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Rationality and Analysts' Forecast Bias

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ABSTRACT

This paper proposes and tests a quadratic-loss utility function for modeling corporate earnings forecasting, where financial analysts trade off bias to improve management access and forecast accuracy. Optimal forecasts with minimum expected error are optimistically biased and exhibit predictable cross-sectional variation related to analyst and company characteristics. Empirical evidence from individual analyst forecasts is consistent with the model's predictions. These results suggest that positive and predictable bias may be a rational property of optimal earnings forecasts. Prior studies using classical notions of unbiasedness may have prematurely dismissed analysts' forecasts as being irrational or inaccurate.

A LARGE BODY OF RESEARCH has examined the properties of financial analysts' earnings forecasts within the context of the rational expectations hypothesis. Earnings estimates from brokerage firms are systematically collected by services such as I/B/E/S, Zacks, Standard and Poor's, and First Call, and are routinely held to the "market test" every three months. Because analysts' livelihoods depend on the accuracy of their forecasts, it seems reasonable to treat these forecasts as if they were the analysts' best expectations.

Prior empirical evidence suggests that analysts' forecasts of corporate earnings do not meet the classical standards of the rational expectations hypothesis. Earnings forecasts have been found to be positively biased,[1] and the extent of bias is predictable from publicly available information.[2]

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[1] Abarbanell (1991), Brown, Foster, and Noreen (1985), and Stickel (1990), using Value Line, I/B/E/S, and Zacks data sources, respectively, find that analysts' earnings forecasts are systematically overoptimistic.

[2] Abarbanell and Bernard (1992) and Klein (1990) show that analysts fail to incorporate information in past earnings announcements and stock returns, respectively; Das, Levine, and Sivaramakrishnan (1998), Ackert and Athanassakos (1997), and Han, Manry, and Shaw (1998) document that companies with greater past earnings variability or earnings forecast uncertainty are associated with more optimistic bias; Peters (1993) finds that positive earnings surprises (underestimated earnings) occur less frequently among small stocks.

In this paper, I argue that the unbiasedness of forecasts need not mean they are best or most accurate. Statistically optimal forecasts, in the sense of minimum expected squared error, may be positively and predictably biased. Consider an environment in which professional financial analysts have been delegated the task of producing accurate forecasts of company earnings. The company's management is a key source of nonpublic company information, and managers prefer favorable forecasts because these support higher capital market valuations and, hence, their compensation levels. They may limit or eliminate an analyst's flow of information if the analyst issues unfavorable forecasts, even if these are justified.[3] In this environment, analysts optimally report biased estimates. Positive bias in their estimates acts to decrease mean squared error—which can be decomposed into a squared bias and a variance term—by reducing forecast variance through improved access to managers' information. The optimal forecast under this quadratic loss criterion also exhibits predictable cross-sectional variation in the extent of bias that can be empirically tested. Specifically, companies with more uncertain information environments and analysts for whom building management access is more important are predicted to be associated with more optimistic forecasts.

These results are based on the simple argument that analysts seek to minimize forecast error. They do not draw on alternative hypotheses that have been suggested to explain analysts' seemingly "irrational" behavior. These explanations can be loosely divided into two groups. One argues that analysts face conflicting incentives, such as investment banking relationships or reputation concerns, which are incompatible with producing accurate forecasts. Michaely and Womack (1999) and Dechow, Hutton, and Sloan (1998) suggest that analysts employed by brokerage firms who also have underwriting relationships with the company they follow may have an economic incentive to issue more favorable recommendations or earnings growth forecasts. Scharfstein and Stein (1990) and Laster, Bennett, and Geoum (1996) develop models of how analysts may deliberately report earnings forecasts that are closer to or further from the consensus because of career concerns; however, these models do not explain why estimates are systematically overoptimistic. The second group of explanations draws from the psychology literature to suggest that analysts suffer from cognitive failures. De Bondt and Thaler (1990) argue that analysts have a behavioral tendency to overreact and form expectations that are too extreme. On the other hand, Mendenhall (1991), Abarbanell and Bernard (1992), and Klein (1990) show that analysts appear to underreact to information in past quarterly earnings and past stock returns. Easterwood and Nutt (1999) reconcile these two sets of findings by demonstrating that analysts underreact to negative earnings news but overreact to positive news, and hence appear systematically optimistic.

[3] For example, in the *Wall Street Journal*, Siconolfi (1995) 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."

Related empirical work by Das, Levine, and Sivaramakrishnan (1998) and Francis and Philbrick (1993) finds that earnings estimates from the Value Line ratings service are more positively biased for companies with greater historical earnings variability or that had a sell rating respectively, which can be interpreted to be consistent with analysts seeking to cultivate management access. My study examines a larger and longer survey of earnings estimates collected by I/B/E/S, and proposes and tests a wider set of predicted cross-sectional relationships between forecast bias and company and analyst characteristics.

