Q. Referring to page 52, footnote 51: Please provide complete references to all of these studies together with copies of those available to you. Also, please provide all documentation that investors continue to accept the optimism of analysts' forecasts in forming market prices.

A. The following articles have empirically studied the optimism of analysts' forecasts.

David N. Breman and Michael A. Berry, "Analyst Forecasting Errors and Their Implications for Security Analysis", *Financial Analysts Journal*, May/June 1995. (Please see Attachment A.)

Vijay Kumar Chopra, "Why So Much Error in Analysts' Earnings Forecasts?", *Financial Analysts Journal*, November/December 1998. (Please see Attachment B.)

Kirt C. Butler and Hakan Saraoglu, "Improving Analysts' Negative Earnings Forecasts", *Financial Analysts Journal*, May/June 1999. (Please see Attachment C.)

As stated in response to PUB 67 NLH, we have found only one analysis of analysts' stock recommendations published subsequent to Wall Street's loss of credibility which contains data for the post-2000 period. The referenced article did not assess the degree of optimism, if any, in analysts' forecasts in the post-2000 period. The more general question of whether or not investors continue to accept analysts' forecasts when forming market prices has not been answered definitively. Brokerage firms, however, continue to employ analysts and disseminate analysts' reports. Consensus forecasts continue to be accessible through both I/B/E/S and Zacks. In a September 2001 article entitled "From the Trenches: Analysis Without Analysts" (please see Attachment D), Lisa Meyer writes the following about software based research companies:

> "Some institutional investors question whether these upstart companies will survive only long enough to allow outraged investors an opportunity to express their displeasure with sell-side analyst research; such institutions believe investors will return to professional research once the market improves, partly because it's easier and faster to turn to ready-made recommendations and partly because investing will seem less risky again."

Analyst Forecasting Errors and Their Implications for Security Analysis

David N. Dreman and Michael A. Berry

A comparison of 66,100 consensus estimates of Wall Street analysts with reported earnings for a large sample of NYSE, Amex, and OTC companies demonstrates that their forecasts differ significantly from actual reported earnings. A minority of estimates fall within a range around reported earnings considered acceptable to many professional investors. The error rates are not meaningfully affected by the business cycle or industry groupings. The average error also appears to be increasing over time. These findings question the use of finely calibrated earnings forecasts that are integral to the most common valuation models and indirectly question the valuation methods themselves.

A large part of the research budget of the brokerage industry is expended on hiring top analysts to provide accurate earnings estimates. Professional investors also rely on commercial earnings forecasting services such as Institutional Broker's Estimate System (IBES), Zacks, Value Line, and First Call, which maintain records of all estimates and rapidly relay brokerage house earnings forecast changes to the marketplace. First Call, for example, provides instant release of analysts' estimate changes together with detailed analysis for each company.

Financial academics and investment professionals agree that earnings are a major determinant of stock prices. The heart of modern security analysis centers on the attempt to predict stock price movements by fine-tuning near-term earnings estimates. This practice has continued in spite of the warnings by Graham and Dodd in the early 1930s and by other knowledgeable market observers over the decades about the difficulties of forecasting earnings precisely. A significant component of the research effort of the brokerage industry is directed at producing accurate short-term earnings estimates. The requirement for precise earnings estimates has been increasing in recent years. An examination of the reactions of stock prices to earnings surprises indicates that very small percentage misses may cause large changes in price.[1] Indeed, many market professionals consider a forecast error magnitude of plus or minus 10 percent of actual or forecast earnings enough to trigger a major stock reaction.[2]

Accurate earnings estimates are also essential for most contemporary stock valuation models. The intrinsic value theory of stock selection that is used extensively in earnings, dividend, and cash flow discount models is based on the ability of practitioners to forecast earnings accurately often a decade or more into the future. The growth and momentum schools of investing also require finely calibrated, precise earnings estimates years into the future to achieve the valuations they place on securities.

We examined the forecasting accuracy of analysts by comparing their consensus forecasts with reported earnings. We demonstrate that consensus forecasts, revised as recently as two weeks prior to the end of the quarter for which the earnings forecasts were made, deviate significantly and consistently from actual earnings. Using four different surprise measures, we found that only a relatively small percentage of earnings estimates fall into what many professional investors consider to be acceptable ranges around the reported earnings.[3] We believe that analysts' forecast errors are systematically too large for many analytical valuation methods to provide consistent results. This finding allowed us to hypothesize about some

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behavioral aspects of the earnings forecasting process.

LITERATURE REVIEW

Neiderhoffer and Regan examined the 50 best-performing and the 50 worst-performing stocks listed on the NYSE in 1970 with respect to actual and forecast earnings.[4] The median earnings forecast was 7.7 percent for the "best" group, although the average increase in earnings was 21.4 percent. This forecast resulted in a price appreciation of the sample median by 44.4 percent. Earnings for the bottom 50 stocks declined by a median of 56.7 percent and price declined by 83 percent. The authors concluded that "it is clear that an accurate earnings estimate is of enormous value in stock selection (p. 71)."

Copeland and Mariani reviewed management estimates, because most institutional analysts interview management to fine-tune their earnings estimates.[5] They used deviation as a percent of actual 1968 earnings to compare the estimates of 50 executives published in the *Wall Street Journal* against year-end results. The absolute error was 20.1 percent. Green and Segall, McDonald, and Basi, Carey, and Twark also analyzed and compared management forecasts against actual results for the 1970–71 period.[6] Basi et al. used both absolute deviation and percentage of actual earnings to measure the size of analyst and management forecast errors. They showed that analysts and management, on average, tend to overestimate earnings. Both groups generated an average error greater than 10 percent. Company management in these four studies exhibited an average error of 14.5 percent, even after outliers resulting from nominal forecasts had been deleted.

