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Earnings Predictability and Bias in Analysts' Earnings Forecasts

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ABSTRACT: This paper examines cross-sectional differences in the optimistic behavior of financial analysts. Specifically, we investigate whether the predictive accuracy of past information (e.g., time-series of earnings, past returns, etc.) is associated with the magnitude of the bias in analysts' earnings forecasts. We posit that there is higher demand for non-public information for firms whose earnings are difficult to accurately predict than for firms whose earnings can be accurately forecasted using public information. Assuming that optimism facilitates access to management's non-public information, we hypothesize that analysts will issue more optimistic forecasts for low predictability firms than for high predictability firms. Our results support this hypothesis.

Key Words: *Earnings forecasts, Earnings predictability, Forecast bias, Forecast optimism.*

Data Availability: *Data are commercially available from the sources identified in the text.*

I. INTRODUCTION

Overview

Financial analysts are an important source of information to stock market participants in the valuation of firms. It has been well established that analysts' earnings forecasts are more accurate (i.e., have smaller unsigned forecast errors) than predictions from

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the past time-series of earnings. For example, Brown et al. (1987) compare the accuracy of analysts to time-series models based on historical earnings data. They attribute analysts' superiority to a timing advantage (more information is publicly available if the forecasts are made after the public announcement dates) and an informational advantage (more information is used by the analysts than historical earnings data). Fried and Givoly (1982) provide evidence that analysts' forecasts errors have incremental value above and beyond errors from time-series models in explaining forecast period returns. Despite analysts' superiority over time-series models, several papers have documented the prevalence of forecast optimism, i.e., forecasts that exceed true earnings (Brown et al. 1985; O'Brien 1988; Butler and Lang 1991). The primary goal of this paper is to further our understanding of analysts' forecasting behavior by investigating a determinant of cross-sectional differences in forecast optimism.

In performing the primary tasks of issuing earnings forecasts and stock recommendations, sell-side analysts can be viewed as providing two broad types of services to the investment community (Schipper 1991). The first is the assimilation and processing of publicly available information, and the second is the acquisition and dissemination of new information. We hypothesize that the demand for additional information is a function of how much information already exists in the public domain (e.g., past earnings, prices), and how reliably future earnings can be predicted from the available public information. If a firm's earnings can be predicted relatively accurately based upon public information, the extent to which additional non-public information improves upon the market's earnings expectation is limited. Consequently, an analyst may be less inclined to expend effort to acquire non-public information (e.g., from the firm's management) for such a firm. In contrast, there is likely to be a greater demand for additional information about firms whose earnings are difficult to predict based upon public information (hereafter, low predictability firms). As a result, the analyst has relatively more to gain from efforts to acquire non-public information for these firms.

In a competitive market for analysts' forecasts, we hypothesize that analysts strive to meet the higher demand for non-public information on low predictability firms. One of the most important sources of non-public information for analysts is corporate management (Financial Executive Research Foundation 1987). There is considerable anecdotal evidence indicating that managers penalize analysts based upon the content of their forecasts by limiting or cutting off analysts' future contact with management (Berg 1990; Laderman et al. 1990; Scism 1993; Dirks and Gross 1974). Mr. Siconolfi, for example, writes "It's a fact of life among Wall Street securities analysts: Bash a company in a research report and brace for the deep freeze. [M]ore and more companies...are lashing out if analysts write negative reports" (Siconolfi 1995). Further, Siconolfi suggests that managers retaliate against bearish analysts by excluding the analysts from mailings, meetings, outings and conference calls with top company executives. The implication is that "positive" reports may facilitate analysts' access to managers and their information (i.e., a *quid pro quo*). If deliberate optimism increases analysts' access to non-public information, and such information is in greater demand for low predictability firms (more likely to lead to revisions of the market's expectations), then a greater degree of analyst optimism will be observed for low predictability firms.

Absent such incentive considerations, we would not expect earnings forecasts to be systematically biased. Forecasts could vary in accuracy across firms, but inaccuracy *per se* does not translate into a bias. Absolute forecast errors may be larger for firms which are hard to predict, but analysts should err equally in both directions (under- and overestimates of future earnings) if they reveal their true, undistorted expectations. However, while biasing a forecast, *ceteris paribus,* reduces accuracy, a biased forecast can be *more* accurate than an unbiased forecast if the former is based on more precise information. In other words, analysts concerned with the accuracy of their predictions will benefit from biasing their forecasts whenever the gains from the consequent information access outweigh the accuracy loss from biasing *per se.* That is, analysts are willing to incorporate optimism into their forecasts because they can be more accurate with the increased information and bias than with unbiased forecasts based solely on public information.

Consistent with our hypothesis, we document a negative association between earnings predictability and forecast optimism. Our results are robust to alternative measures of predictability based on (1) past time-series of earnings, (2) past time-series of earnings and market returns, and (3) Value Line predictability rankings. Finally, our results indicate that although earnings predictability and earnings variability are related, the variability in a firm's earnings stream does not seem to drive the association between predictability and forecast bias.

Prior Research

Several papers address optimism in analysts' forecasts. Francis and Philbrick (1993) examine the hypothesis that forecast bias is driven by analysts' desire to curry favor with management. This management-relations hypothesis underlies our analysis as well. The difference is that Francis and Philbrick (1993) establish a relationship between optimism and the Value Line stock recommendations. They find that analysts incorporate optimism into their forecasts to repair management relations, following sell recommendations. In contrast, we focus on a firm characteristic, i.e., earnings predictability as a potential determinant of analyst forecast bias.

Lin and McNichols (1993) and Dugar and Nathan (1995) provide evidence that analysts exhibit greater optimism for firms that are underwriting and investment banking clients. These papers suggest that the optimism helps the analyst by maintaining/building client relationships. These papers specifically examine settings in which analysts face a conflict between pleasing their firms' clients and issuing accurate forecasts, and provide evidence that the consequent incentives give rise to analyst optimism. In an experimental setting, Hunton and McEwen (1997) also find that underwriting opportunities intensify analysts' tendency to issue optimistic earnings forecasts.[1] In contrast, we focus on situations in which there is no investment banking or underwriting relation, and seek evidence about whether forecast optimism is related to analysts' need to have access to management for the purpose of issuing accurate forecasts. Accordingly, we examine forecasts issued by Value Line analysts, who do not have underwriting or brokerage relations with the firms they follow.

