Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?

Roger K. LOH
Singapore Management University
Business Building #03-56
469 Bukit Timah Road
Singapore 259756
Tel: (65) 68220708
rogerloh@smu.edu.sg

and

G Mujtaba MIAN
National University of Singapore
Department of Finance and Accounting
The NUS Business School
1 Business Link, Singapore 117592
Tel: (65) 68743015
bizgmm@nus.edu.sg

12 March 2003

We received useful suggestions from Kalok Chan, Charles Lee, Allaudeen Hameed, Guan Hua Lim, John Sequeira and Chee Kiat Low. We especially thank Louis Ederington for his detailed comments. The Financial Databases (FDB) of the NUS Business School provided the data for this study. Discussions with Thomson Financial helped clarify critical data issues.

Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?

ABSTRACT

We carefully construct measures of earnings forecast accuracy and recommendation profitability that enable us to examine the association between the qualities of these two key outputs of individual security analysts. We find that analysts with superior earnings forecasts issue significantly more profitable recommendations than those with less accurate forecasts. The average annual recommendations return of top one-third analysts sorted on forecast accuracy exceeds that of the bottom third by 10.8% during our sample period. Our results suggest that imperfectly efficient markets allow information gatherers like security analysts to be rewarded for their costly activities. Our findings also provide direct empirical support for the recent "valuation" models in accounting and finance literature (Ohlson (1995) and others) that emphasize the role of future earnings in predicting stock price movements.

Keywords: Earnings Forecasts, Stock Recommendations, Earnings-based Valuation Models
JEL Classification: G14, G24, G10

I. 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. The extant studies, however, either focus on earnings forecasts or stock recommendations in isolation. There is hardly any study that examines these two analyst outputs in tandem[1].

This is surprising given that such an analysis 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 to itself, but a tool for them 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 or not the resources spent on producing precise appraisals of earnings do provide analysts with a competitive edge in appraising the investment potential of companies.

Second, the abnormal earnings valuation model (see, for example, Ohlson (1995)) envisages a central role of future corporate earnings in determining the intrinsic value of a stock. The advent of this model in the 1990s has drawn renewed attention of researchers, especially in the accounting literature, to the *predictive* role of earnings. Indeed, one strand of the ensuing "valuation" or "fundamental analysis research" takes up the question: would it be possible for an investor to employ superior estimates of future earnings (along with an earnings-based stock valuation model) to generate superior stock returns. Most of these studies conclude that earnings, more than the cash flows or the dividends, could be combined with a stock valuation model 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)). While these studies take a somewhat "normative" approach and evoke the possibility that investors *could* convert their earnings forecasts into more profitable investment strategies, they do not provide direct empirical evidence that real-world investors are in fact able to do so. Our study aims to examine this issue using the specific setting of sell-side security analysts. Analysts issue both earnings forecasts and stock recommendation for firms in their respective industries, and hence, provide a unique setting in which the opinions about investment potential and future earnings of an economic agent can be observed simultaneously. This enables us to focus on the question: do investors with superior earnings forecasts indeed earn superior returns. An affirmative answer to this question would provide direct empirical support for fundamental analysis or valuation research.

Third, investigating the association between the quality of recommendation and the quality of earnings forecasts could also provide additional evidence on the existence and the sources of analysts' ability to issue profitable stock recommendations. Prior evidence on the profitability of analysts' investment advice has been mixed (Womack (1996) and Barber, Lehavy, McNichols,

[1] A notable exception is the paper by Bradshaw (2002) that tests the hypothesis that analysts utilize the abnormal earnings valuation model of Ohlson (1995) in transforming their earnings forecasts into stock recommendations.

and Trueman. (2001)). Besides, more recently, reports in the popular media and certain academic studies (Jegadeesh et al. (2001), and Cornell (2001)) suggest that analysts' recommendations are based on ad hoc heuristics, instead of being the result of sound economic analyses. Relating investment advice to the quality of the underlying earnings forecasts could shed light on whether or not any observed profitability of recommendations is real or not. 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. It is commonly perceived that superior analysts score high on all four of these criteria, implying a correlation between 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, though 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, for example, 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 the 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.

In this paper, we first construct a measure of an analyst's earnings forecasting ability *relative to* other analysts in the same industry-year. This measure carefully controls for the firm, industry and time horizon effects. Using this industry-year perspective, we also construct corresponding measure of recommendation profitability of an analyst. We then examine whether an analyst's recommendation profitability is related to his earnings forecast accuracy. Our results suggest that better earnings forecasts, perhaps an indication of better assessment of future prospects of a company, indeed enables analysts to issue more profitable stock recommendations. Analysts with superior earnings forecasts earn annual returns significantly superior to those with inferior forecasts.

The remainder of the paper is organized as follows. In Section II, we construct our measures of forecasting skill and investment profitability of an individual analyst. In Section III, we describe the data and present summary statistics. Section IV presents our findings. Finally, we discuss the implications of our findings and conclude the paper in Section V.

II. Measures of Forecast Accuracy and Recommendation Profitability

We use an industry-year perspective to evaluate an analyst for his stock recommendation and earnings forecasting skills. It is well known that analysts are evaluated at the industry level, evident from market surveys such as *Institutional Investor*'s annual ranking of analysts within industries (O'Brien (1990). This is understandable considering the existence of industry-specific characteristics which render across industry comparisons somewhat meaningless. Hence, the measures of recommendation profitability and forecast accuracy we develop and employ in our analysis evaluate and compare analysts within the same industry – signified by the 2-digit SIC code. The yearly yardstick we use to measure an analyst's ability is also consistent with the market's appraisal of analysts. For example, Stickel (1992) and Michaely and Womack (1999) report that an analyst's ranking in the *yearly* opinion polls exerts a critical influence on his compensation.

To avoid the messy problem of non-overlapping horizons, we exclude from our sample firms whose financial years do not end in December. Following Richardson, Teoh, and Wysocki (2001), we specify the fiscal year (FY) as the period between the successive annual earnings announcement dates rather than between calendar year-ends. So, for example, if a company announces its earnings in February every year, then the fiscal year t would cover a period of February t to February $t+1$. Though the announcement dates of firms may differ, the bulk of December year-end companies report their earnings by February. Hence the fiscal year horizon we consider should still be very similar across firms.

For the rest of the paper, we use the term *calendar year* to denote the financial year ending December 31st so as to avoid confusion with our usage of the term *fiscal year.* Our eventual sample period of FY1994-1999, thus, corresponds to a calendar period of approximately February 1994 to February 2000. In all empirical specifications following this section, we use the sub-notations i, j, k, t to denote an individual analyst, firm, industry, and fiscal year, respectively. In the following pages, we proceed to construct variables that proxy an analyst's earnings forecasting skill and stock picking ability.