The literature on analysts' forecast errors is similar. Basi et al. also studied the error rate of analysts for the 1970–71 period and found it to average 40 percent greater than that of the executives. Richards and Frazer found that analysts' mean consensus error for 1973 was 22.7 percent; in addition, analyst forecasts tended to cluster.[7] Richards, Benjamin, and Strawser used error as a percent of actual earnings to examine analysts' estimates between 1972 and 1976.[8] They found an average annual error rate of 24.1 percent. Analysts exhibited average error rates of 59.6 percent in 1974. This study also showed that the consensus earnings forecast deviated significantly from realized earnings and that individual estimates clustered.

Dreman noted in reviewing early studies that the composite forecast error from 1960 through 1976 was 16.6 percent.[9] He posited that practicing analysts try to fine-tune their earnings estimates to within a very narrow range, normally well under plus or minus 10 percent of reported earnings, so the average error rates found on consensus estimates are highly significant. Little and Rayner and Brealey also documented the randomness of earnings changes.[10] Cragg and Malkiel studied the earnings projections of large groups of security analysts. The researchers found that most analysts' estimates were simply linear extrapolations of recent trends.[11] Dreman postulated that if changes in earnings follow a random walk, projecting current trends into the future, as Malkiel suggests that analysts do, should lead to the significant forecasting errors that the literature demonstrates.[12]

Recently, researchers have reexamined the hypothesis that analysts are poor forecasters. Imhoff and Pare compared the forecasts of analysts and management using four surprise metrics: percent of forecast, percent of actual, absolute difference between forecast and actual, and percent of the standard deviation of the actual.[13] They also used four different types of naive econometric models for comparative purposes. They measured the relative errors between forecast and actual earnings and concluded that no significant differences are observed between the forecast agents. This result implies that analysts do not outperform naive econometric models in forecasting earnings.

Ou and Penman developed a single financial statement measure to forecast the change in direction in a company's earnings per share (EPS) during the next year.[14] Strober tested this measure and found that it has earnings forecasting value up to 36 months into the future.[15] He surmised that the measure impounds a risk factor not perceived by analysts in their expectations for future earnings and concluded that this forecasting model provides direct evidence of the inability of analysts to forecast earnings with a high degree of accuracy.

Ali, Klein, and Rosenfeld suggested that neither markets nor analysts recognize the time series properties of quarterly earnings surprises.[16] In their study, Ali et al. cited Bernard and Thomas.[17] Ali et al. also showed that analysts, on average, underestimate the permanence of the previous year's forecast error when forecasting earnings. Abarbanell and Bernard found that analysts do not use the time series properties of earnings correctly in forecasting earnings.[18] These results provide evidence supporting the hypothesis that analysts systematically misforecast future earnings.

Thus, the literature from 1967 forward clearly suggests that analysts consistently misforecast earnings but does not provide a rationale for the persistence, size, or increasing trend of the error.

METHODOLOGY

We analyzed consensus earnings estimates derived from the Abel Noser data base. This data base comprises approximately 1,200 companies followed by analysts from 1972 through March 1991. The study begins in 1974 to allow two years of previous earnings to form "standardized" surprise metrics. The Abel Noser data base was used because it contains 17 years of quarterly earnings estimates, the longest such data base that we are aware of.[19] In addition, we used the same measure the market appears to use to capitalize a firm's expected earnings, a single consensus point estimate of earnings. We analyzed 69 quarters of earnings surprise data. Because increasing error rates were noted after IBES and Zacks introduced quarterly estimate reporting in 1984, we concluded that the effect of not having formalized reporting in the early 1970s through the early 1980s by all the services is minimal.

The sample size increased over this timeframe. In 1974, the sample yielded 2,451 surprise observations with valid estimates; in 1990, it yielded 4,057 surprise observations. The data base contained 66,100 observations from the first quarter of 1974 through the first quarter of 1991, each representing a single firm's quarterly consensus earnings estimate.

The stocks in the Abel Noser sample were matched to the Compustat data base to determine the fiscal year and adjustment factors for stock splits for each company. Only companies with fiscal year-ends in March, June, September, or December were included in the study. A firm's share price was verified by matching Abel Noser data to the Compustat data base.

After 1981, companies included in the Abel Noser data base must have been followed by at least four analysts. In 1993, an Abel Noser company was followed by an average of 11 analysts. To eliminate the possibility of survivorship bias, we tracked all stocks deleted from the Abel Noser data base from 1980 forward. The returns derived from this sample of firms experiencing bankruptcies, mergers, and insufficient analyst coverage were similar to the results for the principal sample.

Two "standardized" surprise measures were calculated by dividing the difference between actual and forecast earnings per share by the standard deviation of actual earnings per share for the past eight quarters (SURP8) and the standard deviation of the change in actual earnings per share for the past seven quarters (SURPC7). This standardization permitted a test of a volatility-adjusted error on the sample as a whole and for each industry yearly and for the entire period. Standardized surprise metrics such as SUEs (standardized unexpected earnings) are often used in the academic literature to correlate with returns rather than to provide a measure of the size of the surprise. Note that the absolute and standardized measures cannot be directly compared with each other and that the value to investors of one versus the other is not at issue in this paper. We documented that the sizes of these surprises are large, on average, relative to contemporary investment practice.

In total, we defined the following four earnings surprise metrics:[20]

