Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?

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Abstract

We find that analysts who issue more accurate earnings forecasts also issue more profitable stock recommendations. The average factor-adjusted return associated with the recommendations of analysts in the highest accuracy quintile exceeds the return for analysts in the lowest accuracy quintile by 1.27% per month. Our findings provide indirect empirical support for valuation models in the accounting and finance literatures (e.g., Ohlson, 1995) that emphasize the role of future earnings in predicting stock price movements. Our results also suggest that imperfectly efficient markets reward information gatherers, such as security analysts, for their costly activities in generating superior earnings forecasts.

Keywords: earnings forecasts, stock recommendations, earnings-based valuation models.

JEL Classifications: G10, G14, G24.

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1. Introduction

Security analysts play an important role as financial intermediaries in modern day financial markets. Not surprisingly then, their two key outputs—earnings forecasts and stock recommendations—have been the subjects of a burgeoning literature in finance and accounting. Most existing studies, however, either focus on earnings forecasts or stock recommendations without attempting to link the two. A notable exception is the recent paper by Bradshaw (2004), which focuses on the consensus recommendations of analysts in order to identify the valuation models they use in transforming earnings forecasts into stock recommendations. Nevertheless, there is hardly any study in the extant literature that examines whether the relative superiority of an individual analyst in issuing earnings forecasts is associated with the higher profitability of her stock recommendations.

This is surprising given that such an examination could prove useful for at least four reasons. First, from a resource allocation perspective, the large amount of resources that analysts devote to forecasting earnings does suggest that an accurate earnings forecast is not merely an end in itself but is a tool to gauge the investment potential of a company's stock. As observed by Schipper (1991), earnings forecasts are "not a final product but rather an input into generating a final product" (p. 113). It is therefore important to know whether the resources spent on producing relatively more precise appraisals of earnings do indeed provide an analyst with a competitive edge in assessing the investment potential of companies.

Second, the abnormal earnings valuation model (see, e.g., Ohlson, 1995) envisages a central role for future corporate earnings in determining the intrinsic value of a stock. Indeed, one strand of the ensuing valuation or fundamental analysis research conclude that estimates of earnings, more than estimates of cash flows or dividends, could be combined with this model to yield superior estimates of stock values; which in turn could allow investors to earn abnormal stock returns (Frankel and Lee, 1998; Dechow, Hutton, and Sloan, 1999; Lee, Myers, and Swaminathan, 1999; also see the survey in Lee, 1999). By underlining the critical role of estimated earnings in stock valuation, these studies evoke the possibility that superior forecasts of earnings could provide an important advantage to investors in generating abnormal returns. Our study examines the usefulness of accurate earnings forecasts using the specific setting of security analysts. These analysts issue both earnings forecasts and stock recommendations for firms and hence, provide a unique setting in which the opinions of economic agents about the investment potential and future earnings of a stock could simultaneously be observed. This enables us to focus on the question: Do market participants with superior earnings forecasts indeed earn superior returns? An affirmative answer to this question would provide further empirical support for the critical role of earnings envisioned by fundamental analysis or valuation research.[1]

Third, investigating the association between the quality of recommendations and the quality of earnings forecasts could also provide additional evidence on the existence and the

[1] As noted earlier, a related paper Bradshaw (2004) attempts to identify the model that analysts use to transform their forecasts of earnings into stock recommendations. He converts consensus earnings forecasts into stock valuations using various valuation models, and compares the consensus recommendations to the ratios of the derived valuations and market prices to see which model's valuations are most consistent with the observed consensus recommendations. Our paper's objective and methodology are quite distinct from his. His study treats analysts covering a firm as a homogenous group and focuses on the *collective* opinion of the analysts. In contrast, our focus is on the differential performances of analysts relative to each other—we examine whether the superior earnings forecasts of some analysts relative to others allow them to issue *relatively* more profitable recommendations.

sources of analysts' ability to issue profitable stock recommendations. Prior evidence on the profitability of analysts' investment advice has been mixed (Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001, 2003a, thereafter BLMT; Mikhail, Walther, and Willis, 2004). Besides, more recently, reports in the popular media and certain academic studies (Cornell, 2001; Bradshaw, 2004; Jegadeesh, Kim, Krische, and Lee, 2004) suggest that analysts' recommendations are based on ad hoc heuristics, rather than on sound economic analyses. Relating investment advice to the quality of the underlying earnings forecasts could shed light on whether the observed profitability of recommendations is real. If the analysts with the most profitable recommendations also exhibit superior forecasting skills, it would suggest that their stock picking ability is real, and that it is founded on economic rationale.

Fourth, it is well known that analysts are evaluated on four criteria—stock picking ability, earnings forecast accuracy, written reports quality, and overall service (Stickel, 1992). Annual polls by practitioner journals such as *Institutional Investor* and the *Wall Street Journal* describe these as the determining qualities of top-ranked analysts. Common perception is that superior analysts score high on all four of these criteria, implying a correlation among them. This is also implicitly assumed by studies such as O'Brien (1990) and Stickel (1992), who identify superior analysts by focusing on only one of the four criteria. This notion, although intuitively appealing, has never been tested empirically. We note, as other researchers do, that the latter two criteria are of a subjective nature and are difficult to examine empirically (see, e.g., O'Brien, 1990). However, objective evaluations can be applied to empirical data on the first two criteria, thus providing an opportunity to put this assumed correlation to test. The existence or absence of such correlation has particular practical significance for buy-side fund managers who rely on the services of analysts and seek the best sources of advice for both investment calls and earnings forecasts.

Our methodology adopts a firm-year perspective: For each firm-year, we sort analysts into quintiles based on the accuracy of their forecasts of annual earnings. This empirical strategy does not impose an aggregate rank on an analyst but allows her to appear in different quintiles if her relative forecast accuracy differs for different firms. This treatment is consistent with our objective of exploring the association between firm-specific forecast accuracy and firm-specific recommendation profitability. We then form long and short calendar-time portfolios that mimic the daily average recommendation ratings of analysts within each quintile.

Our results show that both the favorable and unfavorable recommendations of analysts in the highest accuracy quintile contain positive investment value for investors. A zero-investment strategy that is long in the stocks favorably recommended and short in those unfavorably recommended by the most accurate analysts yields statistically significant average monthly returns of 0.737% (the four-factor alpha). On the other hand, the recommendations of analysts in the lowest accuracy quintile contain negative value for investors. Following the advice of these analysts yields statistically significant monthly returns of –0.529%. Overall, the recommendations of the most accurate analysts generate profits that exceed those of the least accurate analysts by 1.27% per month.

We surmise that accurate analysts have better inputs (i.e., earnings forecasts) that facilitate superior stock valuations, which in turn lead to more profitable stock recommendations. We test whether differences in the average earnings forecasts of analysts in the two extreme quintiles are large enough potentially to lead to significantly different firm valuations. As discussed in detail in Section 5.5, we calculate the average hypothetical stock valuations for the two quintiles based on a simple formulation of the residual income model of Frankel and Lee (1998). Our results indicate that the mean (median) stock valuation of the least accurate analysts deviates from that of the most accurate analysts by 27.0% (13.2%). This provides evidence that the differences in the earnings forecasts of analysts sorted into the two extreme quintiles are indeed large and could potentially lead to different firm valuations.

Although we emphasize the significance of our results, some caveats are in order at the outset. First, the empirical framework of this study is exploratory and not predictive. That is, we investigate the contemporaneous association between forecast accuracy and recommendation profitability and do not attempt to present a model that predicts the profitability of future recommendations based on the analyst's historical forecast accuracy.[2] The contemporaneous setting, coupled with the nontrivial empirical process of forming daily rebalanced portfolios, indicates that the reported abnormal returns are strictly not implementable profit opportunities. Second, the study runs into an unavoidable sample selection bias because we cannot utilize all available observations from the Institutional Brokers Estimate System (I/B/E/S) database. To produce measures of relative performance, we carefully filter the raw data and include only analyst-firm-year observations for which the twin measures of forecast accuracy and recommendation profitability could be reliably computed. Finally, it is possible that the uncovered association between forecast accuracy and recommendation profitability is an empirical artifact. In response, we address other potential explanations with a battery of tests.

[2] Mikhail et al. (2004) report persistence over time in analysts' stock picking ability but find that trading strategies that attempt to benefit from it cannot generate abnormal gains after accounting for transactions costs. Although not the focus of our paper, it is plausible that the predictability of the future profitability of analysts' recommendations could be enhanced by inspecting analysts' past earnings forecast accuracy. We leave this question to future research.

These additional tests strengthen our claim considerably but cannot fully eradicate the likelihood that some other unknown factor is driving the empirical relation between forecast accuracy and recommendation profitability.

The remainder of the paper is organized as follows. In Section 2, we lay out our research design in detail. The data and summary statistics are described in Section 3. Section 4 reports our main results. In Section 5, we conduct several robustness checks to ensure the validity of our inferences. Finally, we conclude our paper in Section 6.

2. Research design

2.1. Annual sorting of analyst-firm observations for forecast accuracy

We adopt a firm-year perspective to evaluate an analyst's earnings forecasting skill. For each year, we sort all analysts issuing forecasts for a firm into quintiles based on the relative accuracy of their earnings forecasts. The sorting is done for our final sample of analyst-firm-year observations that meet several inclusion criteria, listed and motivated in Table 2 of Section 3. We highlight below some of the criteria that are helpful in understanding our research design.

