5.51	0.12953 32.38	0.06735 18.93	590.4	31.6	
Model 2	-0.0725 -28.15	-0.02325 -6.34		0.13561 35.16	0.06517 18.38	772.2	31.2	

This table presents the results of regressing the analyst net income forecast superiority on the decile ranks of the analyst forecasts superiority (AFS) of *SALE*, *OPEXP*, *OPPROF*, and *NONOP*. Model one includes all components. Model 2 excludes *RAFS_OPEXP*, which is highly correlated with *RAFS_SALE*.

Table 5: Analyst forecast superiority relative to RW disaggregated forecasts (AFS), by terciles.

<i>Panel A: Mean values of AFS - Terciles based on accuracy of RW EPS forecasts.</i>					
	FY_{t+1}				
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Most accurate</i>	0.052	0.081	0.001 [^]	0.008	0.006
<i>II.</i>	0.079	0.111	0.006	0.016	0.017
<i>III. Least accurate</i>	0.101	0.127	0.017	0.049	0.062
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-10.11	-10.58	-6.69	-9.49	-11.05
<i>I with III</i>	-15.50	-14.15	-14.77	-26.97	-34.64
<i>II with III</i>	-6.45	-4.68	-9.43	-20.22	-26.24
	FY_{t+2}				
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Most accurate</i>	0.074	0.106	-0.004	0.007	0.003
<i>II.</i>	0.097	0.135	-0.002 [^]	0.014	0.011
<i>III. Least accurate</i>	0.100	0.144	0.000 [^]	0.037	0.043
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-4.39	-5.71	-1.67	-6.30	-5.78
<i>I with III</i>	-4.15	-6.42	-2.05	-18.62	-19.57
<i>II with III</i>	-0.43	-1.38	-0.82	-13.50	-14.72
	FY_{t+3}				
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Most accurate</i>	0.109	0.145	-0.005	0.009	0.003
<i>II.</i>	0.134	0.177	-0.006	0.015	0.008
<i>III. Least accurate</i>	0.116	0.174	-0.015	0.038	0.040
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-2.71	-3.68	0.36	-3.39	-2.04
<i>I with III</i>	-0.66	-3.10	2.95	-10.91	-10.99
<i>II with III</i>	1.55	0.27	2.48	-8.07	-8.94
<i>Panel B: Mean values of AFS - Terciles based on historical sales growth rank.</i>					
	FY_{t+1}				
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Lowest Sales Gr</i>	0.021	0.046	0.002	0.033	0.035
<i>II.</i>	0.052	0.093	0.001	0.018	0.021
<i>III. Highest Sales Gr.</i>	0.160	0.181	0.019	0.024	0.032
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-12.19	-18.49	1.42	10.04	8.87
<i>I with III</i>	-43.42	-46.55	-9.46	5.65	3.83
<i>II with III</i>	-37.85	-28.86	-17.25	-4.67	-7.21
	FY_{t+2}				
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Lowest Sales Gr</i>	-0.042	0.020	-0.024	0.020	0.011
<i>II.</i>	0.094	0.136	-0.001 [^]	0.015	0.017
<i>III. Highest Sales Gr.</i>	0.218	0.227	0.020	0.022	0.028
<i>t-stats of difference in mean AFS values across terciles.</i>					

<i>I with II</i>	-26.17	-23.33	-14.24	3.27	-3.11
<i>I with III</i>	-43.28	-35.74	-24.30	-0.90	-8.30
<i>II with III</i>	-21.34	-16.29	-12.74	-4.47	-6.19
FY_{t+3}					
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Lowest Sales Gr</i>	-0.035	0.047	-0.036	0.022	0.009
<i>II.</i>	0.132	0.178	-0.005	0.015	0.016
<i>III. Highest Sales Gr.</i>	0.267	0.270	0.016	0.024	0.025
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-17.25	-14.74	-10.41	2.82	-2.01
<i>I with III</i>	-29.04	-23.83	-15.93	-0.39	-4.65
<i>II with III</i>	-13.10	-10.28	-6.90	-3.42	-3.09

Panel C: Mean values of AFS - Terciles on firm size (total sales).