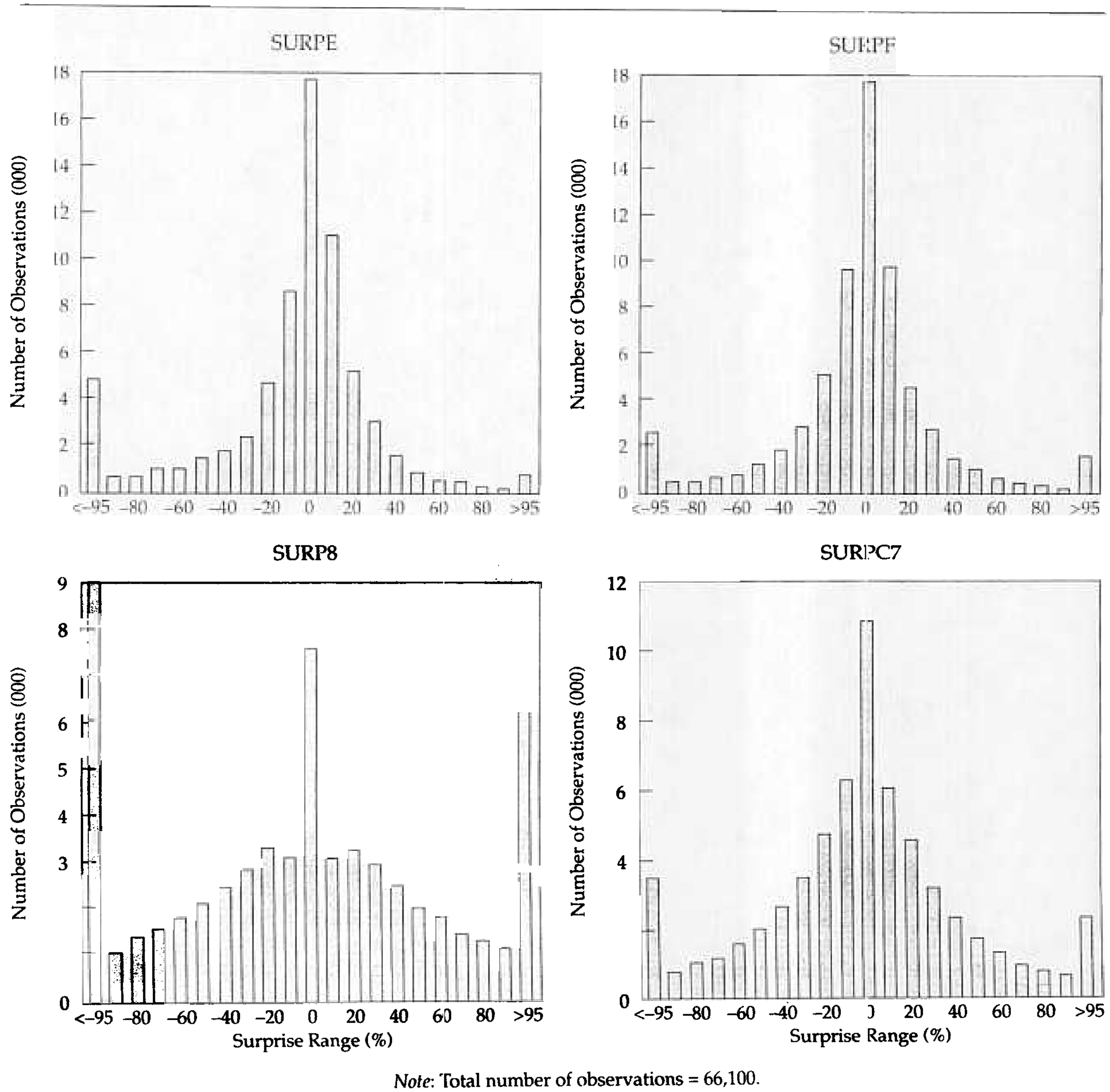
- SURPE: Consensus EPS surprise as a percent of absolute value of actual EPS—(Actual EPS − Forecast EPS)/|(Actual EPS)|
- SURPF: Consensus EPS surprise as a percent of absolute value of forecast EPS—(Actual EPS − Forecast EPS)/|(Forecast EPS)|
- SURP8: Consensus EPS surprise as a percent of the past eight-quarter volatility of actual EPS—(Actual EPS − Forecast EPS)/(Standard deviation of trailing eight-quarter actual EPS).
- SURPC7: Consensus EPS surprise as a percent of the past seven-quarter volatility of change in actual EPS—(Actual EPS − Forecast EPS)/(Standard deviation of trailing seven-quarter change in EPS).

The summary statistics and sampling distributions of these metrics were estimated and observations made regarding the absolute magnitude, central tendency, and distribution of observations of each of the metrics. Results of these tests are consistent with the previous forecasting literature.

For each year, the four quarterly consensus earnings surprises were estimated for each company in the sample. The sample was pooled across all companies and years, and *t*-statistics were estimated for each surprise metric to test the hypothesis that the mean surprise was different from zero. Descriptive statistics were estimated for positive and negative surprises for each surprise metric separately.

A second sample was created by deleting all surprises with reported or forecast EPS between

Figure 1. Histograms of Earnings Surprise Measures, Quarterly Observations, First Quarter 1974–Fourth Quarter 1991



Note: Total number of observations = 66,100.

plus and minus 10 cents for all four surprise metrics. This number was reduced to 55,650 stocks after the deletions. We had two motives for creating this sample. Neiderhoffer and Regan pointed out the difficulty of using an error metric with actual earnings as the denominator because this technique "becomes statistically cumbersome whenever the base (actual or forecast earnings) is small or negative."[21] By deleting all stocks with EPS between plus and minus 10 cents, we were able to control for a large part of this negative bias problem for the SURPE and SURPF results. Second, by using this technique, we controlled for the potential for outliers to dominate the results. We were able to determine the impact of large errors on stocks with small actual or forecast earnings on the distribution. Using this approach, we found that the impact of nominal earnings and forecasts is negligible and that large errors are valid misses, not outliers.[22]

RESULTS

The distributional results of each of the surprise metrics for the total sample are shown in Figure 1, the frequency distributions of earnings surprises. These histograms of quarterly earnings surprises appear to be approximately normally distributed with a central tendency around zero percent. The tails are "fatter" than expected, however, and the distribution slightly more peaked and negatively skewed in each case. This configuration is consistent with research showing that analysts tend to be overly optimistic in making earnings forecasts. The sampling distribution of the SURPE metric is skewed slightly to the positive side of the surprise distribution with the exception of a large number of large negative surprises.[23] This distribution is a result of the definition of this surprise metric, which tends to increase the size of negative surprises. The histogram of the SURPF metric (percent of forecast) appears to be more symmetric with fewer negative and more positive outliers than the SURPE metric. The two metrics representing standardized surprises exhibit a larger number of outliers, and the tails of these distributions appear to be "fatter" than normal, even though the mean and median more nearly coincide. One general conclusion from an inspection of the histograms is that a large number of outliers exist when surprise is measured by any of the four criteria. The four surprise metrics were reestimated for a reduced sample that excluded all actual and forecast earnings between plus and minus 10 cents. The results were not significantly different from those obtained for the full sample. The appendix addresses the issue of the identification and importance of outliers in this analysis.