Following existing conventions, we focus on firms whose fiscal years end in December to avoid the problem of non-overlapping forecasting horizons (Easterwood and Nutt, 1999; Hong, Kubik, and Solomon, 2000; Hong and Kubik, 2003). Moreover, to evaluate analysts at the same forecast horizon, we follow Hong and Kubik (2003) and measure the relative accuracy of all analysts following a firm during fiscal year y based on their forecasts of annual earnings outstanding on a common cut-off date of June 30. Using alternative cut-off dates of May 31 (to reduce differences in forecast recency) or July 31 (to increase the sample size) does not affect our conclusions. Also, to avoid the problem of stale forecasts, we do not include forecasts that were issued before the announcement of year y–1's actual earnings.

To sort analysts into forecast accuracy quintiles for each firm-year, we adopt the methodology of Hong and Kubik (2003) with some modifications. Table 1 illustrates our methodology using the example of IBM in 1996. We start by computing absolute forecast errors as follows:

$$AFE_{ijy} = \left| Actual_{ijy} - Forecast_{ijy} \right| \tag{1}$$

where AFE_{ijy} (referred to subsequently as AFE for simplicity) represents analyst i's absolute forecast error for firm j in fiscal year y. Analysts that are less accurate, by being either more optimistic or more pessimistic, would thus have larger absolute forecast errors. We do not standardize AFE here because we sort analysts within the same firm-year.

[Table 1 here]

Each analyst then receives a rank based on her AFE, where the analyst with the lowest AFE gets a rank equal to one (see column 4 of Table 1). Analysts with the same AFE are assigned the same rank. Next, we subtract 0.25 from the rank and divide the resulting number by the maximum rank in the firm-year to compute a percentile score for each analyst (see column 5).[3] Finally, we sort analysts into quintiles based on the following percentile score intervals: [0, 0.2], (0.2, 0.4], (0.4, 0.6], (0.6, 0.8], and (0.8, 1]. To ensure that there is at least one analyst in each quintile, we include only firm-years that have at least five unique values of AFE. This ensures that analysts in each accuracy quintile issue recommendations for the same set of firms.

[3] Without the subtraction of 0.25 from the rank in the numerator, the procedure allocates more analysts to the least accurate quintile compared to the most accurate quintile. Choosing to subtract a number between 0 and 1 from the rank serves to equalize the observations allocated to the extreme quintiles. Our conclusions remain unchanged without this subtraction.

Hence any differences in the recommendations profitability across quintiles would not be due to differences in the firms covered.

2.2. Yearly interval for associating forecast accuracy with recommendation profitability

Our objective is to measure forecast accuracy and recommendation profitability contemporaneously. Accordingly, as shown in Figure 1, we examine the profitability of stock recommendations of each accuracy quintile over the 12-month period from April 1 to March 31. We call this yearly interval the *return accumulation year*, in contrast to our use of the term fiscal year that refers to the period from January 1 to December 31. We choose this return accumulation year instead of a fiscal year to cumulate returns because it allows for the maximum overlap between the recommendation evaluation period and the annual earnings forecasting cycle. For a typical December year-end firm, annual earnings for the previous year are announced by March 31 of the current year. New forecasts for the current year are usually announced within two to three months of this date.[4] Hence the April 1 to March 31 period, rather than any other 12-month interval, best represents the annual forecasting cycle of a typical December year-end firm.

[Figure 1 here]

[4] About 81% of the forecasts outstanding on June 30 in our final sample are issued during the April to June period. The remaining 19% are issued before April 1. To the extent that analysts had the option but chose not to update these forecasts through the months of April to June, these older forecasts can also be construed to represent analysts' post-April 1 opinions. Such forecasts are less likely to suffer from the analysts' self-selection problems shown by McNichols and O'Brien (1997) since our sample's analysts do not discontinue coverage of the firm, that is, they have at least one stock recommendation outstanding for the firm in the corresponding return accumulation year.

2.3. Computing calendar-time returns associated with the stock recommendations of each quintile

To determine if analysts in the most accurate quintile issue more profitable stock recommendations, we construct calendar-time portfolios akin to BLMT (2001, 2003a) based on the average recommendation rating of each firm within each quintile. Specifically, the average within-quintile rating $\overline{A}_{j\tau-1}$ for firm *j* on day τ–1 is determined by:

$$\overline{A}_{j\tau-1} = \frac{1}{n_{j\tau-1}} \sum_{i=1}^{n_{j\tau-1}} A_{ij\tau-1} \tag{2}$$

where $n_{j\tau-1}$ is the number of analysts sorted into the quintile and $A_{ij\tau-1}$ is analyst *i*'s outstanding recommendation on day τ–1. It should be noted that on some days, the average quintile rating in Eq. (2) could be based on the recommendation of only one analyst. It is also possible for a firm's average rating to be *missing* when no analyst in the quintile has an outstanding recommendation on the day. Consistent with Womack's (1996) findings that analyst recommendations retain investment value for up to six months, we remove an individual analyst's recommendation from our computations if it was issued more than six months (specifically 183 days) ago and was not reiterated. We do this to ensure that our analysis is not contaminated by stale recommendations.

Within each quintile, we use the average ratings given by Eq. (2) to sort the covered firms into long and short portfolios as of the close of trading on date τ–1. A firm is allocated to the long (short) portfolio of the quintile if its average quintile rating is *favorable* (*unfavorable*). In deciding whether an average rating is favorable, we note that the individual analyst recommendations we employ are coded by I/B/E/S on a 5-point system as follows: 1 = Strong Buy, 2 = Buy, 3 = Hold, 4 = Underperform, and 5 = Sell. Given the well-known bias for optimistic recommendations, we categorize an average recommendation rating as *favorable* only if $\overline{A}_{j_{\tau-1}} \leq 2$ and *unfavorable* if $\overline{A}_{j_{\tau-1}} > 2.5$. Average recommendations are classified as *neutral* if $2 < \overline{A}_{j_{\tau-1}} \leq 2.5$—such firms are absent from both long and short portfolios. To an extent, our classification scheme mirrors that of BLMT (2001) who divide average recommendation ratings into five categories. We classify their top two categories as *favorable* and their bottom two categories as *unfavorable*. Our results are robust to sorting each covered firm into long or short portfolios depending on whether the stock's average rating is above or below, respectively, the average level of recommendation optimism for the year.

After determining the composition of each portfolio at the close of trading of day τ–1, we compute daily value-weighted returns for day τ as follows:

$$R_{p\tau} = \sum_{j=1}^{n_{p\tau-1}} x_{j\tau-1} R_{j\tau} \tag{3}$$

where $R_{j\tau}$ is the day τ return on firm j's stock, $n_{p\tau-1}$ is the number of firms in the portfolio, and $x_{j\tau-1}$ is the day τ–1 market capitalization of firm j divided by the sum of the day τ–1 market capitalization of all the firms in the portfolio. Our conclusions remain qualitatively similar when we use equal-weighted returns, or when we allow for earlier (delayed) responses to average ratings by replacing the day τ return in Eq. (3) with the day τ–1 (τ+1) return.

The daily returns for each of the formed portfolios are then compounded to monthly returns:

$$R_{pt} = \left[\prod_{\tau=1}^{n_t} (1 + R_{p\tau}) \right] - 1 \tag{4}$$

where n_t is the number of trading days in the month and R_{pt} is the raw monthly return for the portfolio. We determine the average abnormal monthly return of a portfolio by using four alternative methods. First, we calculate the simple market-adjusted monthly returns for a portfolio by subtracting the corresponding monthly market return R_{mt} from R_{pt}. We use the Center for Research in Security Prices (CRSP) NYSE/AMEX/Nasdaq value-weighted index as a proxy for the market portfolio. Second, we estimate the CAPM regression to find the market-beta-adjusted monthly returns for a portfolio:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p RMRF_t + \varepsilon_{pt} \tag{5}$$

where $RMRF_t$ represents the market risk premium obtained by subtracting the risk-free rate from the market return. If a portfolio earns positive returns after adjusting for the portfolio beta, the estimated α_p will be positive and statistically significant. Third, we estimate the Fama and French (1993) three-factor model as follows:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p RMRF_t + s_p SMB_t + h_p HML_t + \varepsilon_{pt} \tag{6}$$

where SMB_t is the difference between the value-weighted portfolio returns of small and large stocks and HML_t is the difference between the value-weighted portfolio returns of high book-to-market and low book-to-market stocks. A positive α_p would indicate that the portfolio earns positive abnormal returns. Finally, we add an additional momentum factor UMD_t to the regression in Eq. (6) (Carhart (1997)). This additional factor is calculated as the difference in the returns of stocks with positive returns momentum and those with negative returns momentum over months t–12 to t–2.

$$R_{pt} - R_{ft} = \alpha_p + \beta_p RMRF_t + s_p SMB_t + h_p HML_t + u_p UMD_t + \varepsilon_{pt} \tag{7}$$

The abnormal returns for the long and short portfolios of the quintiles are compared to assess whether more accurate quintiles generate superior recommendation returns.

3. Data and descriptive statistics

3.1. Sources of data

We obtain annual earnings forecasts of analysts and the corresponding actual earnings from the I/B/E/S Detail File. Analysts' stock recommendations are extracted from the I/B/E/S Detail Recommendations File. Although brokers can have different investment rating scales, I/B/E/S establishes its own 5-point rating system as ranging from 1 (strong buy) to 5 (sell). When a contributing analyst sends in a recommendation, it is mapped onto one of I/B/E/S's ratings. For recording recommendation dates, I/B/E/S states that it follows the same convention as that for its earnings forecast data in that a recommendation is entered into the system within 24 hours of its (electronic) submission by the issuing analyst. To verify this, we compared the issue dates of recommendations in I/B/E/S with those in the actual company reports (or notes) available from First Call Web for about 1,000 recommendations of four large brokers in 1998 and 1999. We found that 92% of the I/B/E/S recommendations dates were the same as those on the actual reports.