This paper is organized as follows. In Section I, I develop more formally how analysts trade off bias for precision when forming minimum-error forecasts of earnings. Section II describes the data sample of individual analysts' forecasts. I identify and exclude from the sample those forecasts that are stale, affected by large discretionary accounting charges, or associated with underwriting relationships. The main empirical analysis presented in Section III shows that the cross-sectional variation in forecast bias is consistent with the model's predictions. Section IV concludes, and discusses implications from these results for tests of analysts' rationality and the predictability of forecast bias.

I. Rational Bias

In this section, I propose a quadratic-loss utility function to characterize earnings forecasting. My main thesis is that biased forecasts may be optimal under the simplest, natural assumption that analysts have been delegated the task of producing accurate estimates of company earnings.

Formally, assume the analyst observes a noisy private signal, I, of earnings, X, through research, company visits, and contact with the company's managers. The analyst produces a forecast, $\hat{X}$, that minimizes the conditional expected squared error, which can be decomposed into a squared mean bias and a variance term

$$\mathrm{Min}_{\hat{X}} E[(\hat{X}-X)^2|I] \equiv \mathrm{Min}_b\, b^2 + \mathrm{Var}(X|I), \tag{1}$$

where b is the (conditional) bias $\hat{X} - E[X|I]$.

To parameterize this model, let actual earnings X be a normal random variable with unconditional mean 0 (without loss of generality) and precision (the inverse of variance) τ_0. The noisy private signal the analyst observes is $I = X + \epsilon$. ϵ is a normal random variable with mean 0 and precision $\tau(b)$, which is a positive, concave function of bias b: This captures the key assumption that the analyst, in publishing a positively biased forecast, can generate more precise private information about the company's actual earnings. With these assumptions, the analyst's quadratic-loss utility function can be rewritten as

$$\mathrm{Min}_b\, b^2 + \frac{1}{\tau_0 + \tau(b)}. \tag{2}$$

The first-order condition characterizing the optimal forecast is

$$b = \frac{\tau'(b)}{2(\tau_0 + \tau(b))^2}. \tag{3}$$

Because τ' is positive, the minimum-error forecast is positively biased.[4] Only in the degenerate case where forecast bias and precision are unrelated ($\tau' \equiv 0$ when management access is useless) would the optimal forecast bias be zero. A static analysis of the first-order condition suggests the following two empirically testable propositions.

PROPOSITION 1: *If earnings are less predictable (τ_0 is small), then bias b increases (because $\delta b/\delta\tau_0 < 0$). When public information about the company's earnings prospects is less readily available, an analyst has more to benefit informationally when trading off some positive bias to gain management access. Companies for whom uncertainty about earnings is greater, or are likely to have poorer financial disclosures, should have more optimistically biased earnings forecasts.*

PROPOSITION 2: *Greater optimism is observed if cultivating management relations is more important for obtaining information (i.e., $\tau'(b) \gg 0$). Analysts employed by smaller regional brokerage firms who have fewer resources, or are junior in tenure and have to build access, are likely to be more reliant on management relations to gain company information.*

The model implies that analysts' forecasts are optimistically and rationally biased. Optimality conditions suggest that the extent of forecast bias can be related to characteristics of the followed company or the analyst. In the next sections, I construct proxies of uncertainty or poor financial disclosure for a company (such as size, coverage, volatility, and past performance) and the importance of management access for an analyst (such as brokerage firm size and experience), and test their predicted relationships with the extent of bias.

II. Data

Forecasts of quarterly earnings reported by analysts at over 300 brokerage firms are extracted from the I/B/E/S Detail files. Each observation represents an individual forecast and contains the company ticker, broker identifier, analyst identifier, earnings estimate, and forecast date. I/B/E/S attempts to retain analyst identifier codes as an analyst moves from broker to broker. Additionally, an analyst/broker names translation file was ob-

[4] This result that a biased estimator can possess the desirable property of having lower sampling error has several analogies in the field of statistical decision theory and econometrics. For example, James and Stein (1961) derive a biased estimator in a linear multiple regression setup that dominates the conventional unbiased least squares-maximum likelihood estimator under a squared loss criterion.

tained from I/B/E/S by special permission. The sample is drawn from the first quarter of 1984 to the fourth quarter of 1996, which provides 52 consecutive quarters of data. This long time span should reduce the sensitivity of my results to aggregate shocks, as discussed in O'Brien (1994).

For comparability with prior literature, I extract and match actual earnings (before extraordinary items) from COMPUSTAT's Industrial Quarterly files, stated on the same primary or diluted per-share basis as the I/B/E/S forecasts.[5] Stock prices, returns, and market capitalization information are obtained from CRSP. To reduce heteroskedasticity across stocks, forecasts (and forecast errors) are expressed as a percentage of the beginning-of-quarter stock price. I exclude companies with a stock price less than 5 dollars (because I do not want a stock price that is too small to enter into the denominator), or whose forecast error exceeds 10 dollars (which probably resulted from a data input error).