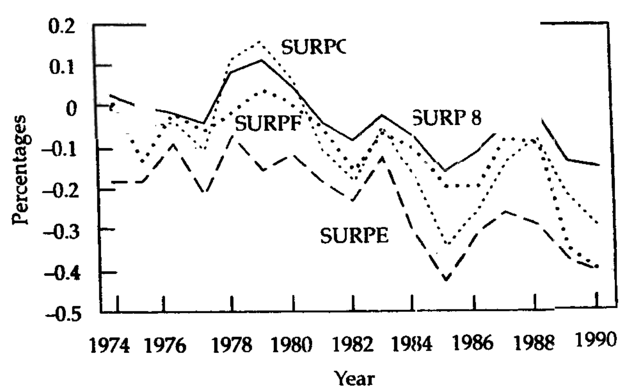
Table 1 makes evident that the mean surprise is negative irrespective of the choice of surprise metric. Specifically, the t-tests indicate that all the metrics generated average surprises that were less than zero at the 99.9 percent level of significance. A priori, we would expect analysts to achieve a mean-zero forecast error. These results verify that analysts tend to be optimistic over time in their forecasts. Negative surprises outnumbered positive surprises (SURPE) by 3,241 out of a sample of 66,100 observations, and the mean of negative surprises was always larger in absolute magnitude than that of the positive surprises. Table 1 also reveals that the average absolute value of the surprise over this period was large, averaging 43.8 percent of actual and 41.5 percent of forecast earnings.

Table 1. Descriptive Statistics for Earnings Surprise Measures, Quarterly Observations, First Quarter 1974–First Quarter 1991

Statistic	SURPE	SURPF	SURP8	SURPC7
All surprises (66,100 observations)				
Average absolute surprise	43.8%	41.5%	81.0%	42.2%
Mean	–0.250	–0.111	–0.136	–0.049
Standard deviation	2.208	1.961	1.409	0.620
Median	0.000	0.000	0.000	0.000
Maximum	49.000	48.000	30.425	30.500
Minimum	–216.000	–282.600	–78.160	–23.270
t-test for difference of mean from zero	–28.14	–14.07	–24.11	–19.64
Positive surprises (26,122 observations)				
Mean	0.234	0.316	0.706	0.392
Standard deviation	0.922	0.961	0.810	0.455
Median	0.117	0.132	0.477	0.254
Maximum	49.000	48.000	30.425	30.500
Minimum	0.002	0.002	0.002	0.001
Negative surprises (29,363 observations)				
Mean	–0.733	–0.514	–0.915	–0.452
Standard deviation	–0.734	2.630	1.530	0.537
Median	–0.184	–0.157	–0.554	–0.284
Maximum	–0.002	–0.002	–0.004	–0.002
Minimum	–216.000	–282.600	–78.160	–23.270

The SURPE and SURPF magnitudes are consistent with the findings of Basi et al. and Richards et al. for the 1972–76 period, thus confirming their findings but more importantly extending these results into a sample period in which one might expect surprises to be diminishing in both size and frequency of occurrence (see Figure 2).

Figure 2. Mean Value of Surprises over Time



PROPORTION OF SAMPLE OUTSIDE OF FORECAST BANDS

As shown in Table 2, the average quarterly earnings surprise for the entire sample in this time period was significantly greater than plus or minus 10 percent. Irrespective of the type of earnings surprise, on average, a minimum of 55.6 percent of SURPE and 55.5 percent of SURPF observations fell outside the 10 percent error bandwidth.[24] This target was exceeded, on average, in every year of the period and overall for both samples and both types of earnings surprises. These results indicate that analysts who try to fine-tune their forecasts to within plus or minus 5 percent or 10 percent of actual earnings are, on average, unsuccessful.

Table 2 also shows the proportion of analyst consensus forecasts that fell outside of practical error bands during this time period. For instance, in the full sample, 73.3 percent of all the SURPE estimates fell outside a plus or minus 5 percent interval around the actual earnings, 55.6 percent fell outside of plus or minus 10 percent, and 43.75 percent fell outside of plus or minus 15 percent. The proportions falling outside of these error bands for the other metrics was equally large. These results are significant in that the sample size is large and the time frame is 18 years. The proportions falling outside the respective error bands did not vary significantly in trend over time. For the reduced sample, the results are equally significant. Even with the largest surprises deleted, the proportions of analysts' estimates outside the three bands for SURPE were 71.1 percent, 50.7 percent, and 37.9 percent, respectively.[25] Both sets of these results imply that analysts miss their targets by at least plus or minus 10 percent half the time and plus or minus 5 percent almost three quarters of the time.[26]

The use of percentage bandwidths for the standardized surprises requires a slightly different interpretation than surprises measured as a percentage of actual or forecast earnings. Technically, the four metrics are not directly comparable. In the case of a standardized surprise metric, such as SURPC7, the measure is a percent of the volatility of the change in actual earnings. To judge the size of a 42.2 percent surprise in this case, we must consider the size of the standard deviation of the dollar change in actual earnings. If we assume a normal sampling distribution for the surprise metric, one standard deviation on either side of the mean encompasses 68.2 percent of the probability in the distribution. Because each year, on average, 62.75 percent of the surprises fell outside of 15 percent of one standard deviation and the absolute magnitude of the mean error was 42.2 percent of one standard deviation of earnings change (from Table 1), these errors appear to be quite large relative to volatility of earnings changes for the entire sample. For example, if the average stan-

Table 2. Proportion of Forecast Errors Outside of Percentage Bandwidths, First Quarter 1974–First Quarter 1991