Compared with its earnings estimates information, which starts from 1976, I/B/E/S's recommendations data are of shorter length, beginning only in late 1993. Accordingly, the sample period for which we compute returns associated with analysts' outstanding recommendations spans the six-year period from April 1994 to March 2000. The recommendations issued in late 1993, which are not yet stale (more than six months old) by April 1994, are part of our sample.[5]

Our stock returns are drawn from CRSP. Specifically, the daily stock returns file is used to measure the profitability of recommendations over their precise durations. We also extract a firm's daily market capitalization. Next, we obtain daily and monthly returns on the CRSP NYSE/AMEX/Nasdaq value-weighted index to serve as a proxy for returns on the market portfolio. Monthly returns for the size, book-to-market, and momentum factors are obtained from the web site of Kenneth French. Finally, the one-month Treasury bill rate, a proxy for the risk-free rate, is obtained from Ibbotson Associates.

3.2. Descriptive statistics of analyst-firm observations

For our sample period, the I/B/E/S Detail Earnings Estimates File contains a total of 180,921 unique analyst-firm-year combinations for firms whose fiscal years end in December. In developing the forecast accuracy measure discussed in Section 2.1, we specified certain filters that we apply to the raw data to ensure that the relative forecast accuracy measure we compute is meaningful and is a good proxy for an analyst's relative forecasting skill. Table 2 lists and motivates these filters chronologically.

[Table 2 here]

Two of these filters, Filters #4 and #6 deserve further mention. Filter #4 removes possible erroneous forecasts from the forecast data using two screens, 25% of price and 200% of the

[5] The sample period of our study is useful to shed light on the quality of analyst recommendations during the period leading to the heightened regulatory scrutiny of analysts. However, we note that the market correction beginning in 2000 and the implementation of certain new regulations, such as that of NASD 2711 in 2002, could potentially affect the quality of analysts' stock recommendations after 2000.

absolute value of actual earnings. Unlike extant literature, which relies on at most one screen, such treatment is prudent to ensure that the analysts we identify as inaccurate are not inaccurate simply because of errors in the raw data. Filter #6 removes earnings forecasts for analyst-firm observations that do not have at least one corresponding outstanding recommendation in the same year. This filter is necessary to ensure that measures of both forecast accuracy and recommendation profitability are available for the relation between the two to be investigated.[6]

As shown in the last row of Table 2, our final sample consists of 32,147 analyst-firm observations across all years. We report the year-by-year descriptive statistics of this final sample in Panel A of Table 3. A total of 1,287 unique firms covered by 3,766 unique analysts are included in our analysis. The number of unique firms (analysts) varies across years and range from a low of 445 (1,345) to a high of 595 (2,126). The I/B/E/S recommendations data contain an unusually large number of recommendations recorded for late 1993 and early 1994; therefore, the year 1994 has a larger number of observations than that in some of the later years. The number of firms and analysts generally increase toward the later years, reflecting the increased coverage of I/B/E/S. Firms in our sample have an average market capitalization of $6.8 billion. This number increases toward the later years of our sample, reflective of the bull market run of the 1990s.

[6] The 37,619 analyst–firm-year observations that we remove by applying this filter represent analysts who issued only earnings forecasts without issuing corresponding stock recommendations for the firm. To examine whether forecast accuracy differs when the analyst issuing the forecast also issues a recommendation, for each firm-year, we calculate the average absolute forecast error, scaled by stock price, for analysts with and without corresponding recommendations. Then using the resulting pooled firm-year observations over our entire sample, we compute the average absolute forecast errors for the two groups of analysts. We find that the average absolute forecast error is 1.59% for analysts who do not issue corresponding recommendations and 1.55% for those who do. The difference between the two is statistically significant. Hence we take note of the caveat that the analysts we include in our sample are somewhat more accurate than those that we leave out.

Panel A also reports analyst coverage statistics. The average number of analysts issuing earnings forecasts for a firm is about 10 and the maximum is 36. The minimum number of analysts per firm is always five because our inclusion criteria mandate a firm-year to have at least five unique AFE for inclusion. The average number of firms covered by an analyst in our sample is approximately three. It is worth noting that the number of analysts per firm and firms per analyst reported in Table 3 are not comparable to those reported in other studies on earnings forecasts. As outlined in Table 2, our research objective necessitates the applications of several filters to the raw forecast data. Hence, the observations that remain after the application of these filters would lead to figures for analysts per firm that are higher, and firms per analyst that are lower, than they would otherwise be without these filters.

[Table 3 here]

Next, Panel B of Table 3 reports the quintile sorting statistics. Using the procedure detailed in Table 2, we sort our final sample of 32,147 analyst-firm-year observations into forecast accuracy quintiles. This sorting exercise allocates 5,536; 7,045; 6,764; 6,862; and 5,940 analyst-firm-year observations to quintiles A1 through A5, respectively. The number of firm-year observations (column 3) is 3,094 for all quintiles because we mandate five unique values of AFE for each firm-year and hence each firm-year is represented in all quintiles. Next, the descriptive statistics of the number of analysts sorted into each quintile in a firm-year are reported in columns (4) through (8). The mean number is 1.79 for quintile A1 and 1.92 for quintile A5, indicating the number of analysts sorted into these two extreme quintiles are fairly similar. We also report in columns (9) through (13) the summary statistics of the number of individual analyst recommendations underlying the within quintile daily average recommendation rating for a firm. Firm-days that have missing average recommendations are excluded when computing these statistics. The average number of individual recommendations making up the daily average recommendation rating of a firm is 1.42 and 1.44, respectively, for quintiles A1 and A5. This indicates that both groups of analysts are equally active in issuing recommendations.

3.3. Descriptive statistics of absolute forecast errors

Because we rely on absolute forecast errors to sort analysts, it is instructive to examine the summary statistics for absolute and signed forecast errors. In Panel A1 of Table 4, we report the summary statistics of AFE for our pooled sample of 32,147 analyst-firm-year observations. The first row reports the statistics for the unscaled AFE. The second and third rows report statistics when AFE is scaled, respectively, by the stock price at the beginning of the return accumulation year (April 1) and the absolute value of actual earnings. The unscaled average AFE for our sample is \$0.289. The average AFE scaled by price (absolute actual earnings) is 1.26% (22.69%). Panel A2 of the table reports corresponding statistics for the signed forecast errors. We see that all the mean and median values of the forecast errors are negative—consistent with analysts issuing optimistic forecasts on average.

[Table 4 here]

To ascertain the economic significance of the differences in forecast accuracy across quintiles, we report in Panel B of Table 4 the summary statistics of the average firm-level AFE across quintiles. Within each quintile, we first compute the average AFE, scaled by stock price, for each firm-year based on the AFE of analysts allocated to the quintile. These AFE are then averaged across all 3,094 firm-years in our sample to compute the average AFE for each quintile. The last row reports the average AFE based on the 15,470 (3,094 × 5) firm-years pooled across all quintiles. The mean (median) firm-level AFE for quintile A1 is 0.756% (0.222%) and is much lower than the corresponding number of 2.199% (1.267%) for quintile A5, indicating that our forecast accuracy sorts are economically meaningful.[7]

3.4. Descriptive statistics of raw recommendations

In Table 5, we report the descriptive statistics of the recommendations in our sample. The first column of the table identifies a period of April 1 in year *y* to March 31 of year *y*+1 as year *y*. The recommendations that we employ in our analyses were issued over the period October 1, 1993 to March 31, 2000. In total, there are 48,723 recommendations, including reiterations and multiple recommendations by an analyst for the same firm-year.

[Table 5 here]

Prior literature finds that the distribution of recommendations across the five rating categories is skewed—there are far more favorable recommendations than unfavorable ones (see, e.g., BLMT, 2001; Jegadeesh et al., 2004). Consistent with this literature, the recommendations distribution presented in Table 5 is also skewed. Strong buy and buy recommendations constitute 26% and 33%, respectively, of the total recommendations in the sample. Hold recommendations make up another 36%. Underperform and sell recommendations together make up a mere 5% of the total. Akin to the findings of BLMT (2003b), the recommendations become increasingly optimistic over the successive years of our sample.

[7] We also find that the analysts allocated to a quintile for a firm-year in our sample tend to be unanimous in being either optimistic or pessimistic in their forecasts. The percentage of firm-years, out of a total of 3,094, whereby the forecast errors of the analysts allocated to the quintile are all of the same sign, is 90% for quintile A1. The percentages for the other four quintiles are 87%, 92%, 93%, and 94%, respectively, for quintiles A2 to A5. These high percentages are partly attributable to a small number of analysts (sometimes only one analyst) being allocated to each quintile in a firm-year. Please refer to Panel B of Table 3 for summary statistics on the number of analysts allocated to a firm-year within each quintile.

4. Characteristics and profitability of portfolios

In this section, we report the characteristics and the monthly returns of the long and short portfolios of each quintile over the six-year (72-month) sample period from April 1, 1994 to March 31, 2000. For each quintile, we also create a third zero-investment portfolio whose returns are the returns of the long portfolio minus the corresponding returns of the short portfolio. Altogether, therefore, we examine the returns for 15 portfolios—three for each quintile. Table 6 reports the characteristics of these portfolios, with Panels A, B, and C describing the long, short, and long–short portfolios, respectively.

[Table 6 here]

The daily average number of stocks included in each portfolio is reported in the last column of Table 6. As Panel A shows, the daily average number of stocks included in the long portfolios of the quintiles ranges from 179 to 198 and is larger than the average number of stocks included in the corresponding short portfolios. As reported in Panel B, the short portfolios typically include about 117 to 121 stocks. However, the average numbers of stocks in the long and short portfolios do not differ much across quintiles A1 and A5. As can be noted from Panel C, the long–short portfolios of the quintiles include on average approximately 300 stocks.