A. Forecast Recency

My preliminary analysis addresses the effects of forecast recency, discretionary accounting charges, and underwriting relationships. First, I define the consensus forecast bias for a company in a quarter as the median of all brokers' latest unrevised estimate of the company's earnings quarter, submitted no more than three months prior to quarter end, minus actual earnings from COMPUSTAT and expressed as a percentage of adjusted stock price. This "timely" composite of estimates[6] is motivated by Brown (1991) who shows that earnings forecast accuracy can be improved by discarding old earnings estimates. Furthermore, these unrevised estimates are more likely to be the forecasts actually held to a market test. Figure 1 shows that a rule requiring three months' recency is appropriate for screening out stale forecasts. Forecast bias decreases with recency, consistent with prior studies such as Kang, O'Brien, and Sivaramakrishnan (1994). The rate of decrease becomes steepest around 55 trading days prior to quarter end, which coincides with more rapid analyst forecast revisions as the prior quarter's earnings are announced.

B. Special Item Charges

I/B/E/S analysts forecast earnings from continuing operations, after discontinued operations, extraordinary charges, and other non operating items have been backed out. This usually corresponds to what GAAP calls "income before extraordinary items." However, I/B/E/S provides no specific instructions to individual analysts about the treatment of noncontinuing items. "Special items" are above-the-line accounting charges (usually large

[5] Although I/B/E/S also supplies reported earnings, Philbrick and Ricks (1991) identify possible misalignment problems in this data file.

[6] This may differ from the Summary median estimate reported by I/B/E/S each month, because I/B/E/S calculates its summaries at fixed dates in the middle of each month and does not discard stale estimates.

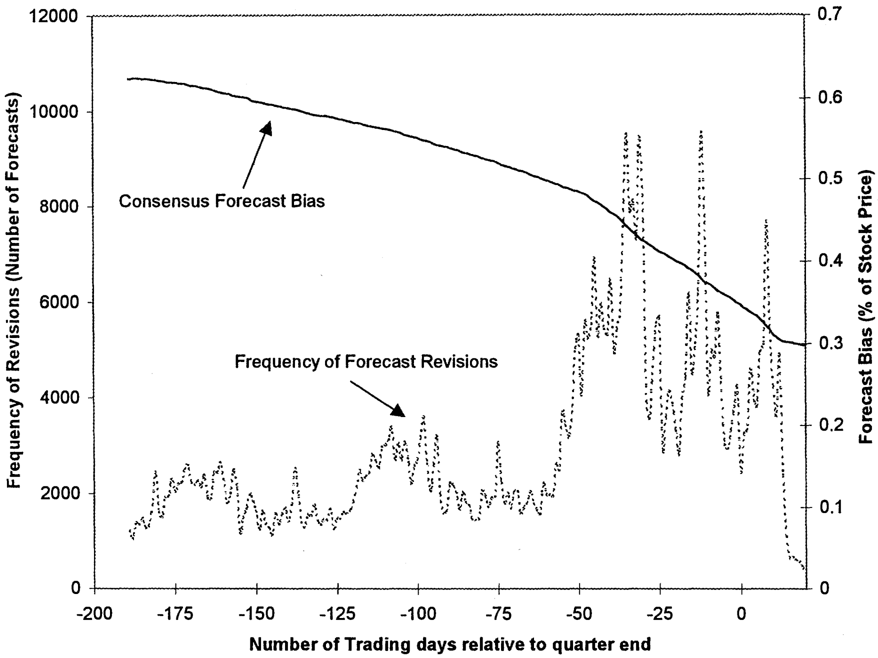

Figure 1. Forecast bias, frequency of revisions, and forecast horizon. This figure plots the average consensus forecast bias and the frequency of forecast revisions from −190 trading days through +20 trading days relative to a forecasted quarter's fiscal end date. The consensus forecast bias is the median of all brokers' latest forecasts available that day minus actual earnings, expressed as a percentage of stock price. The sample period is from 1984 to 1996.

asset write-offs or restructuring expenses) that can be taken at the discretion of management, and reported by COMPUSTAT in pretax EPS before extraordinary items and discontinued operations. Philbrick and Ricks (1991) report that I/B/E/S forecasts appear to exclude special items, while I/B/E/S reported earnings are inconsistent in the treatment of such items. Large discretionary accounting charges may generate extreme negative earnings that skew measures of overall forecast bias. Following Keane and Runkle (1998), I eliminate those observations with large special items charges, reasoning that it is difficult to unbiasedly determine what the analysts are trying to predict for these cases.

Table I shows that the majority of special items are negative charges to income, with a mean (median) of −1.81 (−0.36) percent of price. This reflects the conservative nature of accounting: Management can take large discretionary write-downs, but assets cannot be written up. Special items charges also occur more frequently in the fourth fiscal quarter.