	SURPE			SURPF			SURP8			SURPC7		
Year	+/–5%	+/–10%	+/–15%	+/–5%	+/–10%	+/–15%	+/–5%	+/–10%	+/–15%	+/–5%	+/–10%	+/–15%
1974	0.765	0.611	0.491		0.612	0.493		0.838				
1975	0.778	0.625	0.499		0.623	0.503		0.836				
1976	0.746	0.564	0.421		0.558	0.424		0.819				
1977	0.706	0.507	0.383		0.51	0.391		0.82				
1978	0.698	0.508	0.37		0.516	0.383		0.813				
1979	0.72	0.526	0.398		0.535	0.41		0.827				
1980	0.732	0.549	0.426		0.551	0.429		0.836				
1981	0.728	0.538	0.417		0.538	0.421		0.831				
1982	0.742	0.565	0.458		0.562	0.458		0.811				
1983	0.741	0.566	0.449		0.566	0.451		0.821				
1984	0.727	0.556	0.436		0.551	0.433		0.826				
1985	0.752	0.58	0.474		0.571	0.462		0.843				
1986	0.752	0.57	0.452		0.562	0.449		0.84				
1987	0.718	0.542	0.424		0.543	0.425		0.829				
1988	0.711	0.522	0.397		0.524	0.405		0.833				
1989	0.72	0.532	0.422		0.528	0.416		0.836				
1990	0.718	0.556	0.453		0.551	0.444		0.835				
1991	0.744	0.599	0.505		0.596	0.49		0.837				
Average	0.733	0.556	0.438		0.555	0.438		0.830				

dard deviation of change in earnings is 25 cents, then analysts miss their target, on average, by 10.5 cents and 62.75 percent of the time they would miss actual earnings by a minimum of 4 cents.

We conclude that if analysts try to fine-tune their earnings estimates to within plus or minus 10 percent of actual earnings, they do not perform this task well.

FORECAST ERROR BY INDUSTRY

To determine whether a significant proportion of the overall mean and median earnings surprise was attributable to a small number of industries in a few time periods, we classified our sample by two-digit Standard Industrial Classification Code industries. Sixty-one industry portfolios were created, and all four surprise metrics were estimated for each industry for each year. In addition, we estimated median surprises for each year and industry and percentile ranking indicating the percentage of industries whose mean, median, and standard deviation of surprise exceeded decile limits.

A legitimate concern is whether the preponderance of surprises occur in highly volatile industries, thus skewing the findings for the sample as a whole. Table 3 shows the average results by industry. These statistics include the mean, median, and standard deviation of the absolute value of each of the four surprise metrics for each industry averaged over the entire time period. Irrespective of the metric, the surprises are large and emanate from many industries. Table 3 reveals that, over the entire time period, 90 percent of all industries exhibited mean surprises (SURPE) greater than 21.44 percent and median errors greater than 16 percent. Ten percent of the industries experienced average surprises greater than 84.33 percent of actual EPS. Using the standardized error measure SURPC7, 90 percent of all industries experienced mean errors greater than 27.67 percent of one standard deviation of actual EPS and median errors greater than 27 percent. Ten percent of the industries experienced average surprises over the entire time period greater than 48.06 percent of one standard deviation. Because these results are relative to changes in EPS, we consider this level of error to be large. Moreover, in examining decile boundaries, the distribution of these surprises was surprisingly uniform across industries.

A further conclusion may be drawn from this analysis. Standardized errors are large uniformly across industries, indicating that even on a volatility-adjusted basis, analysts err indiscriminately across industries. There is high earnings volatility in industries that are supposed to have high visibility and thus often are given high valuations. This volatility raises a question about whether many such valuations are excessive.

With respect to specific industry rankings, a number of results are evident. The tobacco products industry, for instance, exhibited the lowest rank for mean, median, and standard deviation of surprise for either of the two absolute measures. Although this industry ranked in the first decile for SURPE, it ranked in the seventh decile for SURPC7. Our expectation was that both mean and median surprise levels should be low in this indus-

Table 3. Deciles of Each Surprise Metric by Industry (Percent Industry Means within Decile)

Metric	10%	20%	30%	40%	50%	60%	70%	80%	90%
SURPE									
Mean	21.44%	27.44%	31.17%	35.39%	43.11%	47.61%	57.89%	69.56%	84.33%
Median	16.00	19.50	25.00	28.50	32.00	38.00	45.50	55.50	67.50
Standard deviation	12.52	17.34	21.76	24.78	32.41	34.98	41.28	53.06	90.00
SURPF									
Mean	20.72	22.22	27.06	29.00	36.83	44.44	54.39	61.61	85.22
Median	14.50	17.50	20.00	23.50	26.00	30.50	37.00	44.00	66.50
Standard deviation	10.29	12.51	16.72	18.79	25.41	37.53	49.41	63.41	101.92
SURP8									
Mean	53.33	64.00	69.33	72.67	76.61	78.78	81.06	86.50	90.61
Median	52.00	57.00	65.00	67.00	71.00	73.00	76.00	80.50	84.50
Standard deviation	13.46	15.31	18.34	20.88	22.61	29.25	35.48	41.97	48.94
SURPC7									
Mean	27.67	32.78	35.56	37.11	38.67	41.44	43.06	44.78	48.06
Median	27.00	30.50	33.50	35.50	37.00	38.50	40.50	41.50	46.00
Standard deviation	6.18	7.60	9.16	9.83	10.63	11.25	15.30	18.35	22.21

try because of the stability of demand, yet standardized surprise measures ranked the mean and medians quite high relative to other industries. In contrast, the food industry ranked in the third and second deciles, respectively, for absolute (SURPE) and standardized measures (SURPC7), indicating a similarity of rankings. Apparently, the choice of surprise metric is important.[27]

THE CYCLICAL BEHAVIOR OF EARNINGS SURPRISES

Another major question that might be raised is whether the large surprises are significantly influenced by periods of business expansion and recession, during which changing economic conditions make an analyst's task more difficult. We examined the surprise metrics in three periods of economic expansion and four periods of recession to determine whether their magnitude varied predictably across economic cycles. We hypothesized that during periods of recession, we would expect to see analysts' forecasts exceed reported earnings because they would not have fully adjusted their forecasting techniques to accommodate slow economic growth; during periods of economic expansion, we would expect to observe their forecasts fall below actual earnings and therefore exhibit more or larger negative errors.