The last row in each panel of Table 6 reflects the portfolios formed on the basis of the recommendations of both quintiles A1 and A5. The daily average number of stocks in these portfolios is simply the sum of the corresponding numbers for quintiles A1 and A5. For instance, the portfolio A1–A5 in Panel A depicts a portfolio that is long in the stocks recommended favorably by quintile A1 and short in those recommended favorably by quintile A5. Because some stocks can have favorable average recommendation ratings from both quintiles on a given day, these stocks would be counted twice in this portfolio. The daily average number of stocks that make up this portfolio is 359.35—the sum of the average numbers of stocks favorably recommended by quintiles A1 and A5.

Columns (2) to (5) in Table 6 report the coefficient estimates of the four-factor model specified in Eq. (7) for each portfolio. Focusing on the market betas (column 2) of the portfolios, none of the long portfolios have betas significantly different from one as revealed in Panel A. However, several short portfolios in Panel B have market betas that are significantly less than 1, indicating that analysts' unfavorable recommendations in our sample are slightly tilted toward low beta stocks. The generally negative values of the coefficients for the SMB factor (column 3) in both Panels A and B reflect the large-firm bias of our sample and contrasts with the results of BLMT (2001). This large-firm bias results from the filters we apply as outlined in Table 2, especially the requirement for firms to have at least five distinct absolute forecast errors for the year.

Comparing the values in column (5) between Panels A and B of Table 6, the difference between the long and short portfolios in their loadings on UMD is noticeable. Column (5) of Panel C reports these differences. Analysts in all quintiles, except for A5, appear to issue unfavorable recommendations for firms with larger negative price momentum. This is consistent with Jegadeesh et al. (2004) who find that analysts tend to issue unfavorable recommendations for stocks that experience recent price declines. Interestingly, analysts in quintile A5 behave differently and do not discriminate among stocks based on their recent price momentum. The portfolio in the last row (that is, A1–A5) of each panel in Table 6 depicts the differences in the characteristics of stocks recommended by the most and the least accurate forecasters. Almost all of the reported coefficients here are statistically insignificant suggesting that stocks recommended by the accurate and inaccurate forecasters have similar factor loadings.

Our main results are reported in Table 7. Following the same structure as in Table 6, we report the monthly returns of the long, short, and long–short portfolios of each quintile in Panels A, B, and C, respectively. Column (2) of the table reports the average monthly raw returns earned by each portfolio. Column (3) reports the market-adjusted returns, which are calculated by subtracting the monthly returns of the CRSP NYSE/AMEX/Nasdaq value-weighted market index from the raw monthly portfolio returns. Columns (4) to (6) in Table 7 report the intercepts of the CAPM, the Fama-French three-factor model and the four-characteristic model, respectively. These intercepts represent the abnormal returns earned by the portfolio after adjusting for the specific factors known to be associated with the cross-section of stock returns.

[Table 7 here]

Focusing on column (6) of Table 7 that reports the alphas of the four-factor model, in Panel A we note that the stocks favorably recommended by superior forecasters earn a statistically significant average abnormal return of 0.344% per month (t-statistic = 2.14), whereas those favorably recommended by inferior forecasters earn a statistically insignificant return of –0.036% per month (t-statistic = 0.21). The difference between the two monthly returns, reported in the row labeled A1–A5, is 0.380% (t-statistic = 2.25). Similar differences for this row are evident in columns (3) through (5) that report abnormal returns using alternative risk adjustments. Hence, the overperformance of the favorable recommendations of quintile A1 relative to those of quintile A5 is both economically and statistically significant. Also noticeable is the fact that only the most accurate forecasters generate statistically significant positive abnormal returns through their favorable recommendations.

In Panel B of Table 7, we report the returns for the unfavorable stock recommendations of the quintiles. Unlike the returns reported in Panel A, lower returns here indicate superior recommendations. Focusing again on the factor-adjusted returns reported in column (6), portfolio A1 (consisting of stocks unfavorably recommended by the most accurate forecasters) produces a statistically significant abnormal return of –0.393% per month (*t*-statistic = 2.13). In contrast, portfolio A5, which contains the stocks negatively recommended by the worst forecasters, generates abnormal positive return of 0.493% (*t*-statistic = 2.01). This indicates that the worst forecasters issue unfavorable recommendations that turn out to be "wrong"—the stocks they recommend unfavorably should be *bought* rather than *sold*. The last row of Panel B shows that superior forecasters outperform inferior forecasters by an average of 0.887% (*t*-statistic = 4.07) per month for unfavorably recommended stocks. This differential performance of unfavorable recommendations is driven by both the superior recommendations of portfolio A1 as well as the inferior recommendations of portfolio A5. Similar superior performance of portfolio A1 compared to portfolio A5 is discernable from the abnormal returns estimated from alternative risk adjustment models in the other columns of Panel B.

Panel C of Table 7 depicts the combined effect of the quality of favorable and unfavorable recommendations of each quintile. Essentially, portfolios A1 to A5 in Panel C are zero-investment portfolios whereby, for each quintile, we long the stocks recommended favorably and sell short those recommended unfavorably. Because the market return cancels out when we subtract the market-adjusted return on a short portfolio from the market-adjusted return of the corresponding long portfolio, the market-adjusted returns on the long–short portfolios in

Panel C are the same as the raw monthly returns. Therefore, we only report one of these two columns for the long–short portfolios in Panel C.

Portfolio A1, consisting of stocks recommended by analysts with the most accurate earnings forecasts, produces a positive factor-adjusted return of 0.737 % (*t*-statistic = 3.20) per month. In contrast, portfolio A5, consisting of stocks recommended by the least accurate analysts, earns factor-adjusted returns of –0.529% (*t*-statistic = 1.91). The outperformance of the superior forecasters turns out to be a sizable 1.266% (*t*-statistic = 3.87) per month (the last row of column 6). This monthly return differential translates into a large annual cumulative return differential of 16.3%. Columns (3) to (5) in Panel C of Table 7, which report abnormal returns using alternative risk adjustments, reinforce this conclusion.

We conclude this section by reminding the reader that the reported abnormal profits are not implementable trading strategies that investors can exploit because we sort analysts based on contemporaneous forecast accuracy that is not known at the time of portfolio formation. The reported gross returns also ignore transactions costs. As BLMT (2001) report, implementing a daily rebalanced calendar-time portfolio can be very costly in terms of transactions costs.

5. Additional robustness checks

Our results indicate a positive association between analysts' forecast accuracy and recommendation profitability. We interpret this as evidence that accurate earnings forecasts do indeed facilitate superior investment recommendations. In this section, we perform additional checks to ensure that our results are not driven by other potential explanations.

5.1. Task complexity as a driver of forecast accuracy and recommendation profitability

Prior studies by Mikhail, Walther, and Willis (1997) and Clement (1999) suggest that an analyst's forecast accuracy is negatively correlated with the number of firms that the analyst covers. They conjecture that covering a smaller set of firms allows greater focus and makes the analyst's job easier. It is possible, therefore, that the real driver of both superior forecast accuracy and recommendation profitability of analysts in quintile A1 is that they cover a smaller set of firms and hence face an easier task. If so, our results merely confirm the association between task complexity and analyst performance.

[Table 8 here]

To examine the validity of this alternative explanation, we check the association between the number of firms an analyst covers during a year and the average accuracy quintile she is assigned to for that year. Table 8 presents the results of this investigation. Using an analyst-year as the unit of analysis, we categorize all analyst-year observations into seven groups according to the number of firms they cover in our sample. These groups are listed in the first column of the table, with the second column reporting the number of analyst-years that belong in the group. We then compute the mean quintile allocation of the analyst-year observations that fall in each group and report these in the last column. For instance, the first row of the table shows that there are 3,566 analyst-year observations that cover only one firm, and the average quintile these analyst-year observations are assigned to is 3.08. Comparing the average quintile of the analyst-years that cover more firms with those that cover fewer firms does not reveal any association between coverage and forecast accuracy. It is unlikely, therefore, that our results can be ascribed to differences in the task complexity of analysts.

5.2. Forecast optimism across forecast accuracy quintiles

It would also be useful to examine if our forecast accuracy quintiles indeed represent differences in accuracy and do not simply reflect differences in optimism across analysts. Given prior research on the annual walk-down in earnings forecasts (Matsumoto, 2002; Richardson, Teoh, and Wysocki, 2004), a potential concern is that the most accurate quintile simply contain those analysts who are the least optimistic. We conduct two tests to address this concern. First, in unreported results, we sort analysts according to their forecast optimism instead of forecast accuracy and examine the differences in the profitability of recommendations across the optimism quintiles. We find that, unlike the accuracy quintiles for which recommendation profitability varies systematically, there are no differences in the recommendation profitability of the optimism quintiles. Second, we find that the proportion of firm-years for which the within-quintile average earnings forecast is optimistic (higher than the subsequently announced actual earnings) is similar across all quintiles (55% for A1 and 56% for A5). This suggests that analysts allocated to various accuracy quintiles do not differ much in their forecast optimism. Hence, our results are unlikely to be driven by forecast optimism disguised as forecast inaccuracy.

5.3. Frequency of portfolio rebalancing across accuracy quintiles

Another potential explanation for the superior performance of the recommendations of quintile A1 is that the analysts in this group revise their recommendations more frequently. If so, the higher recommendation profitability of analysts in A1 can simply be due to the more frequent rebalancing of their long and short portfolios. To investigate this possibility, we report in Table 9 the monthly recommendation revision activity for the long–short portfolios of quintiles A1 and A5 for each calendar month.