If we remove all observations with nonzero special items, average forecast bias would still be positive, but reduced by half from 0.46 percent to 0.23 percent of stock price. Hence discretionary accounting charges cannot solely explain why earnings forecasts are positively biased on average. Most of this

Table I

Special Items Charges

Panel A reports the distribution of nonzero special items charges, as a percentage of stock price, in the pooled sample of companies between March 1984 and December 1996, by fiscal quarter. The sample excludes companies with a stock price less than five dollars. Panel B describes the distribution of consensus forecast bias in the pooled sample, after excluding outlier observations with large special items charges. Outliers are those observations for which special items charges (as a percentage of stock price) exceed a multiple of the standard deviation, σ, of the consensus forecast bias for all observations that have no special items charges. From the last line of this panel, $\sigma = 2.48$ percent of stock price in the sample. Consensus forecast bias is the median of all brokers' latest estimate of a company's earnings in a quarter, submitted no more than three months prior to quarter end, minus actual earnings, expressed as a percentage of adjusted stock price at the beginning of the quarter.

Panel A: Distribution of Special Items

Fiscal Qtr	N	No. Nonzero Special Items	Mean	Std.	Percentile 25	Percentile 50	Percentile 75
1	23,752	2,063	−0.42	5.68	−0.87	−0.10	0.51
2	25,479	2,730	−1.21	5.94	−1.52	−0.23	0.32
3	26,335	3,107	−1.83	7.09	−1.98	−0.31	0.20
4	27,676	5,383	−2.63	7.48	−3.04	−0.69	0.04
All	103,242	13,283	−1.81	6.88	−2.06	−0.36	0.20

Panel B: Consensus Forecast Bias, Excluding Large Special Items

Exclude	N	Mean	Std.	Skew	Percentile 25	Percentile 50	Percentile 75	% Pos.	% Neg.
None	103,242	0.46	3.38	8.88	−0.19	0.00	0.39	49.0	43.6
$\geq \pm 4\sigma$	102,227	0.33	2.60	9.65	−0.19	0.00	0.37	48.7	43.9
$\geq \pm 3\sigma$	101,854	0.31	2.56	9.91	−0.19	0.00	0.37	48.6	44.0
$\geq \pm 2\sigma$	101,121	0.28	2.50	10.38	−0.19	0.00	0.35	48.3	44.2
$\geq \pm 1\sigma$	99,549	0.25	2.45	10.94	−0.19	0.00	0.33	47.9	44.5
All	89,959	0.23	2.48	11.31	−0.19	0.00	0.30	46.8	45.2

reduction in bias comes from eliminating the largest special item charges. Eliminating the 3,693 observations (roughly one-quarter of all occurrences) with special items larger than one standard deviation of forecast bias brings mean bias down to 0.25 percent of stock price, with a standard deviation of 2.45 percent.[7] This is a reasonable cutoff for removing influential cases of special items charges, and the remainder of my analysis uses this truncated sample; the results are not affected by deleting all observations of nonzero special items.

[7] By comparison, the consensus forecast bias of the full sample computed using I/B/E/S actuals had an approximately identical mean (0.32 percent of price) but higher standard deviation (7.61 percent of price).

Table II

Forecast Bias of Lead Underwriter and Other Analysts

This table reports the average consensus forecast bias, over all company-quarters, of lead underwriter minus other analysts, expressed as a percentage of the beginning-of-quarter stock price. The consensus forecast bias of lead underwriter analysts is the median of the latest forecasts from brokers who were also lead underwriters for a secondary equity offering issued within a specified window relative to the quarter-end date. The consensus forecast bias of other analysts is the median of the latest forecasts from brokers who were not lead underwriters. The sample includes companies with fiscal quarter-end dates between March 1984 and December 1996, and excludes companies with a stock price less than five dollars.

Fiscal Quarter-end Relative to Issue Date, in Months	No. Companies	Bias of Lead Underwriter Analysts Minus Bias of Other Analysts (*t*-statistic)
−48 to −42	498	0.01 (0.19)
−42 to −36	599	0.03 (0.92)
−36 to −30	655	0.01 (0.38)
−30 to −24	787	0.01 (0.43)
−24 to −18	916	0.04 (1.39)
−18 to −12	1,002	−0.03 (−1.18)
−12 to −6	1,202	−0.01 (−0.52)
−6 to 0	1,349	0.03 (1.15)
0 to +6	2,088	−0.02 (−1.57)
+6 to +12	2,373	0.01 (0.51)
+12 to +18	2,314	−0.02 (−1.20)
+18 to +24	2,100	0.01 (0.96)
+24 to +30	1,925	0.02 (1.05)
+30 to +36	1,841	−0.01 (−0.66)
+36 to +42	1,652	−0.03 (−2.21)
+42 to +48	1,475	−0.03 (−1.63)

C. Underwriting Relationships

Some of the I/B/E/S forecasts may be from analysts whose brokerage firms have underwriting relationships with the followed company. Michaely and Womack (1999) suggest that analysts working for the lead underwriter have an economic incentive to promote the stock, because the lead investment bank is most involved in "building the book" of committed investors and marketing the IPO. On the other hand, Allen and Faulhaber (1989) argue that investment bankers will have superior information gained through the due diligence process. Also, companies may disclose more information to mitigate the information asymmetry associated with the negative signal of a securities offering. These studies suggest that forecasts from lead underwriter analysts may possess different properties and should be excluded from the main sample.