Table 4 shows the proportion of analyst consensus for each economic expansion and contraction during the sample time period. No significant difference is apparent between the mean size of analyst errors in periods of expansion and recessions. Thus, economic conditions do not seem to affect analysts in making their earnings estimates. Clearly, however, this analysis shows that analysts tend to be overly optimistic in both expansions and recessions. Taking simple averages, the mean positive surprise (SURPE) in expansions was 23 percent and in recessions, 23 percent. For negative surprises, the corresponding statistics were –64 percent and –72 percent.[28] Uniformly across surprise metrics, the negative surprises in recessions appear to be slightly larger in absolute value than in expansions. Larger negative errors during recessions would imply that analysts' projections are optimistic. Clearly, however, the proportion of the

Table 4. Average of Earnings Surprise Measures Across All Expansions and Recessions, January 1974–March 1991
(number of observations in parentheses)

	Expansion Dates						Recession Dates							
Surprise Measure	April 1975–January 1980		August 1980–July 1981		December 1982–July 1990		November 1973–March 1975		January 1980–July 1980		July 1981–November 1982		July 1991–March 1991	
SURPE														
Positive average	0.20	(6,669)	0.24	(1,236)	0.25	(12,447)	0.22	(1,315)	0.20	(1,209)	0.30	(2,224)	0.23	(1,022)
Negative average	–0.60	(5,571)	–0.52	(1,110)	–0.80	(15,748)	–0.67	(1,373)	–0.57	(1,136)	–0.71	(2,673)	–0.93	(1,752)
All average	–0.14	(12,240)	–0.11	(2,346)	–0.31	(28,195)	–0.21	(2,688)	–0.15	(2,345)	–0.23	(4,897)	–0.47	(2,774)
(Zero observations)		(1,862)		(301)		(2,594)		(393)		(259)		(569)		(183)
SURPF														
Positive average	0.27	(6,669)	0.31	(1,236)	0.32	(12,447)	0.37	(1,315)	0.37	(1,209)	0.38	(2,224)	0.31	(1,022)
Negative average	–0.37	(5,571)	–0.38	(1,110)	–0.53	(15,748)	–0.58	(1,373)	–0.40	(1,136)	–0.60	(2,673)	–0.82	(1,752)
All average	–0.02	(12,240)	–0.01	(2,346)	–0.14	(28,195)	–0.10	(2,688)	0.00	(2,345)	–0.14	(4,897)	–0.38	(2,774)
(Zero observations)		(1,862)		(301)		(2,594)		(393)		(259)		(569)		(183)
SURP8														
Positive average	0.79	(6,669)	0.78	(1,236)	0.63	(12,447)	1.00	(1,315)	0.86	(1,209)	0.66	(2,224)	0.59	(1,022)
Negative average	–0.87	(5,571)	–0.86	(1,110)	–0.91	(15,748)	–1.10	(1,373)	–0.85	(1,136)	–0.91	(2,673)	–1.08	(1,752)
All average	0.3	(12,240)	0.00	(2,346)	–0.21	(28,195)	–0.06	(2,688)	0.03	(2,345)	–0.18	(4,897)	–0.44	(2,774)
(Zero observations)		(1,862)		(301)		(2,594)		(393)		(259)		(569)		(183)
SURPC7														
Positive average	0.45	(6,669)	0.41	(1,236)	0.35	(12,447)	0.56	(1,315)	0.46	(1,209)	0.35	(2,224)	0.30	(1,022)
Negative average	–0.46	(5,571)	–0.43	(1,110)	–0.45	(15,748)	–0.54	(1,373)	–0.42	(1,136)	–0.46	(2,673)	–0.46	(1,752)
All average	0.03	(12,240)	0.01	(2,346)	–0.09	(28,195)	0.00	(2,688)	0.03	(2,345)	–0.08	(4,897)	–0.17	(2,774)
(Zero observations)		(1,862)		(301)		(2,594)		(393)		(259)		(569)		(183)

Note: Cycle dates from the National Bureau of Economic Research overall surprise did not emanate from either economic expansions or recessions. Therefore, we concluded that large earnings surprises do not emanate from economic business cycles.

DO ANALYSTS' FORECAST ERRORS INCREASE WITH TIME?

To try to identify a trend in the magnitude of analysts' errors, we regressed the surprise for each stock in time period t against the surprise for the period $t - 1$. We estimated this statistical relationship to determine whether the surprises appear to be increasing over time. This process was replicated, with suitable adjustments for autocorrelation, for each surprise type for the entire time period for both samples, as well as for the positive, negative, and pooled surprise subsamples. The regression equation took the following form:

$$(\text{Avg. surprise})_t = \alpha + \delta\,(\text{Avg. surprise})_{t-1} + \epsilon_t,$$

where $\epsilon_t \sim N(0, \sigma^2)$; $E(\epsilon_i, \epsilon_j) = 0\ \forall i \neq j$.

The interpretation of the regression intercept, α, is the mean error at the beginning of the time period. The coefficient δ may be interpreted as the average percent change in the mean error between two quarters over the entire time period. Thus, if δ is significant and positive, positive errors are increasing over time. Because of the presence of autocorrelation in the residuals, Cochran–Orcutt transformations were applied to the data. Table 5 indicates that analysts errors are increasing over time. We obtained highly significant t-statistics on the slope coefficients, δ. With one exception, these results obtained for the entire sample and for positive as well as negative surprises. In addition, as Table 5 shows, the intercept of each of the regressions is highly significant for all four metrics, indicating that analysts tend to be optimistic in their forecasting. Intercepts for negative surprises were much larger than for positive surprises, reaffirming both an increasing error trend and the analysts' tendency toward overoptimism.