[Table 9 here]

To compute the monthly revision activity, we proceed as follows. Recall that an average rating for a firm within a quintile can belong to one of the three categories: favorable, neutral or missing, and unfavorable. A rating change involving the middle category of neutral or missing is counted as one revision. However, a rating change skipping the middle category is counted as two revisions because it would require simultaneous buying and selling of the stock. For instance, a stock whose rating moves from favorable to unfavorable would be removed from the long portfolio (the earlier long position liquidated) and simultaneously included in the short portfolio (sold short). We then sum the revisions for all the firms within a quintile to obtain the quintile's total monthly revisions. Finally, we average a calendar month's revisions across the six years of our sample and report these in the last column of Table 9.

We then proceed to obtain a rough estimate of the annual turnover of the long–short portfolios of the two quintiles by dividing the number of annual revisions by the average number of stocks held. From the last column of Panel C in Table 6, we note that the average number of stocks held in the long–short portfolios of both quintiles A1 and A5 is approximately 300. We report the estimates of the annual turnover in the last row of Table 9. The long–short portfolio of quintile A1 has an annual turnover of 437%, and the corresponding number for quintile A5 is 413%. The difference in the turnover is minimal and is therefore unlikely to explain the superior performance of quintile A1.

5.4. Correspondence between forecast accuracy and recommendation profitability

In developing our methodology, we ascertain forecast accuracy at a point in time (on June 30 of each year) and recommendation profitability over a period of time (throughout the return accumulation year). Although this set-up has several desirable features, one potential concern is that such a procedure muddles the correspondence between forecast accuracy and recommendation profitability. We conduct two tests to address this concern.

First, we examine the post-June average accuracy of analysts in each quintile based on their forecasts outstanding at the end of each of the subsequent months. The average AFE, scaled by price, for each quintile for the months of June through March are reported in Table 10. The later months' forecasts inform us on the hypothetical likelihood of analysts switching quintiles if we instead sorted them based on those months' forecasts. Because recommendation profitability is assessed throughout the year and not at a point in time, one would hope that an analyst's relative forecasting ability does not fluctuate too much within the year. Reassuringly, we find that quintiles A1 and A5 remain the most and the least accurate, respectively, in each of the months subsequent to their initial classification on June 30. As expected, we also find that for each quintile, the average forecast accuracy improves over each successive month.

[Table 10 here]

Second, we adopt an alternative evaluation strategy by considering only the outstanding June 30 recommendations of analysts. This stricter analysis evaluates the profitability of analyst recommendations based on their June 30 recommendations alone and does not consider their recommendation issued or revised later. We form long and short portfolios based on each quintile's June 30 average recommendation ratings and compute the profitability of these portfolios over each of the subsequent six months from July through December. As before, individual analyst recommendations are considered stale after six months. The key feature of this analysis is that a firm only contributes to a quintile-portfolio's returns up to the time when its average recommendation rating changes category. Hence the number of firms in each portfolio decreases as we move from July to December. Because only a handful of firms remain in the portfolios by December, we do not follow portfolio returns beyond December. In unreported results, we find that the June 30 average recommendations ratings of accurate forecasters (A1) outperform those of inferior forecasters (A5) for every month from July to December. Thus, even when we do not "allow" analysts to revise their recommendations, stock recommendations of accurate analysts still outperform those of inaccurate analysts.[8]

5.5. Potential differences in stock valuations between extreme forecast accuracy quintiles

In our final robustness check, we investigate whether the observed differences in the earnings forecasts of analysts in the two extreme quintiles are large enough to translate into significant differences in stock valuations. The valuation model we utilize is the two-period expansion of the residual income valuation model from Eq. 3.1 of Frankel and Lee (1998, pg. 289).[9]

$$\hat{V}_y = B_y + \frac{(FROE_y - r_e)}{(1 + r_e)} B_y + \frac{(FROE_y - r_e)}{(1 + r_e) r_e} B_y \tag{8}$$

[8] We also confirm the superiority of the recommendations of quintile A1 that are issued after June 30. We form long and short portfolios based solely on the recommendations issued after June 30 and compute their returns from September through March. We start from September in this analysis and ignore the months of July and August, so that enough post-June recommendations accumulate to allow us to form portfolios of meaningful size by September. In unreported results, we find that the post-June recommendations of superior forecasters also outperform the corresponding recommendations of inferior forecasters. The difference in profitability is comparable in magnitude to that reported in Panel C of Table 7. This is consistent with our claim that superior forecasters possess superior fundamental valuations and hence are able to revise their recommendations at the right time after June 30.

[9] Our use of this model does not reflect our belief that all or even majority of the analysts use this valuation model. Instead, the analysis in this subsection merely attempts to highlight the potential of divergent earnings forecasts to lead to different stock valuations. It is also possible that analysts in the extreme quintiles employ different methods of stock valuation. For example, Bradshaw (2004) and Asquith, Mikhail, and Au (2005) argue that analysts use the multiples approach whereas Cornell (2001) assumes that analysts employ the discounted cash flow model. Moreover, for our analysis, we cannot rule out the possibility that besides possessing superior inputs of earnings forecasts, analysts in quintile A1 also employ superior valuation models.

$FROE_y$ is the forecasted return on equity for the firm in year y given by $Forecast_y / B_{y-1}$ where $Forecast_y$ is the FY1 forecast of year y's earnings per share. B_y, the predicted book value per share of the firm in year y, is given by $B_{y-1}\left[1+(1-k)FROE_y\right]$, where k is the predicted dividend yield estimated by taking dividends paid in the most recent year (Compustat item 21) divided by net income before extraordinary items (Compustat item 237). B_{y-1} is taken from Compustat item 60 of the previous year, and r_e is the cost of equity capital. This model assumes that the forecasted *ROE* for the current year is earned in perpetuity, and represents a simple earnings capitalization model modified to capture "clean surplus" accounting. It is suitable for our purposes because our empirical methodology utilizes only the one-year ahead forecast for determining forecast accuracy. By combining terms, the above equation can be simplified to:

$$\hat{V}_y = \frac{B_y}{r_e} FROE_y \tag{9}$$

Eq. (9) allows us to obtain hypothetical differences in the valuation estimates of analysts in quintile A1 and A5 based on their forecasted earnings in our sample. We denote $\hat{V}_y^{A1} = (B_y^{A1} / r_e) FROE_y^{A1}$ and $\hat{V}_y^{A5} = (B_y^{A5} / r_e) FROE_y^{A5}$ to represent the different valuations of analysts from the two extreme quintiles of forecast accuracy. For tractability, we assume that analysts in both quintiles utilize the same r_e. Thus, the percentage absolute deviation of $\hat{V}_y^{A5}$ from $\hat{V}_y^{A1}$ is

$$\left| \frac{\hat{V}_y^{A5}}{\hat{V}_y^{A1}} - 1 \right| = \left| \frac{\left[1+(1-k)FROE_y^{A5}\right] FROE_y^{A5}}{\left[1+(1-k)FROE_y^{A1}\right] FROE_y^{A1}} - 1 \right|. \tag{10}$$

We compute estimates of Eq. (10) for the firm-years where the necessary Compustat data are available. $FROE_y^{A1}$ and $FROE_y^{A5}$ are defined as the average forecasted *ROE* of analysts within quintiles A1 and A5, respectively. We include only firm-years in which both these values are positive because the model yields negative valuations when *FROE* is negative. We also adjust each forecast using the I/B/E/S Stock-Splits Adjustment File so that the computed *FROE* would be appropriate for that firm-year. Finally, we winsorize the estimated deviations at the 98th percentile to mitigate large values that could arise because of a small denominator in Eq. (10).

Untabulated results indicate that the mean (median) residual income valuation of A5 analysts deviates by 27% (13.2%) from those of analysts in A1. The 25th and 75th percentiles are 6.9% and 27.5%, respectively. Therefore, it is plausible that such differences drive the divergent stock recommendations issued by analysts in the extreme quintiles. This illustration, although admittedly based on simplified assumptions, strengthens our case that differences in forecast accuracy could potentially translate to significant differences in stock recommendation profitability.

6. Conclusion

In this paper, we examine the relation between the accuracy of analysts' earnings forecasts and the profitability of their stock recommendations. Our results indicate that the recommendations of superior earnings forecasters significantly outperform the recommendations of inferior forecasters. Superior earnings forecasts, thus, do appear to facilitate superior investment recommendations. The positive correlation between forecast accuracy and recommendation profitability we show in this paper not only has relevance for fund managers who seek the best advice from analysts for both future earnings and recommendations but is also reassuring for academic studies (e.g., O'Brien, 1990; and Stickel, 1992) that presume such correlation.

Our findings also allow for conjectures concerning the informational efficiency of financial markets. Grossman and Stiglitz (1980) observe that market prices cannot fully reflect all available information; otherwise, information gatherers like security analysts would not be rewarded for their costly activities. Considering the tremendous amount of resources that analysts plough into their earnings analyses, our findings are comforting. We provide support for the Grossman and Stiglitz view of markets in which analysts who spend resources in generating superior earnings expectations data are able to gain a competitive advantage in issuing profitable stock recommendations.

Finally, our results suggest the usefulness of the fundamental accounting analysis in investment decisions. A large body of fundamental analysis research in accounting and finance literatures envisages a predictive role of earnings for future stock price movements. We show that, in the unique setting of security analysts, in which expectations of individual economic agents about both future earnings (i.e., earnings forecasts) and future stock price movements (investment recommendations) can simultaneously be observed, a better appreciation of future earnings is associated with a better assessment of future stock price movements.