McNichols and O'Brien (1997) suggest an alternative explanation for the existence of *ex post* optimism in analysts' forecasts. They posit that the observed bias in analysts' forecasts is the result of self-selection, whereby analysts with relatively unfavorable information choose to drop out of the pool of forecasters. Hayes (1995) demonstrates that such forecasting behavior can be justified in the presence of commission-based compensation and short-sales restrictions. However, both of the above papers assume that, conditional on forecasting, analysts report their information undistorted. In contrast, our paper belongs to the body of literature that posits the existence of incentives that motivate analysts to issue

[1] Additionally, they demonstrate that the existence of other motivational incentives, such as the promise of continued employment with the same brokerage firm and the continued following of the same firm, also intensify the propensity to issue optimistic forecasts.

forecasts that differ from their true expectations. Specifically, we examine whether earnings predictability is a determinant of this strategic bias.

Kross et al. (1990) examine the cross-sectional determinants of analysts' forecast advantage over that of mechanical time-series models. They measure analysts' forecast advantage as the difference between the absolute forecast error of the mechanical time-series model and the absolute forecast error of Value Line forecasts. They find that the analysts' advantage is positively related to the variance of the time-series model error term and to the amount of coverage in the *Wall Street Journal.* Their result indicates that the relative advantage of analysts over time-series models is greater for firms that have a larger time-series model error variance. Lys and Soo (1995) find that the absolute value of analysts' forecast errors is positively related to the mean absolute forecast error from time-series models and negatively related to firm size and the number of analysts following the firm. They do not find a significant association between analysts' accuracy and the amount of coverage in the *Wall Street Journal.* Together these two studies indicate that firms which are difficult to predict using time-series models are also difficult for analysts to predict, although the relative advantage of analysts over time-series models is greater for firms that have a larger time-series model error variance. Butler and Lang (1991) examine individual analysts' forecasting behavior relative to the consensus. After controlling for earnings variability, they find that individual analysts tend to be systematically optimistic or pessimistic relative to an optimistic consensus. However, on average, there are no systematic differences in the analysts' overall accuracy. In contrast to the above papers, our paper links earnings predictability to forecast bias as opposed to forecast accuracy. Under the premise that managers prefer optimism, our paper tests the hypothesis that analysts issue optimistic forecasts to obtain access to management information in order to enhance forecast accuracy, even with the bias.

The paper proceeds as follows. Section II describes the data and sample selection. In section III, we present our methodology. Section IV presents results and tests of robustness. Finally, section V provides concluding remarks.

II. DATA AND SAMPLE SELECTION

We use forecast data from Value Line Survey. The use of Value Line forecasts is motivated by several factors. First, Value Line is neither a brokerage nor an underwriter, and thus any potential biases in Value Line forecasts cannot be attributed to incentives for promoting security transactions. Second, Value Line analysts report a measure of earnings predictability that is useful for our analysis. Finally, we can partially control for the effects documented in Francis and Philbrick (1993) by using timeliness rankings provided by Value Line.

Following prior work on this topic, we restrict our attention to December year-end firms (e.g., see O'Brien 1988; Francis and Philbrick 1993). To obtain Value Line forecast data, we first select a sample of 785 December year-end firms, by choosing, sequentially, one out of every three December year-end firms from the 1994 annual Compustat Primary, Supplementary and Tertiary data tapes. We are able to acquire forecast data from Value Line for 605 of these firms for the period 1989–1993. We require complete forecast data for the firms in order to estimate bias for each firm, and therefore eliminate 137 firms for which forecasts are missing during the period 1989–1993. For the remaining 468 firms, we require that annual earnings-per-share data (annual data item #58) and related information be available for all years between 1969 and 1994, and that quarterly earnings-per-share data (quarterly data item #19) and related information be available for *all* years between 1979 and 1994. We impose these stringent requirements to ensure that there are enough observations to estimate time-series expectation models of annual earnings per share. This requirement reduces the sample size to 274 firms.

For each firm, the data set provided by Value Line contains four forecasts per year. We refer to these forecasts as Horizon 1, Horizon 2, Horizon 3 and Horizon 4 forecasts, respectively. The Horizon 1 forecast is the forecast issued the farthest from the fiscal year-end and the Horizon 4 forecast is the closest to the fiscal year-end. We examine the forecasting behavior on a horizon-by-horizon basis following Kang et al. (1994), who document a horizon effect in forecast bias. We are able to extract the price and returns data from the CRSP database for all of these firms. We access the I/B/E/S database for a measure of the number of analysts following each firm. This information is available for 241 out of the 274 firms. Our final sample size is 239 firms because the timeliness ranking is missing for two firms.

In table 1, we list industries (two-digit SIC code) that are represented by more than ten firms in the sample, along with the percentage of firms belonging to these industries in the Compustat Primary, Supplementary and Tertiary database. Relative to Compustat, our sample exhibits especially high concentrations for Plastics, Pharmaceuticals & Chemicals (SIC two-digit code 28), Machinery & Equipment, and Electrical, Electronics & Appliances (SIC two-digit codes 35 and 36), and Utilities (SIC two-digit code 49). This prompts us to examine whether these concentrations affect our results.

III. RESEARCH DESIGN

To the extent that historical earnings and other public information allow analysts to make fairly accurate predictions of annual earnings, there is less need to obtain private

TABLE 1
Industries Represented by Ten or More Firms in the Sample
Sample size = 274 firms

Two-Digit SIC code	*Industry Name*	*Number of Firms*	*Percentage[a] of Sample*	*Percentage[b] in Compustat*
20	Food and Kindred Products	10	4	2
26	Paper	17	6	1
28	Plastics, Pharmaceuticals & Chemicals	32	12	4
29	Petroleum Refining, Paving and Roofing Materials	14	5	1
33	Iron & Steel Metal	11	4	2
35	Machinery & Equipment	22	8	3
36	Electrical, Electronics & Appliances	16	6	3
49	Utilities	51	19	6

[a] All percentages rounded off to the nearest integer.
[b] Percentages of firms in the 1995 Annual Primary, Supplementary and Tertiary Compustat database.

information for that purpose. In contrast, when future earnings are difficult to predict using information available in the public domain, there is more scope for non-public information to improve the accuracy of such predictions. The management-relations hypothesis posits that analysts' access to non-public information may depend on analysts' willingness to provide optimistic forecasts in order to maintain relations with managers who provide that information. Taken together, the greater demand for information for low predictability firms, and the necessity of biasing forecasts to gain access to that information implies an inverse relationship between earnings predictability and an optimistic bias in analysts' forecasts. In this section, we describe the procedure to examine this relationship.