A. Measure of Earnings Forecast Accuracy

To measure an analyst's forecast accuracy for a firm, we adopt Clement's (1999) performance measure which compares an analyst's absolute forecast error to the average absolute forecast error of other analysts following the same firm. Formally, analyst i's forecast accuracy is defined by his proportional mean absolute forecast error (PMAFE), given by,

$$PMAFE_{ijt} = \frac{AFE_{ijt} - \overline{AFE_{jt}}}{\overline{AFE_{jt}}} \tag{1}$$

where AFE_{ijt} represents analyst i's absolute forecast error for firm j in fiscal year t, and $\overline{AFE_{jt}}$ is the mean absolute forecast error of all analysts issuing FY1 forecasts on firm j in fiscal year t. Subtracting the mean absolute forecast error from the analyst's absolute forecast error controls for firm-year effects. Firm-year effects result from firm or year-specific factors that make certain firms' earnings tougher or easier to forecast in certain years. For instance, some firms may engage more actively in earnings management (Abarbanell and Lehavy (2000)), or some years may contain macro-economic shocks which influence absolute forecast errors upwards (O'Brien (1990)). Scaling the numerator by $\overline{AFE_{jt}}$ controls for the heteroscedasticity of forecast error distributions across firms (Clement (1999)).

The measure $PMAFE_{ijt}$ can be interpreted as analyst *i*'s fractional forecast error relative to the average of analysts' absolute forecast errors for firm *j* in fiscal year *t*. Negative values of $PMAFE_{ijt}$ represent above average performance whilst positive values represent below average performance. Zero, by definition, signifies an average performing analyst. To obtain meaningful values of this *relative* measure of accuracy, we include only those firms in our analysis that have at least four analysts issuing forecasts of its earnings.

Not all analysts issuing forecasts for firm *j* are included in our analysis. We restrict our sample of analysts to those who issue forecasts for firm *j* within the first 30 calendar days of the fiscal year[2], choosing their latest forecast within this window. This is because analysts who initiate coverage later in the fiscal year might be copying the forecasts of other analysts rather than actually covering the firm itself (see, for example, Cooper, Day, and Lewis (2001)). We select this 30-day window for two reasons. First, this is the window period whereby year *t*–1's earnings are recently announced and forecasting activity is at its highest. Second, and more importantly, the short length of the window controls for the forecast recency effect. Past research has shown that when all forecasts are not equally recent, analysts who make forecasts later have an information advantage (see, for example, O'Brien (1990), and Sinha, Brown, and Das (1997)). Our method of using a window to control for recency is analogous to that employed by Sinha et al. (1997).

Recall that the objective is to measure an analyst's forecast accuracy for the *entire* fiscal period, not just for one single horizon. One should not, therefore, base AFE_{ijt} on one single horizon. In doing so, potentially, one may either penalize an analyst for one bad forecast, or glorify him for a single fluke estimate. We suggest, therefore, an aggregate measure that takes into account four salient forecast horizons for the measurement of the yearly (FY1) forecast accuracy. These four horizons are the one-year ahead, three-quarters ahead, two-quarters ahead, and the final unrevised forecast of FY1 earnings (see Figure 1). The absolute forecast error of analyst *i* forecasting for firm *j* in fiscal year *t*, AFE_{ijt} will thus be given by:

$$AFE_{ijt} = \frac{1}{4}\sum_{x=1}^{4}\left|E_{jt} - F_{ijt}^{q-x}\right| \qquad (2)$$

where E_{jt} is the actual earnings for firm *j* in fiscal year *t*, and F_{ijt}^{q-x} is analyst *i*'s forecast of year *t*'s FY1 earnings at the *x*-quarter ahead horizon. From the visual illustration in Figure 1, we observe that the first horizon is the one-year ahead (or four-quarter ahead) forecast, F_{ijt}^{q-4}. Next is the three-quarter ahead forecast (F_{ijt}^{q-3}), followed by the two-quarter ahead forecast (F_{ijt}^{q-2}), and finally, the one-quarter ahead forecast (F_{ijt}^{q-1}). For each of the first three horizons, we pick the latest forecast outstanding based on a 30-day window following the last earnings announcement date. If the analyst did not issue a new forecast in this window, we take his most

[2] That is, within the 30-day window after the announcement of the previous year's annual earnings. In a later section, we also employ a 60-day window to test the robustness of our results.

recent forecast prior to this window period. This assumes that he had the opportunity, but chose not to revise his expectations of year t's earnings.

For the final one-quarter ahead forecast horizon, we select the final unrevised forecast prior to year t's earnings announcement date. The final unrevised is chosen as the last horizon because it is the last forecast made by the analyst for the given fiscal year. It is also one forecast that is most likely to be subject to a market test - since the analyst sees no more need to revise that forecast. Data to calculate all four horizons must be available for an analyst to be included in the sample. This criterion ensures that the selected analysts were following the firm for the *entire* fiscal year.

For each analyst i, we aggregate the forecast performance measure $PMAFE_{ijt}$ (earlier given in equation 1) for all the firms that he covers in industry k. This is represented by:

$$PMAFE_{ikt} = \frac{1}{n_f} \sum_{j=1}^{n_f} PMAFE_{ijt} \qquad (3)$$

where $PMAFE_{ikt}$ is simply the average of $PMAFE_{ijt}$ across all the n_f firms covered by analyst i in industry k in fiscal year t. To ensure that there can be meaningful comparison of relative performance within the industry, we include only industries where there are at least five eligible analysts issuing forecasts. Also, we remove industries which have less than five eligible firms after all previous screening criteria – so as to focus on reasonably sized industries.

Finally, as Hong and Kubik (2003) argue, the yearly performance measures such as the one in equation (3) could be a noisy proxy for the underlying forecasting skill of an analyst. Therefore, the final step in our assessment of the forecasting skill of an analyst is to aggregate this yearly measure for analyst i across all six years in our sample to obtain the aggregate measure of forecasting skill.

$$PMAFE_{ik} = \frac{1}{T} \sum_{t=1994}^{1999} PMAFE_{ijt} \qquad (4)$$

Where T represents the total number of years an analyst appears in our sample of 1994-99.

B. Measure of Recommendation Profitability

Having formulated the measure for earnings forecast accuracy, we proceed to derive a proxy for an analyst's stock picking ability. In doing so, we cover all the recommendations an analyst issues, inclusive of reiterations.