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Table 1
An Example of Sorting Analysts into Forecast Accuracy Quintiles Using Data for IBM in 1996

For each firm-year, analysts are sorted and ranked according to their ascending absolute forecast errors (AFE) computed based on their outstanding FY1 forecasts on June 30. Our study focuses on December year-end firms only. Analysts tied on AFE are assigned the same rank. Next, a percentile score (column 5) is computed by subtracting 0.25 from the rank (column 4) and dividing this by the maximum rank for the firm-year. Subtracting 0.25 ensures that we have roughly equal analyst-firm-year observations in the extreme quintiles for our entire sample (see Panel B of Table 3). The percentile score allows analysts to be sorted into quintiles 1 through 5 (as reported in column 6), respectively, according to the following intervals: [0, 0.2], (0.2, 0.4], (0.4, 0.6], (0.6, 0.8], and (0.8, 1]. The numbers reported here are actual figures from our final sample for IBM for 1996 (based on the I/B/E/S tape as of March 15, 2001). The actual earnings per share, reported in the I/B/E/S Actuals File is $2.775. The forecasts as well as actual earnings are adjusted for stock splits.

Analysts (1)	Analyst ID (2)	AFE (3)	Rank (4)	Percentile Score $\frac{Rank - 0.25}{Max\,Of\ Rank}$ (5)	Quintile (6)
1	687	0.025	1	0.075	1
2	8065	0.025	1	0.075	1
3	10098	0.040	2	0.175	1
4	10102	0.093	3	0.275	2
5	1028	0.100	4	0.375	2
6	678	0.100	4	0.375	2
7	9236	0.113	5	0.475	3
8	677	0.120	6	0.575	3
9	9192	0.138	7	0.675	4
10	547	0.138	7	0.675	4
11	965	0.160	8	0.775	4
12	585	0.263	9	0.875	5
13	30168	0.475	10	0.975	5

Table II

Description of Filters Applied to the Raw Earnings Forecasts Data

Our raw earnings forecasts and recommendations data are from the I/B/E/S Detail History File and Recommendations File, respectively, as of March 15, 2001. The forecasts cover the period of 1994 to 1999 whereas the corresponding recommendations cover the period from October 1993 to March 2000. The table lists the steps we undertook to clean up the raw data. The objective is to yield meaningful measures of relative forecast accuracy for each analyst-firm-year observation that could then be related to the recommendation profitability.

Filter	Description	Available Unique Analyst-firm-Year Obs.	Motivation in Brief
1	All one-year-ahead earnings forecasts made between January 1, 1994 and December 31, 1999 for firms with December year-ends.	180,921	We focus on December year-end firms so as to avoid the problem of nonoverlapping horizons.
2	Excluded forecasts issued by analysts whose identity is masked in the I/B/E/S files.	176,366	Anonymous analysts are not useful for our study, so we delete their forecasts.
3	Removed forecasts for firms that could not be unambiguously identified in CRSP (or for whom the stock returns data for the corresponding year was not available in CRSP).	148,855	Returns are needed from CRSP for the computation of returns.
4	Removed absolute forecast errors that are greater than 25% of the stock price on April 1 (beginning of return accumulation year) or greater than 200% of the absolute value of the actual earnings. To circumvent the problem of small denominator for the latter filter, we arbitrarily substitute 0.5 for any denominator that is less than 0.5.	147,231	Following prior literature, we remove extreme observations that could be erroneous.
5	Retained only those forecasts for year *y* that were issued after the announcement of the actual earnings of year *y* –1 but before the common cut-off date of June 30 in year *y*.	100,902	We measure forecast accuracy using outstanding forecasts of analysts on the cut-off date of June 30 to ensure a common time frame to evaluate analysts. Forecasts prior to the announcement of year *y*–1's earnings are excluded as they are dated and issued without the knowledge of the actual earnings of year *y* –1. This criterion also removes those firms who report their actual earnings after June 30.
6	Removed forecasts of analysts for a firm that do not have at least one corresponding recommendation outstanding for the same firm during the same return accumulation year (i.e., April 1 in year *y* to March 31 in year *y*+1.	63,283	Because we aim to relate forecast accuracy of an analyst for a firm to the profitability of her recommendations for the same firm, the analyst must be issuing both earnings forecasts and stock recommendations for the firm during the same year. We treat an individual recommendation as stale if it is not reiterated for six months (183 days).
7	Removed forecasts for firms that do not yield at least five distinct absolute forecast errors for the year. We utilize the remaining observations for our analysis.	32,147	For each firm-year, we want to ensure that there is at least one analyst in each quintile so that the firm is represented in all quintiles. Analysts in each accuracy quintile would then issue recommendations for the same set of firms, and any difference in profitability across quintiles would not be due to the coverage of different firms. This filter also implies that each firm would have at least five analysts covering it, so that our relative measure of forecast accuracy will be based on a reasonable number of analysts.

Table 3
Descriptive Statistics for the Analyst-Firm-Year Data Included in Our Sample

Panel A of this table reports the year-by-year descriptive statistics of the analyst-firm observations included in our sample. These represent a total of 32,147 analyst-firm-year observations extracted from the raw I/B/E/S data by applying the filters outlined in Table 2. The year convention in column (1) identifies a period of April 1 in year *y* to March 31 in year *y*+1 as year *y*. Average market capitalizations of the included firms reported in column (4) are recorded at the beginning of the fiscal year. In Panel B, we provide statistics on the allocation of the 32,147 analyst-firm-year observations into the five accuracy quintiles. We use the procedure explained in Section 2.1 to sort analysts into accuracy quintiles for each of the 3,094 firm-years. Columns (4) through (8) provide the summary statistics for number of analysts per firm-year for each quintile. The last row reports statistics for the whole sample (across all quintiles). Columns (9) through (13) report the descriptive statistics for the number of individual analyst recommendations that make up the within-quintile average recommendations for a firm-day.

Panel A: Descriptive statistics for the analyst-firm-year observations

Year	No. of analyst-firm-year obs.	No. of firms	Avg. mkt. cap.($000)	No. of analysts	Analysts per firm-year Mean	Median	Min.	Max.	Firms per analyst-year Mean	Median	Min.	Max.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1994	6,992	595	4,520,669	1,400	11.8	10	5	35	5.0	3	1	46
1995	4,583	447	4,797,217	1,345	10.3	9	5	32	3.4	2	1	32
1996	4,300	445	6,531,463	1,441	9.7	9	5	30	3.0	2	1	28
1997	4,244	454	6,709,776	1,597	9.3	8	5	29	2.7	2	1	31
1998	5,697	577	7,981,726	2,021	9.9	9	5	36	2.8	2	1	33
1999	6,331	576	9,887,509	2,126	11.0	10	5	31	3.0	2	1	34
All years (Total Obs.)	32,147	3,094	6,815,628	9,930	10.4	9	5	36	3.2	2	1	46
All years (Unique Obs.)		1,287		3,766								

Panel B: Descriptive statistics depicting the allocation of analyst-firm-year observations into quintiles

	No. of analyst-firm-year obs.	No. of firm-year obs.	No. of analysts per firm-year Mean	Median	St. dev	Min.	Max.	No. of individual analyst recommendations that make up a nonmissing average rec. rating on a firm-day Mean	Median	St. dev	Min.	Max.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
A1 (most accurate)	5,536	3,094	1.79	1	1.27	1	14	1.42	1	0.83	1	14
A2	7,045	3,094	2.28	2	1.75	1	21	1.66	1	1.12	1	18
A3	6,764	3,094	2.19	2	1.62	1	15	1.63	1	1.05	1	14
A4	6,862	3,094	2.22	2	1.53	1	14	1.61	1	1.00	1	13
A5 (least accurate)	5,940	3,094	1.92	2	1.18	1	22	1.44	1	0.80	1	19
All Quintiles	32,147	15,470	10.4	9	4.83	5	36					

Table 4
Summary Statistics of Forecast Accuracy

Panels A1 and A2 report the summary statistics for the absolute forecast error (AFE) and forecast error (FE), respectively, for the 32,147 analyst-firm-year observations in our sample. The first row reports the statistics for unscaled data. The last two rows report the statistics for AFE and FE after scaling these with the stock price at the start of the return accumulation year (April 1) and the absolute value of actual earnings, respectively. When scaling by the absolute value of actual earnings, we arbitrarily equate the denominator to 0.5 whenever it is less than 0.5 to avoid the problem of small denominators. Panel B reports the summary statistics of AFE scaled by price for each accuracy quintile. Within each quintile, we first compute the average AFE for each firm-year based on the AFE of the individual analysts allocated to the quintile. This yields a total of 3,094 firm-year AFE for each quintile. The summary statistics of these 3,094 firm-year AFE for each quintile are reported in Panel B. The last row of the panel reports the summary statistics of AFE for the entire sample of 15,470 firm-year observations pooled across all quintiles.