We denote the analysts' forecast bias as BIAS and the degree to which earnings are difficult to predict as UNPRED and consider their relationship within the following cross-sectional regression (firm subscripts suppressed):

$$\begin{aligned}\text{BIAS} = {} & a_0 + a_1(\text{UNPRED}) + a_2(\text{FOLLOWING}) + a_3(\text{SIZE}) \\ & + a_4(\text{FOLLOWING*UNPRED}) \\ & + a_5(\text{SIZE*UNPRED}) + a_6(\text{TIMELY}) + \varepsilon. \qquad (1)\end{aligned}$$

We devote the remainder of this section to defining the variables in equation (1) and describing their measurement.

Forecast Optimism (BIAS)

The dependent variable, BIAS, is measured using analyst forecast errors in the period between 1989 and 1993. Specifically, we compute BIAS in horizon n as (suppressing firm subscript):

$$\text{BIAS}_n = \frac{1}{N_n} \Sigma_{t=89}^{93} \frac{A_t - AF_{nt}}{P_t}, \qquad (2)$$

where N_n is the total number of forecasts corresponding to Horizon n in the test period (1989–1993). A_t denotes the annual earnings realization (EPS) for year t, AF_{nt} is the analyst forecast over Horizon n in year t. A negative value of BIAS indicates average optimism for a particular firm over the test period. The stock price, P_t, is used as the scaling variable. In the absence of deliberate optimism, we expect Value Line forecast bias to be zero. Of course, since analysts' forecasts are estimates, the realized forecast error each year will differ from zero. Our variable of interest is the systematic forecast bias that persists over a given period. This bias is best captured by the mean forecast error over time.[2]

Earnings Predictability (UNPRED)

Our objective is to develop a measure of the *inherent* earnings predictability of a firm. Our primary measure, UNPRED, reflects how difficult it is to predict a firm's future earnings from historical earnings information. Because past earnings information is a subset of public information, and our theoretical arguments are based upon a predictability measure conditioned upon all public information, we will examine the sensitivity of our results to two

[2] Further, using the BIAS variable without averaging would also introduce serial correlation in the error terms, affecting the standard errors of the coefficient estimates. A similar averaging procedure is found in Lys and Soo (1995).

additional measures of earnings predictability. The results using these alternative measures are presented in a later section.

In order to understand our primary measure of annual earnings predictability, it is important to recognize that the set of public information available to make predictions changes as the fiscal year progresses and this difference in information availability will affect measured predictability. For example, predictability of annual earnings, measured in the first quarter of a fiscal year, is likely to differ from predictability measured in the last quarter because more public information is available to condition the prediction as time passes. Given our focus on the strategic information acquisition behavior of a financial analyst, we are not interested in this "horizon" effect. Thus, we estimate earnings predictability at different points in time during the course of a fiscal year (i.e., after each quarter) and use these estimates to develop a composite or average measure that captures the underlying common predictability component in these estimates.

We estimate this composite measure using the forecast errors from time-series models. We realize that, absent knowledge of the true time-series process underlying earnings, any chosen time-series model will measure predictability from historical earnings with error. Such misspecification errors will result in earnings appearing less predictable than they actually are, reducing the power of tests of association between predictability and forecast bias. One approach to mitigating this loss of test power is to generate multiple time-series predictions, using a variety of models that assume different structures, and select the model that predicts the earnings of a firm most accurately for each horizon.

Motivated by these considerations, we use a three-step approach to measure predictability of earnings from historical earnings data.

1. We use three annual and two quarterly time-series models to generate predictions over different horizons for a given year. These models are described in the appendix.
2. For each individual model, we construct an accuracy metric using predictions generated by these models for the measurement period earnings (1983–1988), and choose the model that predicts earnings most accurately over each horizon, giving one model for each firm for each horizon. Accuracy is the extent to which a prediction is "close" to the true value, without attaching significance to the direction of the prediction error. We measure accuracy as the absolute value of the difference between the prediction and the actual earnings, deflated by year-end share price.
3. We perform a principal component analysis using, as factors, absolute prediction errors (accuracy) corresponding to each horizon in the measurement period (using the model chosen in Step 2 for that horizon). As an example, consider firm j in Horizon 1. Suppose that the model chosen in Step 2 above for firm j is the submartingale model. Horizon 1's factor is calculated as the absolute value of the difference between the submartingale model's prediction for firm j and firm j's actual earnings, deflated by share price.

   This procedure yields six observations per firm for each factor, covering the six years in the measurement period. We construct four distinct factors corresponding to the four horizons. We stack these observations for all firms in our sample to perform the principal component analysis.[3] For each firm, we use the average of the first principal component scores over the measurement as an estimate of its inherent earnings predictability (UNPRED). High values of UNPRED indicate earnings that are difficult to predict accurately using these time-series models.

We refer the reader to the appendix, for specific details on this three-step procedure.

Our hypothesis predicts a negative coefficient on the variable UNPRED, ($a_1 < 0$), i.e., the higher the value of UNPRED, the lower the earnings predictability and thus the more negative the forecast bias (i.e., the greater the forecast optimism).

Analyst Following (FOLLOWING)

We control for the impact of analyst following on forecasting behavior. Bhushan (1989) and O'Brien and Bhushan (1990) suggest that analyst following is determined by firm size and degree of institutional holdings, but do not examine how analyst behavior is influenced by the number of analysts following a firm or vice versa. It can be argued that analysts can extract higher rents by following less predictable firms because the demand for non-public information is the highest for these firms. If issuing optimistic forecasts facilitates attaining non-public information (as we hypothesize), there would be a negative relationship between forecast bias and analyst following. Furthermore, a large analyst following for a given firm suggests greater competition among analysts, which may also influence the level of bias. We use the average number of analysts, over the period 1989–1993 reported in the I/B/E/S summary tape, as the measure of analyst following.