I identify public equity offerings, issue dates, and lead underwriter investment banks from the Securities Data Company (SDC) database. Analysts employed by an investment bank (or subsidiary or the parent of the bank) acting as the lead manager for the offering are classified as "lead underwriter analysts." Table II examines the average difference between the forecast bias of "lead underwriter analysts" and "other analysts," for four years around a seasoned equity offering. In none of the six-month periods around the issue date is the difference significantly greater than zero. This finding is consistent with Lin and McNichols (1998), who document that although lead underwriter analysts tend to issue more optimistic recommendations, their earnings forecasts are not any more biased. Because quarterly earnings estimates can be easily evaluated, perhaps analysts tend to promote stocks more through subjective recommendations or longer-term forecasts instead.

The most positive difference in bias appears at 24 months prior (0.04 percent of stock price) and 30 months after (0.02 percent) an equity issue date. I exclude all forecasts from lead underwriter analysts for quarter-end dates that fall within this four-and-a-half-year window. In the cross-sectional tests, I also require that price data be available for one year prior to the beginning of the fiscal quarter, hence eliminating all forecasts for 15 months after new listings as well. My results are insensitive to changing this window to four years before and after the issue date, or to excluding all companies within two years of an equity issue (not reported for brevity).

III. Empirical Results

A. Company Characteristics

The first set of empirical tests examine the cross-sectional variation of forecast bias across company characteristics. Proposition 1 states that companies with more informational uncertainty should be associated with more optimistically biased forecasts. The general information environment is likely to be richer for companies that are larger[8] and covered by more analysts. I also examine measures of company uncertainty based on historical earnings and recent stock price volatility. For every company in each quarter, I compute the market capitalization (LNSIZE); number of analysts providing annual earnings forecasts[9] (LNCOVER); historical earnings variability (EPSVAR); and the standard deviation of weekly[10] excess stock returns (SIGMA) that represents a more timely capital markets-based measure of company-specific uncertainty.

Earnings uncertainty is also likely to be greater when companies are sitting on bad news, as managers tend to be less forthcoming. In contrast, when companies have good news, managers have every incentive to push

[8] See Ho and Michaely (1988). The FASB's and SEC's disclosure requirements also suggest that disclosure costs are decreasing in company size. For example, the SEC has separate 10K and 10Q filing requirements for small companies, to facilitate the access of small business issuers to the public markets.

[9] Although my study focuses on quarterly earnings forecasts, the number of analysts providing forecasts of annual (FY1) earnings is a better measure of analyst coverage, as some analysts who provided annual forecasts did not provide quarterly estimates, particularly in the earlier part of the sample period.

[10] As in Adamek et al. (1998), I use weekly returns based on Wednesday-to-Wednesday closing prices to mitigate nonsynchronous trading or bid-ask bounce effects inherent in daily prices. A one-year estimation period was chosen to provide a reasonable number of observations.

this news out to investors as quickly as possible. Consistent with this view, Hong, Lim, and Stein (2000) show that stock price momentum effects are stronger and more persistent for poor performers, indicating that bad news diffuses more slowly than good news to the investing public. Lang and Lundholm (1993) find that analysts' ratings of companies' disclosures are lower for poor-performing companies. After past earnings disappointments (i.e., past positive forecast bias PREVBIAS) or stock price declines (negative ALPHA), analysts would want to report more positively biased forecasts and appear to not fully revise their earnings estimates downwards.

Finally, the dependent variable, consensus forecast bias (BIAS), is expressed as a percentage of adjusted stock price 12 months prior to the beginning of the quarter. I use a "stale" stock price to reduce any endogeneity effects with the other company characteristic variables. The conclusions are not changed if contemporaneous prices or fundamental values are used. To mitigate the effects of outliers, all observations in the tail 2.5 percent of BIAS values each quarter are excluded.

To examine the univariate relationships, I form quintile portfolios of companies by ranking on each company characteristic every quarter. The average consensus forecast bias is computed for each group, and the time series means and standard errors are reported in Table III. Because I expect bias to be negatively related to ALPHA, LNSIZE, and LNCOVER, I rank companies in descending order for these characteristics (as indicated by a "minus" prefix in the table), so that, for example, the largest company is in quintile 1 and the smallest in quintile 5.

For (minus) ALPHA, the relationship is approximately flat in the first 2 quintiles, and is most positive for quintiles 3–5—the stocks that had performed most poorly. PREVBIAS shows more of an increasing relationship across all quintiles, and is also steepest in quintiles 4 and 5. This is consistent with the "underreaction effect" found by prior studies, but this effect is asymmetric. When a company is sitting on bad news, maintaining optimism and management access is likely to be more important; hence analysts appear to underreact more to negative information.

The sorts on (minus) SIZE, (minus) LNCOVER, EPSVAR, and SIGMA show similar patterns. Their relationships with forecast bias are generally increasing, and most of the positive bias is concentrated in quintiles 4 and 5—the smallest or most volatile companies. The correlation for EPSVAR is weak;[11] because this variable estimates historical earnings variability from a small number of data points and does not reflect other more current sources of information, it may not be as good a measure of current company uncertainty.