Panel A1: Overall sample AFE					
	Mean	Median	St. dev.	Minimum	Maximum
Unscaled ($)	0.289	0.140	0.449	0.000	8.760
Scaled by price (%)	1.26	0.59	2.03	0.00	24.65
Scaled by absolute value of actual earnings (%)	22.69	10.00	32.34	0.00	200.00
Panel A2: Overall sample FE					
Unscaled ($)	–0.076	–0.010	0.529	–8.760	5.200
Scaled by price (%)	–0.36	–0.03	2.25	–24.65	23.80
Scaled by absolute value of actual earnings (%)	–10.13	–0.96	38.19	–200.00	200.00

Panel B: Summary statistics of firm-level AFE averaged within each accuracy quintile

	AFE scaled by Price (%)				
Absolute forecast accuracy quintiles	Mean	Median	St. dev.	Minimum	Maximum
A1 (most accurate)	0.756	0.222	1.540	0.000	17.474
A2	1.062	0.465	1.796	0.007	18.637
A3	1.326	0.661	2.011	0.015	21.600
A4	1.635	0.876	2.289	0.032	22.486
A5 (least accurate)	2.199	1.267	2.829	0.038	24.649
Overall	1.396	0.670	2.196	0.000	24.649

Table 5
Sample Characteristics of the Recommendations

This table reports the year-by-year descriptive statistics of the 48,723 recommendations (including reiterations), issued between October 1993 and March 2000 that we employ for return calculations in the subsequent analyses. An analyst must be ranked for her forecast accuracy of a firm during the year for her recommendation for the same firm to be included in our analysis. The year convention in column (1) identifies a period of April 1 in year *y* to March 31 in year *y*+1 as year *y*. The rating categories in column (3) through (7) are based on I/B/E/S's ratings, which range from 1 (strong buy) to 5 (sell). Recommendations that are not reiterated are treated as stale after six months (183 days). The number of recommendations in each of the five rating categories is reported in columns (3) through (7). The number of recommendations in each category as a percentage of total recommendations during a year is also reported in parentheses below the number.

		Recommendations by category (% of total recommendations)				
Year	Total no. of new rec.	Strong buy	Buy	Hold	Underperform	Sell
1993	6,089	1,301	1,820	2,645	130	193
		(21%)	(30%)	(43%)	(2%)	(3%)
1994	7,083	1,685	2,136	2,842	208	212
		(24%)	(30%)	(40%)	(3%)	(3%)
1995	7,115	1,676	2,096	2,823	208	312
		(24%)	(29%)	(40%)	(3%)	(4%)
1996	5,975	1,680	1,968	2,039	141	147
		(28%)	(33%)	(34%)	(2%)	(2%)
1997	6,679	1,789	2,181	2,412	143	154
		(27%)	(33%)	(36%)	(2%)	(2%)
1998	8,844	2,279	3,469	2,828	151	117
		(26%)	(39%)	(32%)	(2%)	(1%)
1999	6,938	2,075	2,649	1,962	153	99
		(30%)	(38%)	(28%)	(2%)	(1%)
Total	48,723	12,485	16,319	17,551	1,134	1,234
		(26%)	(33%)	(36%)	(2%)	(3%)

Table 6
Characteristics of Long and Short Portfolios Formed on the Basis of Recommendations by Analysts Sorted on Forecast Accuracy

For every firm-year, we sort analysts into quintiles according to the accuracy of their outstanding earnings forecasts on June 30. Eligible analysts are those remaining after applying the filters in Table 2. We then compute for each firm-day in a quintile the average recommendation rating of analysts within that quintile. We categorize this average rating as favorable if ≤2, unfavorable if >2.5, and neutral if >2 and ≤2.5. We then form corresponding long and short portfolios for favorable and unfavorable recommendations, respectively, for each quintile. For each quintile-portfolio, we compute the daily value-weighted returns of the recommended firms from April 1 of year *y* to March 31 of year *y*+1. Our return accumulation sample period is from April 1, 1994 to March 31, 2000. The estimates reported here are those from a time series regression of each portfolio's excess monthly returns ($R_p - R_f$) on the four-factors: market risk premium ($R_m - R_f$ in column 2), a zero-investment size portfolio (SMB in column 3), a zero-investment book-to-market portfolio (HML in column 4), and a zero-investment price momentum portfolio (UMD in column 5). Column (7) reports the average number of firms in each portfolio. The *t*-statistics are shown in parentheses below the estimates. Levels of significance represent that the estimates are different from zero (different from one for RMRF). Panels A, B, and C report the characteristics of the long, short, and long–short portfolios, respectively.

Panel A: Long portfolio

EPS forecast accuracy quintiles	Coefficient estimates for the four-characteristic model				Adj. R^2 (%)	Avg. no. of firms recommended
	RMRF	SMB	HML	UMD		
(1)	(2)	(3)	(4)	(5)	(6)	(7)
A1 (most accurate)	1.017	-0.122	0.014	-0.015	92.04	180.44
	(0.38)	(2.91)***	(0.18)	(0.33)		
A2	1.020	-0.144	-0.053	-0.032	92.11	197.52
	(0.46)	(3.36)***	(0.69)	(0.67)		
A3	1.001	-0.083	-0.021	-0.012	92.54	197.68
	(0.03)	(2.06)**	(0.29)	(0.28)		
A4	1.018	-0.086	-0.065	0.007	90.59	196.81
	(0.36)	(1.82)*	(0.77)	(0.14)		
A5 (least accurate)	1.032	-0.105	0.008	-0.094	91.42	178.91
	(0.69)	(2.36)**	(0.1)	(1.94)*		
A1–A5	-0.015	-0.017	0.006	0.079	-0.43	359.35
	(0.33)	(0.39)	(0.07)	(1.64)		

Panel B: Short portfolio

A1 (most accurate)	0.912	-0.038	0.121	-0.183	87.08	119.28
	(1.74)*	(0.78)	(1.39)	(3.47)***		
A2	0.865	-0.081	0.178	-0.279	83.11	117.57
	(2.34)**	(1.46)	(1.78)*	(4.59)***		
A3	0.853	-0.160	0.017	-0.218	84.79	116.53
	(2.66)***	(3.02)***	(0.17)	(3.79)***		
A4	0.904	-0.029	0.221	-0.220	84.62	121.08
	(1.74)*	(0.55)	(2.34)**	(3.84)***		
A5 (least accurate)	0.904	-0.138	0.086	-0.113	79.40	120.66
	(1.45)	(2.16)**	(0.75)	(1.63)		
A1–A5	0.009	0.101	0.035	-0.069	0.81	239.94
	(0.15)	(1.77)*	(0.34)	(1.12)		

Table 6 (Continued)

Panel C: Long–short portfolio

EPS forecast accuracy quintiles	Coefficient estimates for the four-characteristic model				Adj. R^2 (%)	Avg. no. of firms recommended
	RMRF	SMB	HML	UMD		
(1)	(2)	(3)	(4)	(5)	(6)	(7)
A1 (most accurate)	0.104	-0.085	-0.107	0.167	21.10	299.72
	(1.66)*	(1.40)	(0.99)	(2.55)**		
A2	0.156	-0.063	-0.231	0.247	43.64	315.10
	(2.28)**	(0.96)	(1.96)*	(3.45)***		
A3	0.148	0.077	-0.038	0.206	30.85	314.21
	(2.19)**	(1.19)	(0.33)	(2.92)***		
A4	0.113	-0.057	-0.286	0.227	44.99	317.89
	(1.69)*	(0.89)	(2.48)**	(3.24)***		
A5 (least accurate)	0.128	0.033	-0.078	0.020	7.54	299.57
	(1.70)*	(0.46)	(0.60)	(0.25)		
A1–A5	-0.024	-0.118	-0.029	0.148	1.00	599.29
	(0.27)	(1.38)	(0.19)	(1.59)		

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.
* Indicates statistical significance at the 0.10 level.

Table 7
Monthly Percentage Returns Earned by Portfolios Formed on the Basis of Recommendations by Analysts Sorted on Forecast Accuracy

For every firm-year, we sort analysts into quintiles according to the accuracy of their outstanding earnings forecasts on June 30. Eligible analysts are those remaining after applying the filters in Table 2. We then compute for each firm-day in a quintile the average recommendation rating of analysts within that quintile. We categorize this average rating as favorable if ≤2, unfavorable if >2.5, and neutral if >2 and ≤2.5. We then form corresponding long and short portfolios for favorable and unfavorable recommendations, respectively, for each quintile. For each quintile-portfolio, we compute the daily value-weighted returns of the recommended firms from April 1 of year *y* to March 31 of year *y*+1. Our return accumulation sample period is from April 1, 1994 to March 31, 2000. Market-adjusted returns in column (3) are obtained by subtracting the returns on the CRSP NYSE/AMEX/NASDAQ value-weighted index from raw monthly returns. The capital asset pricing model-based (CAPM) abnormal returns in column (4) are the estimated intercepts from time-series regressions of portfolio returns ($R_p – R_f$) on the market excess returns ($R_m – R_f$). The intercepts from the Fama-French model reported in column (5) are estimated by regressing portfolios' excess returns on: market excess returns, returns from a zero-investment size portfolio (SMB), and returns from a zero-investment book-to-market portfolio (HML). Finally, the intercepts from the four-factor model reported in column (6) are estimated by adding returns from a zero-investment price momentum portfolio (UMD) as additional explanatory variable to the Fama-French three factor regression. The *t*-statistics are shown in parentheses below the returns, which are reported in percentages. Panel A and B reports the returns of the long and short portfolios, respectively, and Panel C reports the returns of the long–short portfolios, which are essentially zero-investment portfolios formed by buying the long portfolio and selling short the short portfolio of each analyst group. Column (2) of Panel C is intentionally left blank because it will report exactly the same return as column (3) after we subtract the short portfolio's return from that of the long portfolio.