Firm Size (SIZE)

We include a control for firm size (SIZE) for two related reasons. First, firm size has often been used as a proxy for the amount of information that is publicly available about a firm. Relative to smaller firms, larger firms are typically more closely watched by the investment community and there is a greater amount of public information available. This implies that market participants can better assess the future performance of larger firms and that there would be smaller bias for larger firms. Therefore, we include the variable SIZE to ensure that our inferences regarding the association between predictability and forecast bias are not driven by firm size. Second, Bhushan (1989) finds that size and analyst following are related—larger firms are, on average, followed by more analysts than are smaller firms. If analyst following influences forecast bias, independent of size considerations, including SIZE increases the explanatory power of the regression by controlling for the component of analyst following that is highly correlated with size, but uncorrelated with forecast bias (Brown et al. 1987). As in Bhushan (1989), we use the logarithm of average year-end market value over the test period as our SIZE measure.

Interaction Variables (FOLLOWING*UNPRED and SIZE*UNPRED)

To the extent analyst following for a low predictability firm is systematically different from the analyst following for a high predictability firm, the influence of UNPRED on BIAS is likely to be systematically different for firms with different levels of analyst following. For example, the influence of UNPRED on BIAS could be lower for firms with greater analyst following because each individual analyst's incentive to engage in optimism

[3] Performing the principal component analysis in this cross-sectional fashion restricts factor loadings to be the same for all firms. We make this restriction because we have only a few observations for each firm. This restriction adds noise to our construction of the measure for inherent earnings predictability that is likely to bias the results against finding the hypothesized association between predictability and forecast bias.

may be less pronounced. To capture such potential interactions, we include the interaction variable FOLLOWING*UNPRED. In a similar vein, if earnings predictability and firm size are related, then the influence of UNPRED on BIAS will vary with firm size. That is, if larger firms are, on average, more mature and thus have more predictable earnings than smaller firms, then the relationship between UNPRED and BIAS will be different across firm size. To capture this effect we introduce the variable SIZE*UNPRED into our analysis.

Value Line Stock Recommendations (TIMELY)

Using Value Line forecast data, Francis and Philbrick (1993) document that analysts are more likely to follow sell recommendations with subsequent forecasts that are more optimistic than the forecasts that follow buy or hold recommendations. They interpret this evidence as consistent with analysts using forecast optimism to repair management relations. To control for the portion of optimistic bias that may be driven by mending motives, we include the average timeliness ranking (TIMELY) issued by Value Line over the test period (1989–1993) as an explanatory variable. The Value Line timeliness ranking is an ordinal rank on a scale of 1 to 5, with 1 indicating a strong buy and 5 indicating a strong sell. However, we caution the reader that this measure is an approximate control, since the lagged nature of the association between the stock recommendation and the period-specific forecast bias is central to the Francis and Philbrick (1993) inquiry. We are unable to capture this lagged effect more appropriately because we measure systematic forecast bias as the mean forecast error over the test period.

IV. RESULTS

Table 2 provides descriptive statistics on key variables. Table 2 indicates that the average forecast error is negative (indicating optimism) for all four horizons.[4,5] The percentage of observations with negative forecast errors is far greater than the percentage with positive forecast errors. In particular, approximately 60 percent of the observations are negative for Horizons 1 and 4, while approximately 70 percent of the observations are negative for Horizons 2 and 3. The null hypothesis that the average forecast error is zero is rejected for all four horizons.

The Pearson correlation coefficients (not reported in table 2) indicates that FOLLOWING and SIZE are highly, positively correlated ($\rho = 0.70$; $p < 0.01$), consistent with the results of Bhushan (1989). However, neither FOLLOWING nor SIZE are significantly correlated with the earnings predictability measure, UNPRED.

We estimate equation (1) using the mean of each variable over the test period (1989–1993) except for UNPRED. Recall that UNPRED is estimated using data from the measurement period (1983–1988; see previous section and the appendix). In doing so, we assume that predictability of firms remains unchanged from the measurement period to the test period (1989–1993). As described earlier, forecast bias (BIAS) is measured as the mean of the difference between actual earnings and analysts' forecasts over the test period.

[4] We computed the forecast errors in a manner similar to Francis and Philbrick (1993), who examine undeflated forecast errors as well as forecast error as a percentage of actual earnings over the period 1987–1989. The mean and median forecast errors in our sample over a comparable horizon for this period is slightly higher (on average, across all four horizons, forecasts exceed actual earnings realizations by 25 cents per share or 15 percent of actual EPS) but of the same order of magnitude.

[5] In computing the statistics for inference, we use a fixed-effects model similar to O'Brien (1988) to control for potential cross-sectional correlations in forecast errors induced by unanticipated time-period specific economy-wide shocks. We also purge out effects specific to Pharmaceutical, Machinery and Electrical, and Utilities, industries owing to sample concentration in these industries.

TABLE 2
Descriptive Statistics (computed for the period 1989–1993)
Sample size = 239–274 firms (1195–1370 firm-year observations)

Variable Name[a]	*Mean*	*Median*	*Std. Dev.*	*Min.*	*Max.*	*% of Obs. with Negative Values*
ASSETS ($ in millions)	8124	2144	22119	33	251506	NA
BIAS:						
Horizon 1	−0.030***	−0.005	0.141	−2.670	0.887	60.35†
Horizon 2	−0.035***	−0.007	0.127	−2.528	0.656	72.24†
Horizon 3	−0.027***	−0.004	0.122	−2.442	1.435	69.67†
Horizon 4	−0.015***	−0.001	0.093	−2.442	0.635	62.17†
UNPRED	−0.086	−0.126	0.173	−0.248	0.919	NA
FOLLOWING[b]	23	22	15	1	61	NA
SIZE ($ in millions)	4073	1367	8037	12	89527	NA
TIMELY	3.109	3	0.826	1	5	NA

*** Significant at the one percent level. This significance is computed after controlling for potential cross-sectional correlation induced by period-specific economy-wide shocks. Specifically, a fixed-effect model incorporating an effect for each calendar year in the sample is used to purge year-specific effects in computing the significance statistic.

† Significant at the one percent level. Statistical significance is computed by assuming an unconditional probability of observing a negative forecast error of 0.5, and using the normal approximation to a binomial distribution.

[a] Variable definitions:

ASSETS = total assets (Compustat data item #6).