The rates of change for the entire sample, σ, were large and highly significant for each of the four metrics. These rates were approximately the same, and the intercept terms were also highly significant for all metrics. The rate of change for positive surprises for the four metrics appeared to be larger than for negative surprises and was highly significant.

This observation supports the previous one: The size and trend of consensus forecast errors make the dependence on most forecasting techniques that require single-point earnings estimates to be close to actual earnings unreliable as a primary investment technique.

Table 5. Regression Test Results, Trend in Analysts' Forecasting Errors (Full Sample)

Metric	α^a	t-Statistic	δ^a	t-Statistic
All surprises				
SURPE	–0.094	–3.46***	0.636	6.48***
SURPF	–0.031	–2.51**	0.745	8.61***
SURP8	–0.052	–2.53**	0.652	7.23***
SURPC7	–0.022	–2.21*	0.603	6.35***
Positive surprises				
SURPE	0.041	2.45**	0.825	11.80***
SURPF	0.120	3.84***	0.617	6.34***
SURP8	0.137	3.45***	0.796	14.47***
SURPC7	0.063	2.90**	0.828	15.29***
Negative surprises				
SURPE	–0.395	–4.89***	0.447	4.01***
SURPF	–0.242	–4.38***	0.519	4.82***
SURP8	–0.517	–5.05***	0.428	3.83***
SURPC7	–0.389	–6.95***	0.138	1.12

[a] Estimated value from the first equation.
* Statistically significant at the 95 percent level of confidence.
** Statistically significant at the 99 percent level of confidence.
*** Statistically significant at the 99.9 percent level of confidence.

If earnings surprises are increasing over time, these results suggest that despite increased availability of data bases and real-time reporting services, the analysts' processes for forecasting earnings are flawed. The large size of the forecasting error, even after controlling for the business cycle and industry groupings, casts doubt on the viability of valuation methodologies such as the growth or discounted cash flow approaches that require accurate near- and long-term, single-point estimates of earnings.

HOW WELL DO ANALYSTS FORECAST?

To quantify the size of forecast errors, we regressed the actual earnings for a company on the consensus forecast. We estimated the following model:

$$(\text{Actual Earnings})_t = \alpha + \beta(\text{Forecast})_t + \epsilon_t,$$

where $\epsilon_t \sim N(0, \sigma^2)$.

This regression framework was estimated for the entire sample pooled, as well as for positive and negative surprises. In addition, the regression parameters were estimated for each year for the entire sample and for positive and negative surprises respectively. The regression framework as applied to each of the error metrics provides an estimate of the size of surprise and a test of analyst overoptimism. This framework is independent of the construction of the error metric, relying instead on the regression of actual earnings on the consensus forecasts.

We tested the α and β coefficients for statistical significance using Student's t-tests and compared the coefficient of determination, R^2, across positive and negative surprise samples to ascertain differential forecasting ability. If analysts are excellent forecasters at the consensus level, we would expect the β coefficient to be equal to 1 and the α coefficient to be zero. We report results for the SURPE statistics only. In particular, we sought to determine the following:

- Do analysts miss their forecasts by a statistically significant amount?
- What is the estimate of the percent size of the miss?
- Are analysts optimistic or pessimistic on average?
- Is the error increasing over time?

Table 6 shows the results of this regression analysis. The alphas were statistically significant at the 99.9 percent level for the entire sample. This finding means that analysts overestimate earnings, on average, by a significant amount. Pooling all stocks (those with both positive and negative surprises) revealed that analysts tended to overestimate earnings by an average of 3.6 percent; the error was much larger (15 percent) on those stocks that received negative surprises. Those receiving positive surprises exhibited earnings that were, on average, 8 percent above the forecast level. This analysis reconfirms the negative bias to surprises and the tendency toward analyst optimism that we observed previously. Results from the reduced samples were similar and confirm these findings.

Table 6. Regression Results, Actual Quarterly EPS on Consensus Analyst's Forecasts
(t-statistics in parentheses)

Coefficient	Full Sample	Positive Surprises	Negative Surprises
	66,100	26,122	29,363
	0.99	1.03	1.00
	(305.68)***	(275.75)***	(196.52)***
α	–0.01	0.08	–0.15
	(–7.05)***	(34.37)***	(–42.33)***
R^2	0.58	0.67	0.56
Sample 2[b]			
Observations	52,582	23,735	23,766
β	1.02	1.06	1.00
	(286.80)***	(238.24)***	(193.69)***
α	–0.03	0.05	–0.14
	(–11.43)***	(17.92)***	(–36.95)***
R^2	0.60	0.66	0.60

[a] Includes all observations regardless of the value of quarterly earnings or consensus forecasts, first quarter 1974–first quarter 1991.

[b] Excludes observations with absolute values, quarterly earnings, or consensus forecasts less than 10 cents, first quarter 1974–first quarter 1991.

*** Statistically significant at the 99.9 percent level of confidence.

CONCLUSION

In this study, we examined a data base of consensus analysts' forecasts from 1974 through the first quarter of 1991 and found that errors are larger than one might expect; that they are increasing over time; and that analysts are optimistic on average, because the mean error is significantly negative irrespective of the surprise metric. Forecasting errors also appear to be large across industries and through various stages of the business cycle.