B.1. Compounded Stock Return in the Recommendation Period

To determine the actual profitability of the recommendation, we look at the holding period stock return for the duration of the recommendation. This is the daily return, inclusive of dividends, of a firm's stock, compounded across the entire duration for which the recommendation remains outstanding. More specifically, the duration of the recommendation is defined as the recommendation date to the earlier of the next recommendation date or the end of the fiscal year. Therefore the compounded return of firm *j* for the duration of analyst *i*'s recommendation *h* in fiscal year *t* is given by:

$$Raw\ returns_{ihjt} = \prod_{\tau=1}^{d} (1 + RET_{j\tau}) - 1 \tag{5}$$

where $RET_{j\tau}$ is the daily return of firm *j*'s stock on day τ, and *d* is the duration of the recommendation in *trading* days. Note that the left hand side in equation (5) is the *raw* stock return of firm *j* for the duration of recommendation *h*. In order to evaluate the stock picking ability of an analyst, one must adjust these` raw returns with the returns on the overall market index, or better still, returns from a portfolio of stocks with similar risk characteristics. We obtain this adjustment by computing the *size-adjusted* (and alternatively, *market-adjusted*) stock return, r_{ihjt}, as follows:

$$r_{ihjt} = Raw\ returns_{ihjt} - \left[\prod_{\tau=1}^{d} (1 + MKTRET_{j\tau}) - 1 \right] \tag{6}$$

where $MKTRET_{j\tau}$ is the daily return on the corresponding CRSP decile (or alternatively, CRSP NYSE/AMEX/Nasdaq value-weighted market index) to which the stock belongs at the start of the calendar year, on day τ. *d* is the duration in trading days for which recommendation *h* remains effective.

In computing r_{ihjt}, we track the recommendation based on the exact date specified in I/B/E/S's "Recommendation Date" field. Technically, this is the date that the recommendation was entered into the I/B/E/S system. This is the same day that the recommendation was issued to the market since the submission process is an electronic one and is almost instantaneous. However, the fact that clients could receive the recommendation before it was issued to the market should still warrant the use of an earlier date to start tracking returns. We follow Francis and Soffer (1997) in defining the start date of a recommendation as the day –1 instead of day 0. In a later section, we also repeat all our analyses using day 0 as the start dates of the recommendations as a robustness check. We find that the choice of the start date (day 0 or –1) is immaterial in affecting our conclusions. Thus, all subsequent tabulated results are based on day –1 as the first date of recommendation.

B.2. Treatment of the Five Recommendation Categories

The compounded stock return derived above is then converted to actual recommendation returns based on the type of recommendation issued. While brokers may have different investment ratings scales, I/B/E/S establishes its own five-point rating system as follows: 1 = Strong Buy, 2 = Buy, 3 = Hold, 4 = Underperform, and 5 = Sell. When a contributing broker sends in a recommendation, it is mapped onto one of I/B/E/S's standard ratings and entered into the database.

Prior literature finds that the distribution of recommendations across the five categories is skewed – there are far more favorable recommendations than the unfavorable ones (see, for example, Jegadeesh et al. (2001), and Barber et al. (2001)). In our sample, the 1,858 analysts issue a total of 56,113 recommendations. Consistent with prior studies, the percentage of strong buy and buy recommendations in our sample are about 26% and 35%, respectively. Another 35% are hold. The unfavorable recommendations (underperform and sell) make up only 4 % of all the recommendations.

In our analysis, we need to differentiate analysts in their stock picking skills. To calculate the returns for each individual recommendation, therefore, we treat the five recommendation categories as follows. We calculate the return for buy recommendation by simply equating raw recommendation returns, R_{ihjt} to r_{ihjt}. However, for strong buys, we calculate returns, R_{ihjt}, as twice that of $2\,r_{ihjt}$. This assumes that investors make twice the investment in stocks that are strong buys than those that are buys.

The case for hold recommendations is unique. The well known dearth of sell recommendations, also evident in our sample, makes researchers wonder if some sells are actually hidden behind the euphemism of holds (Barber et al. (2001), and Hirst et al. (1995))[3]. We follow the previous studies and treat holds as sell, and set $R_{ihjt} = -r_{ihjt}$. This implies investors short-sell the securities that are rated hold by analysts. Finally, for underperform and sell recommendations, we set $R_{ihjt} = -2r_{ihjt}$, assuming that one shorts the stock by double the amount than for stocks with simply a hold recommendation.

B.3. Firm Recommendation Profitability

An analyst could make more than one recommendation for the same firm in the same fiscal year. One way to handle multiple recommendations for one firm is to take the arithmetic mean return of all of an analyst's recommendations for the firm in a year. However, this is not representative of the *actual* returns generated by following the analyst's recommendations for the firm for the entire fiscal year. Conceptually, one finds that the method of geometrically

[3] Barber at al. (2001) in their paper form five portfolio consisting of firms whose consensus recommendations vary from most favorable to least favorable. Holds (consensus recommendation code=3) actually featured in the second most unfavorable portfolio, which they eventually sell short when computing return differences.

compounding the recommendation returns more appropriate. Hence, we calculate analyst *i*'s recommendation profitability for firm *j* in fiscal year *t*, $PROF_{ijt}$ as:

$$PROF_{ijt} = \left[\prod_{h=1}^{H} \left(1 + R_{ihjt}\right) \right] - 1 \tag{7}$$

Subject to the condition: $R_{ihjt} \geq -1$ (8)

In equation 7, *H* is the total number of recommendations that analyst *i* issues for firm *j* in fiscal year *t*. The condition given by equation 8 is necessary in order to address a mathematical predicament. Since we allow for shorting of a security, it is possible (though highly unlikely) that a sell recommendation yields a return $R_{ihjt} \leq -1$. This literally means that firm's stock, after being recommended as a *sell* by analyst *i*, *appreciates* by more than 100% in the duration of the recommendation. Mathematically, one observes that a negative $(1 + R_{ihjt})$ renders equation 7 meaningless. Therefore, one has to correct this hitch by winsorizing all $R_{ihjt} \leq -1$ to be $= -1$[4].

B.4. Industry Recommendation Profitability

From an analyst's firm level recommendation profitability, we obtain his industry level profitability. This we define as the average recommendation profitability of all the firms he covers in the industry.

$$PROF_{ikt} = \sum_{j=1}^{n_r} CAPWT_{ijt} \times PROF_{ijt} \tag{9}$$

$PROF_{ikt}$ is analyst *i*'s recommendation returns for all the n_r firms that he follows in industry *k*. $PROF_{ikt}$ can be understood as the average recommendation returns (in percent) generated when one mimics the recommendations of an analyst by investing or shorting stocks that the analyst recommends for the duration of a fiscal year. $CAPWT_{ijt}$ is the market capitalization of the recommended firm divided by the total market capitalization of all the firms recommended by analyst *i* in year *t*. Market capitalization data is recorded at the beginning of the calendar year[5].