BIAS = average signed forecast error, computed as actual EPS realization as reported by Value Line less forecast divided by year-end share. Horizon 1 refers to the time period between the date of the first Value Line forecast issued for a fiscal year and the end of that fiscal year. Horizons 2, 3 and 4 are defined similarly with respect to the first Value Line forecast issued after the end of the first, second and third fiscal quarters, respectively.

UNPRED = this variable is based on a principal component analysis using the absolute prediction errors for the period 1983–1988 from four time-series predictability metrics as factors. The principal component analysis is conducted cross-sectionally. For each firm, the first component scores are averaged over this period to yield a value for UNPRED. High values of UNPRED indicate that earnings are difficult to predict using time-series models. The time-series models are estimated using data from the period 1969–1982 (see the appendix for details).

FOLLOWING = average number of analysts following a given firm in the period 1989–1993, as reported in I/B/E/S summary tape.

SIZE = logarithm of the average market value of equity for the period 1989–1993. Market value of equity computed by multiplying year-end outstanding shares (Compustat data item #25) with closing share price (Compustat data item #24).

TIMELY = mean Value Line timeliness ranking over the test period (1989–1993). The Value Line timeliness ranking ranges from 1 to 5, with a rank of 1 representing a strong buy recommendation and a rank of 5 representing a strong sell recommendation.

Table 3 presents results from estimation of equation (1). The null hypothesis that the coefficient of UNPRED equals zero is rejected for all four horizons. As predicted, this coefficient is negative (at the five percent levels or below) in each horizon. This coefficient ranges from −0.076 in Horizon 1, to the most negative value of −0.135 in Horizon 3. The estimated coefficient of FOLLOWING is insignificant in all four horizons. The null hypothesis that the coefficient of SIZE equals zero is rejected for Horizons 3 and 4. A positive coefficient of SIZE in these horizons implies that forecast optimism is less for larger firms, which is consistent with the argument that there is less incentive for the analyst to engage in deliberate optimism for larger firms. The interaction term UNPRED*SIZE is not significant in any horizon. However, the interaction term UNPRED*FOLLOWING is significant in Horizons 3 and 4. Because the main effect of predictability on bias (as represented in the coefficient on UNPRED) and this interactive effect are opposite in direction, the overall effect of unpredictability on bias is not immediately clear for these two horizons. A closer examination of the results pertaining to Horizon 3 indicates that the incremental effect of

TABLE 3
Association Between Earnings Predictability and Analysts' Forecast Bias

Regression: $BIAS = a_0 + a_1(UNPRED) + a_2(FOLLOWING) + a_3(SIZE) + a_4(UNPRED{*}FOLLOWING) + a_5(UNPRED{*}SIZE) + a_6(TIMELY) + \varepsilon$

Independent Variable[a]	Horizon 1	Horizon 2	Horizon 3	Horizon 4
Intercept (a_0)	~0.000 (0.02)[b]	−0.017 (−0.69)	−0.024 (−1.06)	−0.024 (−1.27)
UNPRED (a_1)	−0.076 (−2.01)**	−0.124 (−3.25)***	−0.135 (−3.91)***	−0.128 (−4.54)***
FOLLOWING (a_2)	~−0.000 (−0.32)	~0.000 (0.61)	~0.000 (0.32)	~0.000 (0.68)
SIZE (a_3)	0.003 (0.87)	0.005 (1.50)	0.007 (2.18)**	0.006 (2.20)**
UNPRED*FOLLOWING (a_4)	~0.000 (0.11)	0.002 (1.28)	0.003 (2.00)**	0.003 (2.56)**
UNPRED*SIZE (a_5)	0.001[c] (0.61)	~0.000 (0.36)	~0.000 (0.09)	~0.000 (0.04)
TIMELY (a_6)	−0.017 (−2.67)***	−0.019 (−3.14)***	−0.018 (−3.07)***	−0.013 (−2.62)
R-squared	0.05	0.09	0.10	0.11
F-statistic	3.18***	5.07***	5.49***	6.07***
Observations	239	239	239	239

*,**,*** significant at ten, five and one percent levels, respectively.
[a] All variables are as defined in table 2. The variable SIZE is used in logarithmic form.
[b] t-statistic reported in parenthesis.
[c] Times 10^{-3}.

predictability on bias is given by $-0.135 + 0.003$*FOLLOWING (taking the partial derivative of equation (1) with respect to UNPRED for this horizon). The mean (median) value of this incremental effect is -0.064 (-0.069), which is negative and significant ($t = -22.86$, $p < 0.01$). Further, only 21 out of 239 sample firms show a positive incremental effect. Thus, the overall relationship between bias and predictability is negative. A similar argument holds for Horizon 4.

Because of the high degree of correlation between FOLLOWING and SIZE, we conduct collinearity diagnostics, which suggest that multicollinearity does not present a severe problem in our analysis.[6] Finally, the null hypothesis that the coefficient of TIMELY equals zero is rejected for all four horizons. In particular, this coefficient is negative in all four horizons. Since a high value of TIMELY indicates "strong sell" recommendation, a negative coefficient on TIMELY suggests more pronounced (BIAS is more negative) forecast optimism for sell as opposed to buy recommendations. This finding is consistent with the results of Francis and Philbrick (1993).

We examine the impact of extreme observations on our results by winsorizing all variables at the 99th percentile level. Results are materially the same. We also examine how industry concentration affects our results. Referring to table 1, our sample is characterized by a concentration in Pharmaceuticals, Manufacturing and Utilities industries. Therefore, we allow both intercept as well as the slope coefficient of the variable UNPRED in equation (1) to be different for these three industries. The null hypothesis that the coefficient of UNPRED equals zero is rejected for all four horizons (at similar levels of significance as table 3). This coefficient ranges from -0.066 in Horizon 1, to a maximum of -0.131 in Horizon 3. The intercept and slope dummies corresponding to the Pharmaceutical and Utilities industries are not significantly different from zero for all four horizons, indicating that the association between BIAS and UNPRED for these industries is similar to that for the entire sample. For the manufacturing industry, both slope and intercept coefficients are significant and negative for all horizons except Horizon 1, which indicates that the negative association between BIAS and UNPRED is more pronounced for our sample firms in this industry.[7]

Overall, we find evidence consistent with the hypothesis that analysts' forecast bias is more pronounced for firms with less predictable earnings. This result provides empirical support to the notion that the accuracy of prediction based on publicly available past information is associated with the degree of optimism in analysts' forecasts. In the case of firms whose earnings can be reliably predicted (relatively speaking) from past information, analysts do not need to access information controlled by managers to improve accuracy. However, such is not the case for firms whose earnings cannot be reliably predicted by time-series models. For these firms, analysts have more impact on the market's expectations and may deliberately bias forecasts to build better management relations and, in turn, derive informational benefits. In the next section, we test the robustness of our results to alternative specifications of earnings predictability.