Table IV reports the results from a multivariate regression analysis of consensus forecast bias on company characteristic variables LNSIZE, SIGMA, PREVBIAS, and ALPHA. The preliminary analysis in Table I suggests the inclusion of a dummy variable to account for fiscal fourth quarter effects (when more discretionary charges are likely to be taken). Separate quarterly

[11] In additional sensitivity tests, not reported for brevity, measuring historical earnings variability over 4 or 12 trailing quarters yielded similar conclusions.

Table III

Consensus Forecast Bias, Grouped by Company Characteristics

This table reports the time-series mean (standard error) from March 1984 to December 1996 of the quarterly consensus forecast bias for each quintile of companies, regrouped each quarter by a company characteristic. As negative relationships with ALPHA, LNSIZE, and LNCOVER are expected, companies are sorted in descending order with respect to these characteristics (and indicated by a "minus" prefix in the table) to facilitate comparison across characteristics. Consensus forecast bias is the median of all brokers' latest estimate of a company's earnings in a quarter, submitted no more than three months prior to quarter end, as a percentage of adjusted stock price 12 months prior to the beginning of the quarter. Forecasts from lead underwriter analysts are excluded. Sample excludes companies that do not have quarter-end dates in March, June, September or December; with stock price less than five dollars; have large special item charges; or whose consensus forecast bias is in the extreme 2.5 percent tails in a quarter. Company characteristics are: ALPHA: the intercept from a market model regression of weekly stock returns on weekly value-weighted market returns, over the year ending at the beginning of the quarter; PREVBIAS: the consensus forecast bias from the prior quarter, as a percentage of stock price 12 months prior to the beginning of the forecasted quarter; LNSIZE: the log market capitalization 12 months prior to the beginning of the quarter; LNCOVER: the log of one plus the number of analysts providing annual FY1 earnings estimates lagged 12 months from the beginning of the quarter; SIGMA: the standard deviation of the residuals from a market model regression of weekly stock returns on weekly value-weighted market returns, over the year ending at the beginning of the quarter; EPSVAR: the standard error from a trend regression of quarterly earnings (as a percentage of stock price) from nine through two quarters (total of eight quarters) prior to the current quarter, scaled by adjusted stock price at the beginning of the quarter.

	Quintile						Average No.
Grouped by	1	2	3	4	5	All	Companies per Quarter
(minus) ALPHA	0.06	0.09	0.12	0.17	0.30	0.15	1,333
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
PREVBIAS	−0.08	0.01	0.10	0.21	0.49	0.15	1,243
	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	
(minus) LNSIZE	0.08	0.11	0.14	0.18	0.22	0.15	1,333
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	
(minus) LNCOVER	0.09	0.11	0.14	0.17	0.22	0.15	1,333
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	
SIGMA	0.08	0.08	0.12	0.19	0.27	0.15	1,333
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
EPSVAR	0.10	0.14	0.12	0.15	0.20	0.14	1,163
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	

cross-sectional regressions are run and statistical inference is drawn from the time series of the coefficients. To account for intertemporal dependence in the quarterly coefficient estimates, the time series standard errors are computed using a Newey–West procedure with four lags.

The estimated coefficients are all of the predicted sign, and are consistent with the results from the univariate portfolio sorts. Forecast bias is greatest for companies that are small, are more volatile, experienced prior negative earnings surprise, or experienced poor past stock returns. Similar results are obtained in subperiods and size-based subsamples. Adding control re-

Table IV

Regression of Consensus Forecast Bias on Company Characteristics

This table reports the time-series average of the estimated coefficients (autocorrelation-consistent time-series t-statistics in parentheses) from quarterly cross-sectional regressions of consensus forecast bias on company characteristics, between March 1984 and December 1996. Forecasts from lead underwriter analysts are excluded, as are companies that do not have quarter-end dates in March, June, September, or December; with a stock price less than five dollars; that have large special item charges; or whose consensus forecast bias is in the extreme 2.5 percent tails in a quarter. Variable definitions are as in Table III. D_{4Q} is a dummy variable indicating a fiscal fourth quarter; D_{sic} are industry dummy variables based on two-digit SIC codes; BP is the book-to-price ratio lagged 12 months from the beginning of the quarter. The cross-sectional regression equation estimated each quarter t across companies indexed by i is

$$BIAS_{it} = \hat{\beta}_0 + \hat{\beta}_1 LNSIZE_{it} + \hat{\beta}_2 SIGMA_{it} + \hat{\beta}_3 PREVBIAS_{it} + \hat{\beta}_4 ALPHA_{it} + \hat{\beta}_5 D4Q_{it} + \hat{\epsilon}_{it}$$