Panel A: Long portfolio

EPS forecast accuracy quintiles	Raw return	Market-adjusted return	Intercept from CAPM	Intercept from Fama-French	Intercept from Four-factor
(1)	(2)	(3)	(4)	(5)	(6)
A1 (most accurate)	2.220	0.364	0.361	0.324	0.344
	(4.47)***	(2.37)**	(2.2)**	(2.19)**	(2.14)**
A2	2.111	0.255	0.213	0.175	0.216
	(4.14)***	(1.63)	(1.27)	(1.15)	(1.32)
A3	2.095	0.239	0.235	0.213	0.229
	(4.25)***	(1.75)*	(1.60)	(1.50)	(1.48)
A4	2.085	0.230	0.175	0.159	0.149
	(4.06)***	(1.45)	(1.04)	(0.95)	(0.83)
A5 (least accurate)	1.757	-0.098	-0.120	-0.158	-0.036
	(3.47)***	(0.59)	(0.67)	(0.98)	(0.21)
A1–A5	0.463	0.463	0.482	0.482	0.380
	(3.16)***	(3.16)***	(3.07)***	(3.04)***	(2.25)**

Panel B: Short portfolio

EPS forecast accuracy quintiles	Raw return	Market-adjusted return	Intercept from CAPM	Intercept from Fama-French	Intercept from Four-factor
A1 (most accurate)	1.045	-0.810	-0.594	-0.632	-0.393
	(2.33)**	(3.81)***	(2.76)***	(3.41)***	(2.13)**
A2	1.296	-0.559	-0.228	-0.292	0.072
	(2.87)***	(1.93)*	(0.79)	(1.29)	(0.34)
A3	1.568	-0.287	-0.029	-0.092	0.192
	(3.47)***	(1.16)	(0.11)	(0.45)	(0.95)
A4	1.408	-0.448	-0.161	-0.210	0.078
	(3.14)***	(1.74)*	(0.63)	(1.02)	(0.39)
A5 (least accurate)	2.045	0.190	0.402	0.345	0.493
	(4.34)***	(0.75)	(1.54)	(1.50)	(2.01)**
A1–A5	-1.000	-1.000	-0.996	-0.977	-0.887
	(5.25)***	(5.25)***	(4.88)***	(4.82)***	(4.07)***

Table 7 (Continued)

Panel C: Long–short portfolio

EPS forecast accuracy quintiles	Raw return	Market-adjusted return	Intercept from		
			CAPM	Fama-French	Four-factor
(1)	(2)	(3)	(4)	(5)	(6)
A1 (most accurate)		1.175	0.955	0.956	0.737
		(5.19)***	(4.15)***	(4.29)***	(3.20)***
A2		0.814	0.441	0.467	0.144
		(2.79)***	(1.55)	(1.85)*	(0.57)
A3		0.527	0.264	0.305	0.037
		(2.03)**	(1.01)	(1.26)	(0.15)
A4		0.677	0.337	0.368	0.072
		(2.34)**	(1.18)	(1.51)	(0.29)
A5 (least accurate)		-0.288	-0.523	-0.504	-0.529
		(1.15)	(2.04)**	(1.97)**	(1.91)*
A1–A5		1.463	1.478	1.459	1.266
		(5.10)***	(4.81)***	(4.75)***	(3.87)***

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.
* Indicates statistical significance at the 0.10 level.

Table 8
Relation between Firm Coverage and Forecast Accuracy

This table examines the relation between firm coverage and forecast accuracy. For each analyst in each year, we count the number of firms the analyst covers. We then compute the average accuracy quintile the analyst is assigned to for the firms she covers. Using the pooled analyst-year data, we examine the relation between number of firms covered and accuracy quintile allocation. Column (2) reports the number of analyst-year observations that cover the number of firms reported in column (1). Column (3) then reports the average accuracy quintile allocation for the analyst-year observations. For example, there were 3,566 analysts that covered only one firm in a year in our sample, and these were allocated to an average quintile of 3.08. In the last row, the average quintile (column 3) is the average of the above rows weighted by the number of analysts in column (2).

No. of firms covered	No. of analyst-year observations	Average quintile
1	3,566	3.08
2	2,010	3.01
3	1,323	3.03
4	882	2.99
5	601	3.04
6 to 10	1,194	3.01
>10	354	2.98
Overall	9,930	3.04

Table 9
Annual Turnover for the Long–short Portfolios of the Extreme Accuracy Quintiles

For the long–short portfolios of quintiles A1 and A5, for each firm and each calendar month, we count the number of times the average recommendation rating changes across the three categories of favorable, neutral or missing, and unfavorable, counting any change from favorable to unfavorable and vice versa twice. We then sum the changes for all firms within a quintile to obtain the quintile's total monthly revisions. The revisions for each calendar month are averaged across the six years of our sample and reported in the following table. The total of the 12 monthly revisions represent the total annual revisions activity. The last row of the table reports the annual turnover of the long–short portfolios of the two quintiles. To compute this number, we divide the total number of revisions by the average number of stocks held.

Month	A1 revisions	A5 revisions
April	113	96
May	124	117
June	136	109
July	131	128
August	94	110
September	105	106
October	132	122
November	96	88
December	107	89
January	109	113
February	75	82
March	89	79
Total no. of annual revisions	1,311	1,239
Average number of stocks in the portfolio (from Panel C of Table 6)	300	300
Annual turnover	437%	413%

Table 10
Forecast Accuracy of Analysts Sorted on June 30 Forecasts through the Subsequent Calendar Months

This table reports the average absolute forecast errors (AFE), scaled by price, within each quintile based on the sorted analysts' outstanding forecasts in the post-June calendar months. While analysts' are sorted into accuracy quintiles based on their forecasts outstanding on June 30, this table investigates the accuracy of analysts in each quintile through the rest of the year. Within each quintile, for each firm-year, we first average the AFE of the individual analysts to obtain an average firm-level AFE. The AFE for firm-years are then averaged within each quintile and reported in the table. For the months January through March, for those firms whose actual earnings are already announced, we compute the AFE of analysts based on their last outstanding forecasts just before the announcement of the actual earnings.

Forecast accuracy quintile	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.
A1 (most accurate)	0.756	0.757	0.755	0.712	0.623	0.585	0.552	0.527	0.520	0.520
A2	1.062	0.972	0.897	0.835	0.706	0.649	0.610	0.597	0.594	0.594
A3	1.326	1.145	1.028	0.936	0.775	0.715	0.664	0.641	0.640	0.640
A4	1.635	1.381	1.224	1.116	0.928	0.843	0.791	0.753	0.748	0.745
A5 (least accurate)	2.199	1.815	1.553	1.417	1.214	1.113	1.056	1.006	0.998	0.999
Overall	1.396	1.214	1.092	1.003	0.849	0.781	0.734	0.705	0.700	0.699

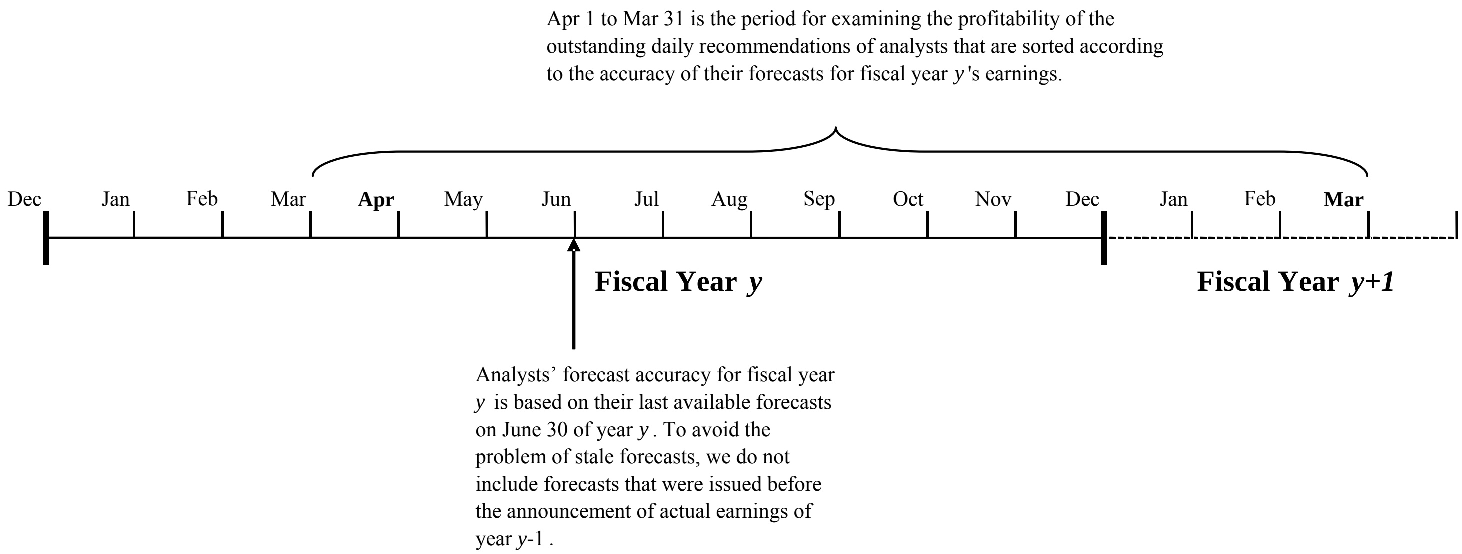

Figure 1. Time interval for computing yearly forecast accuracy and recommendation profitability

We rank all analysts according to the accuracy of their forecasts of annual earnings of fiscal year *y*. To use a common time frame to evaluate analysts, we pick earnings forecasts of analysts outstanding on June 30 of year *y*. From these forecasts, however, we remove those that were issued before the announcement of actual earnings of fiscal year *y*–1 to avoid the problem of stale forecasts. The firms used to evaluate analysts' forecast accuracy must all have December fiscal year-ends. After sorting analyst into quintiles, we compute the monthly returns emanating from the average recommendation ratings of the analyst-firm observations in each quintile over the 12-month period (which we call the return accumulation year) from April 1 in fiscal year *y* to March 31 of year *y*+1.