As a final step, similar to our forecast accuracy measure, we aggregate the yearly recommendation profitability over the six years sample period to obtain the average measure of

[4] Not surprisingly, the number of recommendations that we have to winsorize represents less than 0.01% of all recommendations.

[5] We also use an equal-weighted approach in forming an aggregate measure of an analyst's industry recommendation profitability. The results, not reported in the paper, are similar.

profitability for an analyst, $PROF_{ik}$ [6]. This aggregated measure is likely to be less noisy and more reflective of the true stock picking ability of an analyst.

III. Data and Descriptive Statistics

We utilize I/B/E/S's (Institutional Brokers Estimates Systems) analyst-by-analyst Detail History File for earnings estimates. Each observation in this file represents an individual forecast with the relevant company ticker, broker code, analyst code, forecast period indicator, and estimate date. To ascertain forecast accuracy, we also make use of the I/B/E/S Actuals file. This records the actual reported earnings along with the corresponding company ticker, periodicity indicator, period end date, and report date. Following Lim (2001), we remove observations with forecast errors exceeding 10 dollars as these most probably resulted from a data input error.

We obtain stock recommendations of analysts from the I/B/E/S's Detail Recommendations file. Each observation in this file contains a recommendation code, company ticker, broker code, analyst code, and recommendation date. Compared with its earnings estimates data, I/B/E/S's recommendations data is of a shorter length, beginning only in October 1993 (earnings forecasts history starts in 1976). Consequently, the period of our eventual sample is FY1994-1999.

In order to examine an analyst's stock picking ability, we obtain stock returns from the CRSP (Center for Research in Security Prices) database at the University of Chicago. Specifically, the *daily* stock returns file is used in order to measure the profitability of recommendations over their precise durations. For each firm, we extract daily returns for the period that it is represented in our recommendation sample. For each calendar year end, we extract the firm's exchange code, Standard Industrial Classification (SIC) 2-digit Code, and market capitalization. Finally, to enable computations of adjusted returns, we obtain the daily returns on the CRSP NYSE/AMEX/Nasdaq value-weighted market index for the entire sample period.[7] We also obtain the size-sorted decile returns. We match the capitalization of a stock at

---

[6] There is one notable difference in the measures we develop for forecasting and stock picking skills. The forecasting measure is calculated after adjusting for firm and year effects; whereas stock picking ability is only adjusted for the industry and year effects. For earnings forecasts, it has been well established that forecast errors are not comparable across different firms (see, for example, Clement (1999), O'Brien (1990), and Sinha et al. (1997)). Therefore, in order to correctly rate an analyst's forecasting skill, one needs to pit him against analysts who are forecasting for the same firm. If he were the sole analyst forecasting for the firm, his forecast error would hardly be informative for one to gauge his forecasting ability (Hong, Kubik, and Solomon (2000)). Hence an eligibility screen of at least four analysts issuing forecasts for a firm needs to be imposed so that there is a basis for relative forecasting performance.

However, one does not face such a constraint when measuring stock picking ability. An analyst's stock picking ability is simply the profitability of his recommendations (after adjusting for risk). If he so wishes to pick stocks neglected by his compatriots, one can well allow him to do so. The measure of performance – recommendation returns – will be comparable across firms within the same industry.

[7] About two-third of the firms in our sample are listed in NYSE, with most of the remaining ones listed on Nasdaq. We also select the value-weighted index over the equal-weighted one since it is a better benchmark by which to adjust for the returns on mainly large firms followed by I/B/E/S. However, the eventual results are insensitive to the choice between these two benchmarks.

the start of a calendar year to identify the decile to which a stock belong to, and then use the returns on this decile over the following year to obtain the size-adjusted returns for a particular stock.

The descriptive statistics for our sample are presented in Table I. The sample consists of 2,322 industry-analyst observations for which we are able to compute forecast accuracy, $PMAFE_{ikt}$, *and* recommendation profitability, $PROF_{ikt}$ for at least one of the years during 1994-99. Most analysts would appear in multiple years. In such cases, as mentioned above, we take the average of their yearly performance measures to obtain an overall assessment of their skills. Our sample contains 1,858 unique analysts forecasting for 30 different industries. We define industries using the 2-digit SIC codes. On average, an analyst in our sample covers 1.2 industries. The majority of analysts in our sample, thus, cover only one industry. The most (least) widely followed industry is covered by 288 (8) analysts. The average coverage is 77 analysts for an industry.

IV. Results

A. Persistence in Forecasting and Stock Picking Abilities

If superior forecast accuracy and stock picking were the result of superior underlying skills of analysts (that is, these were not random), and the measures we develop were good proxies for these skills, one should observe some persistence over time in our computations of an analyst's forecasting and stock picking performance. Therefore, we begin our empirical analysis by first examining the persistence over time in our measures.

More specifically, an analyst's forecasting (stock picking) performance in year *t* should be positively related to that analyst's performance in year *t-1*. In order to investigate this for the measure of forecasting ability, we estimate the following regression.

$$PMAFE_{ikt} = \alpha_0 + \alpha_1 PMAFE_{ikt-1} + \alpha_2 DEXP_{ikt} + \alpha_3 DSIZE_{ikt} + \varepsilon_{ikt} \tag{10}$$

Here α_1 represents the relation between the forecasting accuracy of an analyst over the successive years. $DEXP_{ikt}$ and $DSIZE_{ikt}$ are control variables for analyst experience and broker size, respectively. Extant literature shows that these two analyst characteristics positively impact an analyst's forecast accuracy (Mikhail et al. (1997) and Clement (1999)). Analyst experience is proxied by tracking the number of years that the analyst appears in the I/B/E/S earnings forecasts database (similar to the treatment in Hong et al. (2000)), whilst broker size is estimated by counting the number of analysts that a broker employs at the beginning of a calendar year. Similar to earlier studies (Hong et al. 2000), these two variables are included as dummy variables - they take a value of "1" when the analyst belongs to the top quartile of either experience or broker size, and zero otherwise.

We report the estimates of this regression in Panel A of Table II. The estimate of α_1 is positive with a *t*-statistic of 3.67. This indicates persistence in our yearly measure of forecasting skills. The coefficient for the size dummy is negative. This is consistent with prior literature, and suggests that analysts working for large brokerage houses issue more accurate forecasts.