Alternative Earnings Predictability Measures

In the previous section, we measured earnings predictability using the historical time-series of earnings. In this section, we test the robustness of this result to alternative specifications of predictability.

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[6] The largest condition index of 19.69 is well below the upper bound of 30 (Belsey et al. 1980, 105).

[7] The intercepts for the manufacturing industry are -0.014 ($t = -1.18$), -0.027 ($t = -2.33$, $p < 0.05$), -0.029 ($t = -2.79$, $p < 0.01$) and -0.023 ($t = -2.71$, $p < 0.01$) for Horizons 1, 2, 3 and 4, respectively. The corresponding slope coefficients are -0.066 ($t = -0.98$), -0.118 ($t = -1.74$, $p < 0.10$), -0.127 ($t = 2.07$, $p < 0.05$), -0.085 ($t = -1.71$, $p < 0.10$).

First, we include a security price-based metric as an additional factor in the principal component analysis, along with time-series-based metrics of the previous section. Security price movements in a period reflect information about current and future prospects, and such movements are public information that can be used to predict future earnings. Collins et al. (1987) demonstrate that the cumulative abnormal returns over a given year explain 59 percent of the variation in the percentage change in earnings in the next period. Based on this evidence, we use the change in the security price over a given period as the predictor for change in earnings in the subsequent period. Specifically, we estimate the following model:

$$\frac{CEPS_{t+1}}{|EPS_{t+1}|} = \gamma_{0t} + \gamma_{1t}PCPR_t + \kappa^j_{t+1} \tag{3}$$

where $CEPS_{t+1}$ is the change in earnings per share over period t + 1, the denominator is the absolute value of earnings, and $PCPR_t$ is the percentage change in price in period t (inclusive of period t dividends). Period t is defined from April 1 of year t, to March 31 of year t + 1. We chose this period to ensure that the returns reflect year t's financial statement information for all firms (Elgers and Murray 1992). We estimate equation (3) on a firm-by-firm basis, using all data available prior to the period being predicted (i.e., from 1969 to year t − 1). Since our measurement period begins in 1983, we have a minimum of 13 observations for each regression. The parameter estimates are then used to arrive at the predicted change in EPS. The return model accuracy metric is computed for each year in the measurement period (1983–1988) as:

$$RMACC^j_t = \left|\frac{CEPS^j_t}{EPS^j_t} - RETPRED^j_t\right|, \ t = 1983,.., 1988. \tag{4}$$

where CEPS is the actual change in EPS and RETPRED is the predicted change in EPS using the return model given by equation (3). This measure is included as an additional factor in the principal component analysis used to construct the UNPRED variable (see section III and the appendix). The analysis of table 3 is then repeated using this UNPRED construct. Results are qualitatively the same as in table 3 and therefore not reported.

A second candidate for measuring a firm's predictability is the Value Line predictability ranking. Value line constructs a firm-specific index of predictability that ranges from 5 to 100 (unpredictable to predictable). If the Value Line predictability ranking measures the extent to which analysts can benefit from developing relations with firms' management, then there is likely to be a positive association between the predictability ranking and the extent of forecast bias. A limitation in using the Value Line predictability ranking is that these rankings vary from year to year for some firms. For consistency with our previous analysis, we calculate UNPREDV as 100 minus the average Value Line predictability ranking over the test period (1989–1993). Then, using UNPREDV as a measure of predictability, we hypothesize a negative relationship between UNPREDV and forecast bias. Table 4 presents the results replicating our analysis, using UNPREDV in place of the earlier UNPRED measure.

The explanatory power of the regressions is much higher with the Value Line predictability measure as indicated by higher adjusted R-squared values in table 4 relative to table 3. The results in table 4 are, however, subject to the caveat that the Value Line predictability ranking itself is a *reported* measure, and is potentially subject to strategic behavior.

Table 4 indicates the same, strong negative association between bias and predictability for all four horizons that is displayed in table 3. Thus, the major finding of a negative

TABLE 4
Association Between Value Line Based Earnings Predictability and Analysts' Forecast Bias

Regression: $BIAS = a_0 + a_1(UNPREDV) + a_2(FOLLOWING) + a_3(SIZE) + a_4(UNPREDV*FOLLOWING) + a_5(UNPREDV*SIZE) + \varepsilon$

Independent Variable[a]	Horizon 1	Horizon 2	Horizon 3	Horizon 4
Intercept	0.043	0.054	0.046	0.037
(a_0)	(1.61)[b]	(2.07)***	(1.87)*	(1.79)*
UNPREDV	−0.001	−0.001	−0.001	−0.001
(a_1)	(−4.41)***	(−6.24)***	(−5.76)***	(−5.15)***
FOLLOWING	−0.001	−0.001	−0.001	−0.001
(a_2)	(−1.04)	(−1.11)	(−1.38)	(−1.76)*
SIZE	0.001	0.001	0.002	0.002
(a_3)	(0.26)	(2.09)**	(0.61)	(0.72)
UNPREDV*FOLLOWING	0.009[c]	0.010[c]	0.014[c]	0.016[c]
(a_4)	(1.22)	(2.09)**	(2.11)**	(2.86)**
UNPREDV*SIZE	~−0.000	~−0.000	~−0.000	~−0.000
(a_5)	(−0.93)	(−0.50)	(−0.16)	(−0.21)
TIMELY	−0.010	−0.012	−0.011	−0.009
(a_6)	(−0.93)	(−1.95)**	(−1.91)***	(−1.84)*
R-squared	0.16	0.26	0.22	0.14
F-statistic	8.45***	14.94***	12.18***	7.5***
Observations	239	239	239	239