	LNSIZE	SIGMA	PREVBIAS	ALPHA	D_{4Q}	BP	LNCOVER	EPSVAR	D_{sic}
Full period	−0.0252	0.0242	0.0443	−0.1322	0.0196				
1984–1996	(−4.25)	(4.22)	(8.58)	(−12.38)	(0.74)				
Subperiod	−0.0353	0.0375	0.0552	−0.1558	−0.0040				
1984–1990	(−4.27)	(5.35)	(9.54)	(−11.44)	(−0.09)				
Subperiod	−0.0135	0.0087	0.0317	−0.1045	0.0472				
1991–1996	(−4.10)	(2.74)	(6.98)	(−10.39)	(4.14)				
Decile 9–10 (L)	−0.0183	0.0208	0.0491	−0.1275	0.0508				
1984–1996	(−2.82)	(5.15)	(6.10)	(−10.95)	(1.62)				
Decile 7–8	−0.0695	0.0291	0.0666	−0.1283	−0.0070				
1984–1996	(−3.75)	(2.92)	(6.61)	(−8.13)	(−0.34)				
Decile 1–6 (S)	−0.0474	0.0289	0.0675	−0.1719	−0.0336				
1984–1996	(−2.81)	(2.07)	(5.08)	(−5.03)	(−0.53)				
Full period (exclude	−0.0252	0.0201	0.0431	−0.1210	0.0101				
all nonzero	(−4.64)	(3.41)	(7.55)	(−11.07)	(0.41)				
special items)									
1984–1996									
NYSE only	−0.0239	0.0327	0.0466	−0.1429	0.0518				
1984–1996	(−3.78)	(4.10)	(5.85)	(−14.29)	(2.35)				
Full period	0.0070	0.0187	0.0391	−0.1186	0.1261	0.0069	−0.0656	0.0137	Yes
1984–1996	(0.30)	(3.64)	(6.53)	(−10.24)	(1.15)	(0.73)	(−2.59)	(1.82)	

gressors for book-to-price, analyst coverage, historical earnings variability, and industry classification eliminates the size effect (probably due to the strong collinearity with the amount of analyst coverage—the correlation of LNSIZE and LNCOVER is 0.8—that enters with a significantly negative coefficient), but the other coefficients remain significant (*t*-statistics greater than 2.59) and with the predicted signs. The EPSVAR coefficient has the predicted positive sign but, as in the univariate case, the relationship is not as strong (*t*-statistic of 1.82).

B. Analyst Characteristics

I next examine the cross-sectional relation between relative forecast bias and analyst characteristics. Proposition 2 suggests that analysts who are less reliant on management relations and access as a source of company information should exhibit less positive bias. Analysts who are employed by large brokerage firms or have more experience are likely to have less need to cultivate management access. Large brokerage firms have superior resources, such as administrative and research support, database access, and better reputation. Companies often covet coverage by a well-known broker, which represents an important marketing tool for reaching institutional investors. I use the number of analysts employed by a brokerage firm within a rolling 12-month prior period as a measure of brokerage firm size. To measure analyst experience, I compare the fiscal end date of the forecast with the date of the analyst's first forecast in the I/B/E/S database.

The data sample comprises the most recent forecast every company-quarter from each analyst, submitted no more than three months prior to quarter end. Following Clement (1997), I exclude forecasts from analyst teams,[12] because we cannot determine the identity or experience of the team members. Companies with two or fewer eligible forecasts in a quarter are dropped. Each analyst's forecast is expressed relative to all analysts who followed the same company in the same quarter. I consider the following analyst characteristic variables, which are also measured relative to all analysts following the same company in the same quarter: the number of analysts employed (DBROKSIZE); analyst experience (DGENEXP); and a control variable for forecast recency (DSTALE).

The number of brokerage firms ranges from 141 at the beginning of my sample to 281 in 1996. Since I/B/E/S only began recording detailed forecast data in 1983, the mean analyst experience in our sample was just 1.5 years in December 1984, but rose to 4.8 years in 1996. Similarly, the range increased over the period: The first and third quartile values of analyst experience were 0.8 and 2.2 years, respectively, at the end of 1984, and 0.7 and 8.5 years, respectively, in 1996.

[12] Analyst teams are those with names in the I/B/E/S analyst/broker translation file that contain an "&," "/," or an industry name.

Table V

Regression of Relative Analyst Bias on Analyst Characteristics

This table reports the time-series average of the estimated coefficients (autocorrelation-consistent time-series t-statistics in parentheses) from quarterly cross-sectional regressions of relative forecast bias on relative analyst characteristics of individual forecasts for quarter-end dates between December 1984 and December 1996. Forecasts from lead underwriters, of analyst teams, reported more than three months prior to quarter end, or having relative bias in the extreme 2.5 percent tails are excluded. The sample also excludes companies that do not have quarter-end dates in March, June, September, or December; with a stock price less than five dollars; having large special item charges; or having two or fewer eligible forecasts per quarter. Analyst characteristics are: RELBIAS: an analyst's latest forecast, submitted no more than three months prior to quarter end, minus actual company earnings, as a percentage of adjusted stock price 12 months prior to the beginning of the quarter, minus the average for analysts following the company in the quarter; DGENEXP: the log of one plus the number of years before the quarter-end date since the analyst first reported an estimate in the I/B/E/S database, minus the average for analysts following the company in the quarter; DSTALE: the quarter-end date minus the submission date of the estimate, expressed as the log of one plus number of years, minus the average for analysts following the company in the quarter; DBROKSIZE: the log of one plus the number of analysts employed by the brokerage firm within 12 months prior to the quarter end, minus the average for analysts following the company in the quarter. The cross-sectional regression equation estimated each quarter t across analysts indexed by i is