For the measure of recommendation profitability, we estimate the following model.

$$PROF_{ikt} = \alpha_0 + \alpha_1 PROF_{ikt-1} + \alpha_2 DSIZE_{ikt} + Industry\ \ dummies + Year\ dummies + \varepsilon_{ikt} \tag{11}$$

Again our focus is on α_1 in this equation that captures the relation between the recommendation profitability of an analyst over successive years. Extant literature suggests that the size of the brokerage houses might positively impact an analyst's recommendation profitability (Barber et al. (2000)). To control for this, we include $DSIZE_{ikt}$ in equation (11). We also add the industry and year dummies to control for the fact that some industries in certain years outperform or underperform the market averages.

The estimates of this model are reported in Panel B of Table II. The reported value of α_1 is 0.075 with a *t*-statistic of 2.27, indicating persistence in our measure of recommendation profitability. The persistence in both our measures for forecasting and recommendation profitability is reassuring for our subsequent analysis, as it suggests that our measures indeed capture the underlying forecasting and stock picking skills of analysts.

B. Stock Picking Abilities of the Best and the Worst Forecasters

If precise earnings forecasts assist in making superior investment decisions, then analysts with more accurate earnings forecasts should have more profitable stock recommendations. In Table III, we sort the analysts according to their forecast accuracy over the sample period, and divide them into three groups. The first group represents the analysts with the most accurate forecasts, whereas the last group represents the analysts with the least accurate forecasts. We, then, calculate the equally-weighted average of the size-adjusted recommendation profitability of analysts, $PROF_{ik}$, for each group. The last column in Table III represents the difference between the profitability of the most accurate and the least accurate forecasters. If the best forecasters issue the most accurate recommendations, the difference would be positive.

The last row in Table III reports the results for our overall sample, whereas the first five rows report the results for the five largest industries each of which is represented by at least 150 analysts. As the positive values in the last column indicate, the results for the overall sample as well as for each of the top five industries indicate a positive association between forecasting and stock picking skills.

For the overall sample, the analysts with the best forecasting skills have average size-adjusted returns of 7.72% for their recommendations. The analysts with the worst forecasts, on the other hand, have size-adjusted returns of -3.04%. The difference in the average recommendation returns of the best and the worst forecasters is 10.76%. This difference is also statistically significant with a *t*-statistic of 2.69. In addition, for each of the five industries, the analysts with the most accurate forecasts outperform the analysts with the least accurate forecasts. Overall, these results suggest that more accurate forecast facilitate superior investment recommendations.

The negative average returns for the two groups of analysts with less accurate forecasts also indicate that most analysts underperforms relative to the returns on the similar size decile portfolio[8]. Another noticeable feature of the industry wide analysis in Table III is the strong industry factor in recommendation returns. Not surprisingly, some industries significantly outperform others during our sample period.

C. Regressing Recommendation Profitability on Forecasting Skill

To supplement our analysis in the preceding section, we regress the profitability of an analyst's recommendation profitability on his forecast accuracy while controlling for other factors that could affect recommendation profitability. Our model is as follows:

$$PROF_{ik} = \alpha_0 + \alpha_1 PMAFE_{ik} + \alpha_2 DSIZE_{ik} + Industry\ \text{dummies} + \varepsilon_{ik} \tag{12}$$

The coefficient α_1 signifies the extent to which $PROF_{ik}$ (size-adjusted recommendation profitability of analyst *i* for industry *k*) can be explained by his relative forecast accuracy, $PMAFE_{ik}$. If the stock picking ability of an analyst were positively associated with earnings forecasting skill, α_1 would be negative.[9] As mentioned earlier, we use dummy variables in the above model to control for differences in industry returns. Furthermore, as explained above, $DSIZE_{ikt}$ takes a value of 1 if analyst *i* works for the largest quartile of the brokerage houses, and zero otherwise. We add this variable to control for the brokerage house effect in recommendation profitability as documented by Barber, Lehavy and Trueman (2000).

To test the robustness of our results, we estimate the above model for the total sample period as well as for the two sub-periods spanning three years each; first sub-period is 1994-96 and the second sub-period is 1997-99. For the total sample estimation, we aggregate $PROF_{ik}$ and $PMAFE_{ik}$ measures for each analyst over the six-year sample period. However, for the two sub-periods, we aggregate the two performance measures over the respective three-year periods.

We report the results of these estimations in Table IV. The coefficient of $PMAFE_{ik}$ is -0.158 and is reliably different from zero with a *t*-statistic of 2.88. This indicates that an analyst's

[8] Our results in Table III remain unchanged if we adjust the returns using market returns instead of size-based decile returns.

[9] Note that a negative relationship between recommendation profitability and forecast *error* implies a positive association between recommendation profitability and forecasting *ability* (since smaller forecast errors correspond to higher forecast accuracy).

recommendation profitability is positively associated with the accuracy of his earnings forecasts. The relation is also negative and statistically significant for the two sub-periods.

D. Robustness of Results

In this section, we investigate the sensitivity of our results to changes in some of the parameters we used to calculate the forecast accuracy and the profitability measures. First, we examine the effect of using a 60-day window to calculate forecast recency. Recall that in our earlier calculations of yearly forecast accuracy, we employ a 30-day window to judge if an analyst actively follows a firm, and therefore, should be included in the pool of analysts to calculate relative forecast accuracy. Our results remain robust to the use of this alternative window.

Second, we adjust the recommendation returns of analysts with the value-weighted market returns instead of using the similar size decile returns. The estimates of the regression using this alternative definition of abnormal returns are reported in Panel A of Table V. The recommendation profitability of analysts remains positively related to their forecasting skills. Third, we also estimate our model by starting the computation of the recommendation profitability on day 0, that is, on the day on which the recommendation appears in the IBES database, instead of using day -1 as in our previous analysis. The results are reported in Panel B of Table V, and are similar to our earlier results.

Finally, we also test the robustness of our results by computing the profitability of an analyst's multiple recommendations by equally-weighting the profitability of the recommendations for individual firms instead of weighting by market capitalization. The results, not reported here, remain similar[10].

In concluding this section, we would like to point out a caveat. The empirical framework in this paper is *exploratory*, and not *predictive*. That is, while we investigate the contemporaneous association between forecast accuracy and profitability for the cross-section of analysts, we do not attempt to present a model that predicts the future recommendation profitability of an analyst based on the past accuracy of his forecasts.