*, **, *** significant at ten, five and one percent levels, respectively.
[a] Variable definitions:
UNPREDV = 100 − mean Value Line predictability score over the test period (1989–1993). We subtract the Value Line predictability score from 100 to make the sign of UNPREDV consistent with the sign of UNPRED in table 3.
All other variables are defined in table 2.
[b] t-statistic reported in parenthesis.
[c] Times 10^{-3}.

association between bias and predictability is robust to different measures of predictability. The coefficient on the variable TIMELY is also negative and significant in three of four horizons while it is negative and significant in all four horizons in table 3. The null hypothesis that the coefficient of SIZE is zero is rejected for only Horizon 2 in table 4, but for Horizons 3 and 4 in table 3. The null hypothesis that the coefficient on UNPREDV*FOLLOWING is zero is rejected for Horizons 2, 3 and 4 in table 4, while the coefficient on the related interaction term in table 3 is significant in two of the four horizons. As in table 3, the main effect and interactive effect are in opposite directions. An analysis similar to that presented for table 3 indicates that the *overall* relationship between UNPREDV and BIAS is negative.

Predictability vs. Variability

Earnings variability and earnings predictability conditioned on public information are distinct concepts.[8] Consider an earnings stream with a large seasonal component. Although earnings may be highly variable, they are easy to predict with knowledge of the seasonal pattern. Nonetheless, we note that predictability and variability are likely to be associated and we examine whether variability, rather than predictability, may be driving our results. We measure earnings variability as the coefficient of variation of the change in annual earnings using the entire history of annual earnings before the test period (i.e., the period 1969–1988).[9] The Pearson correlation coefficient between UNPRED (as used in table 3) and variability is 0.32. This correlation suggests that predictability and variability are related. However, variability shows no association with BIAS in any of the four horizons. The Pearson correlations between variability and BIAS at horizons 1, 2, 3 and 4 are 0.03, −0.01, −0.01 and −0.01, respectively. This correlation structure provides assurance that forecast bias is not a statistical artifact of cross-sectional differences in variability. We also include the coefficient of variation variable as an explanatory variable in the basic regression model. The results remain qualitatively the same as in table 3.

V. CONCLUSIONS AND LIMITATIONS

Research to date on financial analysts' forecasts of earnings suggests that analysts, on average, are optimistic. In this paper, we examine whether the predictability of earnings based on past information is a determinant of the cross-sectional differences in forecast bias. The motivation for examining such a relationship is based on the premise that if market participants can form relatively accurate expectations independent of analysts' forecasts, analysts gain little by issuing deliberately biased forecasts. On the other hand, firms characterized by low earnings predictability offer the greatest opportunities to improve upon the market's earnings expectations. Thus, we hypothesize that analysts have greater incentives to seek and acquire non-public information for low predictability firms. If issuing biased forecasts facilitates such information acquisition, analysts will overstate earnings more for firms that are hard to predict using publicly available information. Consistent with this hypothesis, we find that analysts' forecasts contain significantly more bias for low predictability firms. This result is robust to the choice of several alternative measures of the earnings predictability.

One limitation of our study is the assumption implicit in our demand-based argument that the inherent predictability of firms is stationary over time. This assumption underlies our use of the time-series-based predictability measure, UNPRED. We have no reason to believe that a violation of this assumption would affect the association between bias and predictability in any systematic way, but is likely to result in a noisier measure of predictability. However, we note that our hypothesis is still supported when we use the Value Line predictability measure, UNPREDV, which is not subject to stationarity concerns. A second limitation of our study is the potential impact of survivorship bias. Only surviving firms make it into our sample because we require a long time-series of earnings for our analysis. Thus, our analysis may not generalize to non-surviving firms.

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[8] In our sample, Hilton Hotels (CUSIP = 432848) exhibits high predictability and high variability. In contrast, Monsanto Co. (CUSIP = 611662) exhibits low predictability (as measured by UNPRED), but high variability.

[9] The absolute value of the coefficient of variation is simply the standard deviation scaled by the absolute value of the mean.

APPENDIX

In this appendix, we provide a detailed description of how we estimate the predictability (UNPRED) measure.

We employ the following time-series models.

Annual models:

$$\text{Annual Random Walk: } A_t = A_{t-1} + \varepsilon_{1t}$$
$$\text{Submartingale Model: } A_t = A_{t-1} + C_t + \varepsilon_{2t}$$
$$\text{Autoregressive Model: } A_t = \phi_0 + \phi_1 A_{t-1} + \varepsilon_{3t}$$

Quarterly models:

$$\text{Seasonal Random Walk: } Q_t = Q_{t-4} + \varepsilon_{4t}$$
$$\text{Foster Model: } Q_t - Q_{t-4} = \phi_3(Q_{t-1} - Q_{t-5}) + \varepsilon_{5t}$$

where A_t and Q_t represent annual earnings per share and quarterly earnings per share for year/quarter t, respectively, C_t is the average growth in EPS computed over years t − 5 to t − 1, and the error terms represent white noise. As in O'Brien (1988), these quarterly models are chosen because of their relative simplicity.

To obtain predictions for a given year t, we estimate the various parameters using all available data from 1969 to year t − 1. For example, to predict the annual earnings for the year 1983, the first year in our measurement period, we use the time-series of earnings from 1969 to 1982 to estimate the annual models (minimum of 14 years), and from 1979 to 1982 to estimate quarterly models (minimum of 12 quarters). We construct predictions for annual earnings from quarterly models by aggregating the realized earnings of elapsed quarters in the year and the predictions for the remaining quarters.

Based on the above time-series models, we develop predictions over four horizons: the annual horizon (Horizon 1), and horizons spanning the last three, two and one quarters (Horizons 2, 3 and 4) respectively. Since Horizon 1 forecasts are issued before the end of the first fiscal quarter, we estimate three annual models and two quarterly models for Horizon 1. However, Horizons 2, 3 and 4 forecasts are issued after the release of first, second and third quarters, respectively. Therefore, we use only quarterly models for these horizons. We use the period from 1983 to 1988 (the *measurement* period) to estimate earnings predictability over each of these horizons and then develop a composite measure. The measurement period is distinct from the *test* period (1989–1993) we use to examine the association between predictability and forecast bias.