$$RELBIAS_{it} = \hat{\beta}_0 + \hat{\beta}_1 DGENEXP_{it} + \hat{\beta}_2 DSTALE_{it} + \hat{\beta}_3 DBROKSIZE_{it} + \hat{\epsilon}_{it}$$

	DGENEXP	DSTALE	DBROKSIZE
Full period	−0.0028	0.3252	−0.0056
1984–1996	(−1.36)	(5.56)	(−2.95)
Subperiod	−0.0034	0.4143	−0.0027
1984–1990	(−0.84)	(4.73)	(−0.99)
Subperiod	−0.0022	0.2362	−0.0084
1991–1996	(−2.28)	(4.22)	(−5.48)
Decile 10 (Large)	−0.0057	0.2810	−0.0038
1984–1996	(−1.94)	(4.58)	(−1.72)
Decile 9 (Medium)	0.0055	0.4201	−0.0104
1984–1996	(1.54)	(6.14)	(−7.03)
Decile 1–8 (Small)	0.0041	0.4493	−0.0089
1984–1996	(1.19)	(6.78)	(−2.93)
NYSE only	−0.0017	0.3125	−0.0047
1984–1996	(−0.95)	(5.24)	(−2.04)

Table V reports results from a multivariate regression analysis of relative forecast bias on the analyst characteristic variables. To mitigate the effects of outliers, all observations in the tail 2.5 percent of RELBIAS values each quarter are excluded. The number of forecasts each quarter ranges from 2,484 in December 1984 to 8,531 in 1996; prior quarters were dropped because these provide significantly fewer observations. As before, statistical inference is drawn from the time series of estimated coefficients from separate quarterly cross-sectional regressions. Time-series standard errors are computed using a Newey–West procedure with four lags.

The average coefficient for brokerage size is reliably negative[13] as predicted (t-statistic = −2.95). This effect is also observed in a subsample of NYSE-listed stocks only; it is not driven by small brokers who are often market markers for Nasdaq-listed stocks, which may create some conflicts of interest.

The coefficient on DGENEXP is weakly negative, indicating that less experienced analysts tend to be more positively biased, but this relationship is not as reliable. The effect is stronger for large companies, but cannot be detected in smaller companies. The estimated coefficient from the second half-period is stronger in significance, perhaps because our measure of analysts' experience is less accurate in the first subperiod just after I/B/E/S began recording individual analysts' forecasts. Furthermore, once individual forecasts are disseminated, less informed analysts can easily mimic the (more informed) consensus. Hong, Kubik, and Solomon (2000) find that younger analysts issue forecasts later and deviate less from the consensus. Hence forecast recency explains more than the predicted effects from the other characteristics.

IV. Conclusion

Some investigators have interpreted a test of unbiasedness to be necessary for inferring rationality. This paper argues that unbiasedness of forecasts need not mean best or most accurate. Rational analysts who aim to produce accurate forecasts may optimally report optimistically biased forecasts. By trading off bias to improve management access and forecast precision, analysts minimize the expected squared error of their forecasts. The extent of positive bias is predicted by optimality conditions to be larger for companies that have more uncertain information environments, and for analysts who are more reliant on management access as a source of company information.

The empirical evidence presented shows that forecast bias varies predictably across companies and analysts in a manner consistent with this model. I find that proxies for the richness of a company's information environment, such as company size and analyst coverage, are inversely related to forecast bias. To the extent that companies who have performed poorly are associated with more uncertainty or poorer disclosures, analysts following these companies refrain from fully revising their estimates downwards, leading to greater positive bias—the underreaction effect previously documented by other researchers. I also find that a capital markets-based proxy for company-specific uncertainty—the standard deviation of weekly excess stock returns—is positively related to forecast bias. Analysts from smaller brokerage firms or, to a weaker extent, those who have less experience produce more optimistic forecasts.

[13] In a similar spirit, Carleton, Chen, and Steiner (1998) report that regional brokerage firms issue more optimistic equity *recommendations* than national brokerage firms.

Positive and predictable bias may be a fundamental property of statistically optimal earnings forecasts. This result follows from a simple, natural argument that minimizing forecast error is a pervasive component of analysts' utility functions, and does not draw on alternative behavioral explanations such as cognitive failures or conflicting incentives. Prior empirical studies that have evaluated analysts' rationality using classical notions of unbiasedness may have prematurely dismissed analysts' forecasts as being too inaccurate or irrational.

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