V. Discussion and Conclusion

In this paper, we examine the relation between the accuracy of analysts' earnings forecasts and the profitability of their stock recommendations. A useful feature of our empirical framework is that, unlike a few prior studies that attempt to link analysts forecast with their stock

[10] In fact, alternative ways of measuring abnormal recommendation returns (for example, adjusting with market returns or similar-size decile returns, or equal- versus capitalization-weighting of multiple recommendations of an analyst) result in profitability measures for analysts that are highly correlated with bivariate correlations exceeding 0.97.

recommendations[11], we do not require any assumption as to *how* analysts translate their EPS forecasts into stock recommendations. Our results indicate that analysts with superior earnings forecasts not only outperform their counterparts with less accurate forecasts, but also outperform the market and the similar size decile returns. Superior earnings forecasts of analysts do indeed appear to facilitate superior investment recommendations. The positive correlation in forecasting and stock picking abilities we document in this paper has relevance not only for fund managers who seek best advice from analysts for both future earnings and recommendations, but is also re-assuring for academic studies that presume such a correlation.

Several previous studies examine the profitability of investment decisions of the professionals including fund managers and security analysts. While the results from these studies have so far been mixed, our paper attempts to relate any observed differences in individual analysts' recommendations profitability to their assessments of future corporate earnings. The existence or absence of a relation between the two allows one to make conjectures as to whether any observed profitability is random or is founded on sound economic analyses. We document a positive relationship between recommendation profitability and earnings forecast accuracy. Our results are, thus, consistent with a sub-set of analysts being able to exhibit superior stock picking skills that are real and not merely the result of chance, as these analysts have corroborating earnings forecasting skills.

This interpretation, in a way, also provides some credence to the analyst profession at a time when they are taking a lot of flak for their over-enthusiastic promotion of stocks in the period leading up to the burst of the tech-bubble. This wave of criticism, though targeted mainly at technology analysts, has repercussions on the way the entire analyst community is now perceived. Certainly there exist black sheep in the profession, but our results suggest that a better assessment of future corporate earnings does allow some analysts to issue superior investment advice.

Further, our findings 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 earnings analysis, our findings are comforting. We provide support for the Grossman and Stiglitz (1980) view of the markets in which a security analyst possessing superior expectations data is able to transform that information into generating better stock recommendations.

Finally, our findings provide support for the fundamental analysis research in accounting and finance that envisages a predictive role of earnings for future stock price movements. We show that, in the unique setting of security analysts, where expectations of individual economic agents about both the future earnings (i.e., earnings forecasts) and the future stock price movements (investment recommendations) can simultaneously be observed, a better appreciation of future earnings is related with better assessment of future stock price movements.

[11] Bradshaw (2002), for example, assumes that analysts use the residual income valuation model, and Cornell (2001) assumes that they use the discounted cash flow model.

REFERENCES

Abarbanell, Jeffrey S., and Rueven Lehavy, 2002, Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts, Working paper, University of North Carolina, Chapel Hill.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analysts' recommendations and stock returns, *Journal of Finance* 56, 531-563.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2000, Are all brokerage houses created equal? Testing for systematic differences in the performance of brokerage house recommendations, Working paper, University of California, Davis.

Bradshaw, Mark T., 2002, How do analysts use their earnings forecasts in generating stock recommendations? Working paper, Harvard University.

Clement, Michael B., 1999, Analyst forecast accuracy: Do ability, resources and portfolio complexity matter? *Journal of Accounting and Economics* 27, 285-303.

Cooper, Rick A., Theodore E. Day, and Craig M. Lewis, 2001, Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383-416.

Cornell, Bradford, 2001, Is the response of analysts to information consistent with fundamental valuation? The case of Intel, *Financial Management* 30, 113-136.

Dechow, Patricia, Amy Hutton, and Richard Sloan, 1999, An empirical assessment of the residual income valuation model, *Journal of Accounting and Economics* 26, 1-34.

Francis, Jennifer, and Leonard Soffer, 1997, The relative informativeness of analysts' stock recommendations and earnings forecasts revisions, *Journal of Accounting Research* 35, 193-211.

Frankel, Richard, and Charles M. C. Lee, 1998, Accounting valuation, market expectation and cross-sectional stock return, *Journal of Accounting and Economics* 25, 283-320.

Grossman, Sanford, and Joseph Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393-408.

Hirst, Eric D., Lisa Koonce, and Paul J. Simko, 1995, Investor reactions to financial analysts' research reports, *Journal of Accounting Research* 33, 335-351.

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, *RAND Journal of Economics* 31, 121-144.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: career concerns and biased earnings forecasts, *Journal of Finance* 58, 313-351.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2001, Analyzing the analysts: When do recommendations add value, working paper, University of Illinois at Urbana-Champaign.

Lee, Charles M. C., 1999, Accounting-based valuation: Impact on business practices and research, *Accounting Horizons* 13, 413-125.

Lee, Charles M. C., James Myers, and Bhaskaran Swaminathan, 1999, What is the intrinsic value of the Dow? *Journal of Finance* 54, 1693-1741.

Lim, Terence, 2001, Rationality and analysts' forecast bias, *Journal of Finance* 56, 369-386.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653-686.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1997, Do security analysts improve their performance with experience? *Journal of Accounting Research* 35, 131-157.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999, Does forecast accuracy matter to security analysts? *Accounting Review* 74, 185-200.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 2002, Do security analysts exhibit persistent differences in stock picking ability? Working paper, Duke University.

O'Brien, Patricia C., 1990, Forecast accuracy of individual analysts across nine industries, *Journal of Accounting Research* 28, 286-304.

Ohlson, James A., 1995, Earnings, book values and dividends in equity valuation, *Contemporary Accounting Research* 11, 661-687.

Richardson, Scott, Siew Hong Teoh, and Peter Wysocki, 2001, The walkdown to beatable analyst forecasts: The roles of equity issuance and insider trading incentives, Working paper, University of Michigan.

Schipper, K., 1991, Commentary on analysts' forecasts, *Accounting Horizons* 5, 105-121.

Sinha, Praveen, Lawrence D. Brown, and Somnath Das, 1997, A re-examination of financial analysts' differential forecast ability. *Contemporary Accounting Research* 14, 1-42.

Stickel, Scott E., 1992, Reputation and performance among security analysts, *Journal of Finance* 47, 1811-1836.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137-167.

Table I
Sample Characteristics

The sample consists of 2,322 industry-analyst observations from FY 1994–1999. The fiscal year convention is based on the period between FY1 earnings announcement dates. Analyst earnings forecasts and stock recommendations data are from I/B/E/S. Included analysts are those whom we are able to compute measures for *both* FY1 earnings forecasts accuracy and stock recommendation profitability for at least one of the fiscal years during our sample period.