For each time-series model, we calculate the standardized absolute prediction error metric as:

$$TSACC^{j}_{nt} = \frac{|A^{j}_{t} - TS^{j}_{nt}|}{P^{j}_{t}} \qquad \text{for } n = \{1,2,3,4\}$$

where A^{t}_{j} is the actual earnings realization for year t, firm j, TS^{j}_{nt} is the time-series prediction for year t, firm j and horizon n, and P^{j}_{t} is the year end share price for year t, firm j. For each time-series model, we compute the mean accuracy over the measurement period (1983–1988), $MTSACC^{j}_{n}$, as:

$$\text{MTSACC}^j_n = \frac{1}{6}\sum_{t=83}^{t=88} \text{TSACC}^j_{nt}.$$

Note that there are 11 measures of MTSACC for each firm, five for Horizon 1 from the three annual time-series models, two each for Horizons 2, 3 and 4 from the two quarterly models. We use the "best" time-series model for each horizon as identified by the smallest value of MTSACC for that horizon. This procedure gives us the one time-series model for each firm over each horizon that best approximates the time-series of earnings from among the models we have considered.

Next, using a principal component analysis, we seek a linear combination of time-series prediction errors over the four horizons that best captures the correlated component amongst them. In particular, to derive this principal component, we use the time-series prediction errors (TSACC) for the period 1983 to 1988, using the model chosen for each of the four horizons for a given firm.[10] Correlations among these prediction errors are highly positive and significant, and range from 47 to 95 percent. We pool data (in the period 1983 to 1988) across firms to compute the weights.[11] The principal component analysis yields the following linear combination for the first principal component (suppressing the firm subscript).

$$\begin{aligned}\text{FIRSTCOMP}_t = {} & 0.51(\text{TSACC}_{1t}) + 0.41(\text{TSACC}_{2t}) \\ & + 0.54(\text{TSACC}_{3t}) + 0.53(\text{TSACC}_{4t}).\end{aligned}$$

We note that FIRSTCOMP_t is standardized to have mean zero and unit variance, and accounts for 81 percent of the total variation in the original variables.[12]

Then, we calculate firm j's inherent predictability as the mean of its first principal component scores:

$$\text{UNPRED}^j = \frac{1}{6}\sum_{\tau=1}^{6} \text{FIRSTCOMP}^j_\tau.$$

[10] Thus, it is possible that for a given firm, different time-series models may be chosen for different horizons in deriving the principal component.

[11] While it would be ideal to conduct this analysis at the firm level, we have only six observations (for the period between 1983 to 1988) for each firm.

[12] In contrast, the second principal component, which by design is orthogonal to the first component, explains only 15 percent of the remaining variation.

REFERENCES

Belsley, D., E. Kuh, and R. Welsch. 1980. *Regression Diagnostics.* New York, NY: John Wiley & Sons.

Berg, E. 1990. Risks for the analysts who dare to say sell. *New York Times* (May 15): C1–C6.

Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* 11: 255–274.

Brown, L., P. Griffin, R. Hagerman, and M. Zmijewski. 1987. An evaluation of alternative proxies for market's assessment of unexpected earnings. *Journal of Accounting and Economics* 9: 159–193.

Brown, P., G. Foster, and E. Noreen. 1985. *Security Analyst Multi-Year Earnings Forecasts and the Capital Market.* Sarasota, FL: American Accounting Association.

Butler, K. C., and L. H. P. Lang. 1991. Evidence of systematic optimism and pessimism. *Journal of Accounting Research* 29 (Spring): 150–156.

Collins, D., S. P. Kothari, and J. Rayburn. 1987. Firm size and information content of prices. *Journal of Accounting and Economics* 9: 111–138.

Dirks, R. and L. Gross. 1974. *The Great Wall Street Scandal.* New York, NY: McGraw–Hill.

Dugar, A., and S. Nathan. 1995. The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations. *Contemporary Accounting Research* 12: 131–160.

Elgers, P., and D. Murray. 1992. Relative and complementary performance of analyst and security price based measures of expected earnings. *Journal of Accounting and Economics* 15: 303–316.

Financial Executive Research Foundation. 1987. *Investor Information Needs and the Annual Report.* Morristown, NJ: SRI International.

Francis, J., and D. Philbrick. 1993. Analysts' decisions as products of multi-task environment. *Journal of Accounting Research* 31 (Autumn): 216–230.

Fried, D., and D. Givoly. 1982. Financial analysts' forecasts of earnings. *Journal of Accounting and Economics* 4: 85–107.

Hayes, R. M. 1995. The impact of trading commission incentives on stock coverage and earnings forecasts decisions by security analysts. Working paper, Northwestern University.

Hunton, J. E. and R. A. McEwen. 1997. An assessment of the relation between analysts' earnings forecast accuracy, motivational incentives and cognitive information search strategy. *The Accounting Review* 72 (October): 497–515.

Kang, S., J. O'Brien, and K. Sivaramakrishnan. 1994. Analysts interim earnings forecasts: Evidence on the forecasting process. *Journal of Accounting Research* 32 (Spring): 103–112.

Kross, W., B. Ro, and D. Schroeder. 1990. Earnings expectations: The analysts' information advantage. *The Accounting Review* 65 (April): 1124–1131.

Laderman, J., C. Hawkins, and I. Recio. 1990. How much should you trust your analyst? *Business Week* (July 23): 54–56.

Lin, H., and M. McNichols. 1993. Underwriting relationships and analyst research reports. Working paper, Stanford University.

Lys, T. and L. Soo. 1995. Analysts' forecast precision as a response to competition. *Journal of Accounting, Auditing and Finance* 10 (Fall): 751–763.

McNichols, M., and P. C. O'Brien. 1997. Self selection and analyst coverage. *Journal of Accounting Research* 35 (Supplement).

O'Brien, P. C. 1988. Analysts' forecasts as earnings expectations. *Journal of Accounting and Economics* 10: 53–83.

———, and R. Bhushan. 1990. Analyst following and institutional ownership. *Journal of Accounting Research* 28 (Supplement): 55–76.

Siconolfi, M. 1995. Many companies press analysts to steer clear of negative ratings. *Wall Street Journal* (July 19): A1, C6.

Schipper, K. 1991. Analysts' forecasts. *Accounting Horizons* 5: 105–119.

Scism, L. 1993. Firms increasingly make end runs around analysts. *Wall Street Journal* (August 30): C1.