FY_{t+1}					
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Smallest firms.</i>	0.078	0.097	0.009	0.030	0.035
<i>II.</i>	0.082	0.117	0.007	0.023	0.027
<i>III. Largest firms.</i>	0.073	0.104	0.008	0.019	0.023
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-1.16	-6.04	1.82	4.77	4.77
<i>I with III</i>	1.60	-2.30	1.12	7.62	7.10
<i>II with III</i>	2.98	4.04	-1.14	3.08	2.59

FY_{t+2}					
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Smallest firms.</i>	0.071	0.111	-0.013	0.022	0.014
<i>II.</i>	0.097	0.136	0.001 [^]	0.019	0.021
<i>III. Largest firms.</i>	0.101	0.135	0.006	0.017	0.021
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-3.85	-4.25	-6.87	1.87	-3.10
<i>I with III</i>	-4.59	-4.06	-10.99	3.08	-3.45
<i>II with III</i>	-0.68	0.28	-4.41	1.29	-0.37

FY_{t+3}					
	SALE	OPEXP	OPPROF	NONOP	NI
<i>I. Smallest firms.</i>	0.085	0.146	-0.034	0.022	0.002 [^]
<i>II.</i>	0.134	0.179	-0.002 [^]	0.021	0.024
<i>III. Largest firms.</i>	0.136	0.170	0.009	0.019	0.023
<i>t-stats of difference in mean AFS values across terciles.</i>					
<i>I with II</i>	-4.28	-3.30	-8.86	0.30	-6.01
<i>I with III</i>	-4.77	-2.51	-12.96	0.98	-6.43
<i>II with III</i>	-0.26	0.89	-4.47	0.77	0.04

In each panel the primary table values are the mean AFS values. Positive (negative) values mean that analysts (RW) forecasts are more accurate. T-statistics that indicate whether the reported AFS values differ across the relevant terciles are provided below the mean values. The AFS values are statistically different from zero at conventional levels ((p-value of <0.05) – most at p-values of <0.01) except for items with [^].

Table 6: Multivariate analysis of the relative importance of the analysts' forecast superiority of the disaggregated components in explaining the net income analysts' forecast superiority. Table values are parameter estimates with t-statistics in below.

$AFS_NI = \alpha + \beta_1 RWGood + \beta_2 RWBad + \beta_3 HighGR + \beta_4 LowGR + \beta_5 Large + \beta_6 Small + \beta_7 Ratio_SE + \varepsilon$									
				\underline{FY}_{t+1}					
Intercept	<i>RWGood</i>	<i>RWBad</i>	<i>HighGR</i>	<i>LowGR</i>	<i>Large</i>	<i>Small</i>	<i>Ratio_SE</i>	F-STAT	R²
0.0060	-0.0188	0.0515	0.0035	0.0069	0.0189	-0.0143	0.0104	285.2	13.0
<i>3.41</i>	<i>-12.32</i>	<i>34.02</i>	<i>2.40</i>	<i>4.81</i>	<i>12.19</i>	<i>-9.27</i>	<i>5.21</i>		
				\underline{FY}_{t+2}					
Intercept	<i>RWGood</i>	<i>RWBad</i>	<i>HighGR</i>	<i>LowGR</i>	<i>Large</i>	<i>Small</i>	<i>Ratio_SE</i>	F-STAT	R²
0.0078	-0.0177	0.0450	0.0091	-0.0088	0.0208	-0.0246	0.0044	142.8	8.6
<i>3.41</i>	<i>-9.13</i>	<i>23.08</i>	<i>4.90</i>	<i>-4.77</i>	<i>10.44</i>	<i>-12.47</i>	<i>1.65</i>		
				\underline{FY}_{t+3}					
Intercept	<i>RWGood</i>	<i>RWBad</i>	<i>HighGR</i>	<i>LowGR</i>	<i>Large</i>	<i>Small</i>	<i>Ratio_SE</i>	F-STAT	R²
0.0080	-0.0208	0.0489	0.0113	-0.0083	0.0243	-0.0402	0.0042	70.7	8.7
<i>1.94</i>	<i>-6.38</i>	<i>15.28</i>	<i>3.66</i>	<i>-2.72</i>	<i>7.36</i>	<i>-12.58</i>	<i>0.85</i>		

This table presents the results of regressing the analyst net income forecast superiority on indicator variables for the highest and lowest RW forecasts accuracy terciles (*RWGood*, *RWBad*), the highest and lowest historical sales growth terciles (*HighGR*, *LowGR*), and the largest and smallest firm size terciles (*Large*, *Small*), and the ratio of the number of analysts providing sales forecasts relative to the number of analysts providing EPS forecasts (*Ratio_SE*).

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