Panel A: Coverage

	Total	Number of times each is represented			
		Mean	Median	Maximum	Minimum
Number of Analysts	1,858	1.2	1	4	1
Number of Industries	30	77.4	57	288	8

Panel B: Descriptive Statistics

	Mean	Median	Maximum	Minimum	St Dev
MAFEik	0.014	-0.013	2.390	-0.868	0.232
PROFik	0.010	-0.095	20.27	-1.00	0.751

Table II
Persistence in Profitability and Accuracy

Panel A reports the results of the following regression.

$$PMAFE_{ikt} = \alpha_0 + \alpha_1 PMAFE_{ikt-1} + \alpha_2 DEXP_{ikt} + \alpha_3 DSIZE_{ikt} + \varepsilon_{ikt}$$

Panel B reports the results of the following regression.

$$PROF_{ikt} = \alpha_0 + \alpha_1 PROF_{ikt-1} + \alpha_2 DSIZE_{ikt} + Industry\ dummies + Year\ dummies + \varepsilon_{ikt}$$

$PMAFE_{ikt}$, measures the average forecast accuracy of analyst *i* in industry *k* for year *t*. It is the average of all $PMAFE_{ijt}$s for the analyst in industry *k,* where $PMAFE_{ijt} = (AFE_{ijt} - \overline{AFE_{jt}}) / \overline{AFE_{jt}}$. AFE_{ijt} is an aggregate measure of absolute forecast accuracy utilizing 4 salient forecast horizons across the whole fiscal year. The dependent variable for regression in Panel B is analyst *i*'s size-adjusted recommendation profitability, $PROF_{ikt}$. Size-adjustment is achieved by subtracting the CRSP NYSE/AMEX/Nasdaq same decile returns from the recommendation's raw returns. $DEXP_{ikt}$ is a dummy variable that takes a value of one if analyst *i* is in the top quartile of analysts sorted on experience. Similarly, $DSIZE_{ikt}$ returns a value of one if analyst *i*'s broker is in the top quartile according to the number of analysts that it employs. *, ** and *** indicate that the estimate is statistically significant at 10%, 5% and 1% levels, respectively.

Panel A: Persistence in Forecasting Ability

Variables	Coefficient Estimates	*t*-statistic
Intercept	0.052 ***	3.34
$MAFE_{ikt-1}$	0.080 ***	3.67
$DEXP_{ikt}$	0.004	0.31
$DSIZE_{ikt}$	-0.075 ***	5.54
Adjusted -R^2	2.64%	
Number of observations	2,936	
F-statistics	27.56	
(*p*-value)	(<0.000)	

Panel B: Persistence in Recommendation Profitability

Variables	Coefficient Estimates	*t*-statistic
Intercept	-0.164 ***	2.75
$PROF_{ikt-1}$	0.075 **	2.27
$DSIZE_{ikt}$	0.033	1.48
Adjusted -R^2	11.37%	
Number of observations	2,936	
F-statistics	12.08	
(*p*-value)	(<.000)	

Table III
Recommendation Returns (in percent) of the Best and Worst Forecasters

The sample period ranges from FY1994 - FY1999. We first sort analysts into three groups according to the relative accuracy of their forecasts, $PMAFE_{ikt}$, which is the average of analyst i's $PMAFE_{ijt}$s in industry k. $PMAFE_{ijt} = (AFE_{ijt} - \overline{AFE_{jt}}) \big/ \overline{AFE_{jt}}$, where AFE_{ijt} is the absolute forecast error of analyst i forecasting for firm j in year t. AFE_{ijt} is an aggregate measure of forecast accuracy utilizing 4 salient forecast horizons across the whole fiscal year. We then report the average of size-adjusted returns ($PROF^{m}_{ikt}$) for the recommendations of all analysts falling in a group. The first five rows report the recommendation profitability of the five industries with the largest coverage. The last row reports all industries. If the best forecasters are better stock pickers, the difference between the returns of top and bottom groups, as reported in the last column, will be positive.

(SIC) Industry	# of Analysts	Analysts Sorted on Forecasting Ability			
		Top Third	Middle Third	Bottom Third	Top - Bottom
(73) Business Services	288	74.54	18.90	34.36	40.19
(28) Chemicals and Allied	191	2.97	-4.58	-3.83	6.80
(36) Electrical	186	34.95	36.73	23.30	11.65
(13) Oil & Gas Extraction	175	-10.26	-9.06	-23.65	13.39
(67) Holding & Other Investment Offices	168	-10.25	-7.17	-11.61	1.36
All Industries	2,322	7.72 %	–1.68 %	-3.04 %	10.76 %
(t-statistic)					(2.69)

Table IV
Recommendation Profitability Regressed Against Forecast Accuracy

The coefficient estimates for three regressions are presented. The model estimated from the main (1994-99) and two sub-samples (1994-96 and 1997-99) is the following:

$$PROF_{ik} = \alpha_0 + \alpha_1 PMAFE_{ik} + \alpha_2 DSIZE_{ik} + Industry \text{ dummies} + \varepsilon_{ik}$$

The dependent variable for all regressions is analyst *i*'s relative size-adjusted recommendation profitability, $PROF_{ikt}$. Size-adjustment is achieved by subtracting the CRSP NYSE/AMEX/Nasdaq same-size-decile returns from the recommendation's raw returns., where the average raw profitability is calculated by tracking analyst *i*'s recommendations for firms he rates in industry *k*. Forecast accuracy is measured by $PMAFE_{ik}$, the average of analyst *i*'s $PMAFE_{ijt}$s in industry *k*. $PMAFE_{ijt} = (AFE_{ijt} - \overline{AFE_{jt}}) / \overline{AFE_{jt}}$, where AFE_{ijt} is an aggregate measure of absolute forecast accuracy utilizing 4 salient forecast horizons across the whole fiscal year. $DSIZE_{ikt}$ returns a value of one if analyst *i*'s broker is in the top quartile for the number of analysts that it employs. The *t*-statistics are reported in parentheses below the coefficient estimates. *,**, and *** indicate that the estimates are different from zero at 10%, 5% and 1% levels of significance, respectively.

Coefficient Estimates	Main Sample (1994-99)	Sub-Sample 1 (1994-96)	Sub-Sample 2 (1997-99)
Intercept	-0.187 ***	-0.142 ***	-0.234 ***
	(5.07)	(3.81)	(4.83)
$PMAFE_{ikt}$	–0.158 ***	-0.069 **	-0.165 **
	(2.88)	(2.05)	(2.43)
$DSIZE_{ikt}$	0.050 *	0.028	0.049
	(1.73)	(1.62)	(1.25)
# of Observations	2,322	1,203	1,780
Adjusted R^2	7.30%	2.87%	9.30%
F-statistics	6.90	2.32	7.08
(*p*-value)	(< 0.000)	(< 0.000)	(< 0.000)

Table V
Recommendation Profitability Regressed Against Forecast Accuracy – Robustness Checks

The model estimated from the main (1994-99) and two sub-samples (1994-96 and 1997-99) is the following:

$PROF_{ik} = \alpha_0 + \alpha_1 PMAFE_{ik} + \alpha_2 DSIZE_{ik} + Industry$ dummies $+ \varepsilon_{ik}$

The dependent variable in Panel A is analyst *i*'s market-adjusted recommendation profitability, $PROF_{ikt}$. Market-adjustment is achieved by subtracting the CRSP NYSE/AMEX/Nasdaq value-weighted market index returns from the recommendation's raw returns. FY1 Forecast accuracy is measured by $PMAFE_{ik}$, the average of analyst *i*'s $PMAFE_{ijt}$s in industry *k*. $PMAFE_{ijt} = (AFE_{ijt} - \overline{AFE_{jt}}) / \overline{AFE_{jt}}$, where AFE_{ijt} is an aggregate measure of absolute forecast accuracy. $DSIZE_{ikt}$ returns a value of one if analyst *i*'s broker is in the top quartile for the number of analysts that it employs. The *t*-statistics are reported in parentheses below the coefficient estimates. *,** and *** indicate that the estimates are different from zero at 10%, 5% and 1% levels of significance, respectively. The dependent variable in Panel B is size-adjusted recommendation profitability, where we start tracking the recommendation from day 0 (that is, the day the recommendation appears in the IBES database), instead of day -1 as in the previous analyses.

Panel A: Using Market-Adjusted Recommendation returns

Coefficient Estimates	Main Sample (1994-99)	Sub-Sample 1 (1994-96)	Sub-Sample 2 (1997-99)
Intercept	-0.183 ***	-0.156 ***	-0.219 ***
	(5.02)	(4.24)	(4.51)
$PMAFE_{ikt}$	–0.161 ***	-0.076 **	-0.170 **
	(2.85)	(2.35)	(2.45)
$DSIZE_{ikt}$	0.050	0.032 *	0.042
	(1.54)	(1.84)	(1.05)
# of Observations	2,322	1,203	1,780
Adjusted R^2	7.43%	2.63%	9.43%
F-statistics	7.01	2.20	7.18
(*p*-value)	(< 0.000)	(< 0.000)	(< 0.000)

Panel B: Using Issue Date as the First Date of Recommendation

Coefficient Estimates	Main Sample (1994-99)	Sub-Sample 1 (1994-96)	Sub-Sample 2 (1997-99)
Intercept	-0.200 ***	-0.151 ***	-0.248 ***
	(5.70)	(3.95)	(5.42)
$PMAFE_{ikt}$	–0.134 **	-0.062 *	-0.138 **
	(2.52)	(1.85)	(2.10)
$DSIZE_{ikt}$	0.032	0.019	0.026
	(1.15)	(1.15)	(0.69)
# of Observations	2,322	1,203	1,780
Adjusted R^2	7.21%	2.58%	9.35%
F-statistics	6.82	2.18	7.12
(*p*-value)	(< 0.000)	(< 0.000)	(< 0.000)

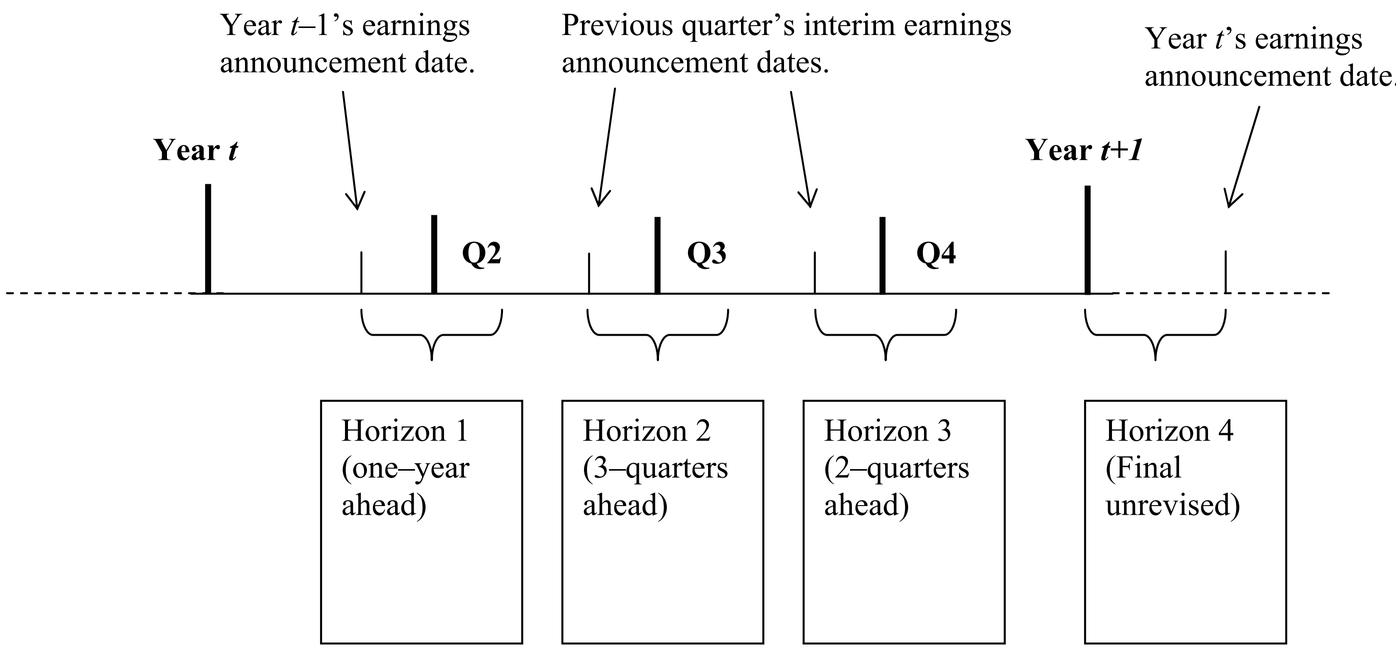

Figure 1. Four Horizons for Measuring Yearly Forecast Accuracy

The timeline illustrates the four forecast horizons chosen for computing an aggregate measure to represent an analyst i's FY1 forecast accuracy for an *entire* fiscal year t. Earnings announcement dates, whether for prior-year earnings or interim quarterly earnings, are denoted by a fine tick mark. Coarse tick marks denote financial year- or quarter-ends. The window periods specified for the first three horizons are 30-day in length for the purpose of mitigating forecast recency effects. Within the window period, the latest forecast outstanding is selected (i.e., nearest to the end of the window). Horizon four is the final unrevised forecast issued just before year t's FY earnings announcement date.