Two major conclusions are evident from the study. The first is that the average forecast error of more than 20 percent of actual EPS (SURPE)—more than 40 percent using nominal estimated and reported earnings—is too high for investors to rely on consensus forecasts as a major determinant of stock valuation. Second, regardless of surprise metric, only a small percentage of estimates fall into a range considered acceptable. On average, 56 percent of the estimates measured as a percent of actuals fall outside a plus or minus 10 percent range, a level that many Wall Street professionals consider minimally acceptable; approximately 45 percent fall outside a plus or minus 15 percent range. These results indicate that, on average, large earnings surprises are the rule rather than the exception.[29]

The observed frequency, size, and increasing trend of all of the error metrics for quarterly earnings estimates bring into question many important methods of stock valuation, which rely on precise earnings estimates sometimes years into the future. The growth, earnings momentum, discounted cash flow, and earnings yield techniques, for example, require fine-tuned estimates often a decade or more into the future. Thus, a significant portion of current security analysis requires a precision in earnings forecasts that is increasingly difficult for analysts to meet.[30]

A final conclusion of this study is that in spite of our own earlier findings, analysts, money managers, and investors appear to ignore the industry's poor forecasting record, although it questions the viability of many important stock valuation methods. Neither the consistency nor the size of forecasting errors, which are well documented, have been addressed. Although the frequency of large surprises in the overall sample is predictably high, market professionals react to forecast errors as though each change is unique and has a very small probability of occurring, thus warranting extensive analysis and earnings revision. We believe this phenomenon may have a behavioral explanation.

If analysts and investment professionals learn from past mistakes, as rational decision makers are expected to do, far less emphasis should be placed on forecasting within their valuation models. Analysts, given the findings, should also use broadband rather than single-point forecasts. At present, they do not. The prevailing belief is that earnings can be fine-tuned. Few recognize the persistent nature of large forecasting errors or have the ability to make adjustments for them.

We believe this lack of recognition of a major shortfall in contemporary investment methodology is likely to have its roots in a behavioral explanation. These findings may be explained by research in the discipline of psychology, which suggests that the accuracy of judgmental forecasts is influenced by cognitive biases that arise when the processing of complex information is simplified (Tversky and Kahneman[31]). Even when warned about the existence of such biases, forecasters appear not to be able to adjust for their effects (Fischhoff[32]).

Our findings raise another interesting question. Is it possible that the "best" analysts' judgmental forecasts may not be the "best" forecasts careerwise? Are analysts drawn to the consensus opinion either openly or unknowingly by the safety of the group? An estimate that is far off the consensus might pose career dangers, whereas an estimate near the group may provide the analyst with a much higher degree of safety, regardless of how inaccurate it may prove to be.

The above conclusions lead us to believe that behavioral factors may play an important role for analysts in forecasting earnings.[33]

FOOTNOTES

1. Analysts' consensus estimates as reported by a number of services, including IBES, Zacks, and First Call, are fine-tuned to the penny. Compaq Computers quarterly estimates would be stated as 75 cents a share for the second quarter of 1994 versus 40 cents one year earlier. The *Wall Street Journal*, *Barron's*, and the *New York Times* provide many examples of sharp stock declines on minimum variance between estimated and actual reported earnings. For example, in a one-week period between April 18 and April 25, 1994, Motorola reported a 46 percent increase in earnings. This increase was 1 cent short of consensus expectations (less than 1 percent), however, and Motorola's price fell 16⅛ dollars, a 15.2 percent decline. Another example was Zoll Medical, which fell 26.4 percent on a 1-cent earnings shortfall to expectations.
2. We use the error metrics, which are percentages of either actual or forecast earnings because these are most often presented in the *Wall Street Journal* and other financial publications, as well as by earnings services such as Zacks and IBES.
3. IBES reports that, since 1979, the mean absolute revision in earnings estimates for S&P 500 stocks is 12.9 percent from the beginning to the end of the year in which the forecast is made. Analysts revise their estimates by 6.34 percent in the first half of the year and 19.51 percent in the second half. This finding indicates that analysts target a high degree of accuracy in earnings forecasts. According to IBES, despite these estimate changes, analysts tend to be overoptimistic. Between 1980 and 1994, they missed their growth targets on the S&P 500 by an average of almost 65 percent (the mean earnings growth forecast was 18.41 percent versus the 6.28 percent average reported). Therefore, we hypothesized that 5 percent, 10 percent, and 15 percent error bands around reported earnings are significant targets sought by analysts and professional investors.
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19. Value Line provided Abel Noser with quarterly earnings estimates prior to 1981. Zacks' quarterly estimates were incorporated in 1981, and IBES's in 1984. Today, Abel Noser uses Zacks, IBES, and First Call to develop consensus estimates.
20. Four different surprise metrics are used because the academic literature lacks consensus on the appropriate form of the metric. Reporting services, such as Zacks, tend to report surprise as a percent of forecast earnings or of actual earnings in their weekly documentation. Each measure has a unique set of statistical and interpretive problems. Our basic results appear invariant over the four metrics we used.
21. Neiderhoffer and Regan, "Earnings Changes, Analysts' Forecasts, and Stock Prices," p. 69.
22. Space considerations prevent these results from being presented here; they are available from the authors upon request.
23. More than 4,000 surprises (SURPE) are less than –95 percent while fewer than 1,000 are greater than +95 percent. In each of the four metrics, large negative errors (> |95 percent|) outnumber large positive surprises.
24. The proportion falling outside 10 percent for the standardized errors was even higher: 82.95 percent of SURP8 and 72.17 percent of SURPC7 errors fell outside the 10 percent bandwidth. Note, however, that these errors are with respect to the standard deviation of the changes in earnings (SURPC7).
25. The small-sample results are available from the authors upon request.
26. The results of the "reduced" sample indicate that SURPE and SURPF are identical as are SURP8 and SURPC7 with respect to proportions falling outside these error bands.
27. To save space, we have not included the ranking statistics or analysis for each of the 61 industries. Nevertheless, three findings stand out from this analysis: Standardized errors were uniformly large across industries; the absolute magnitude of these errors was high, averaging 40 percent; and the absolute measure exhibited higher volatility than the standardized measure in specific years. The findings also show very high earnings volatility in industries that should have high visibility. These results are available upon request.
28. The other surprise metrics yield the following average results:

Metric	*Surprise*	*Expansion*	*Recession*
SURPF	Positive	30%	35%
	Negative	–42	–60
SURPC7	Positive	–40	41
	Negative	–44	–47

29. These results applied to a greater extent with respect to SURPC7 and SURP8, the standardized errors. Although the interpretation is slightly different because of the relative nature of the errors, we found that 62.8 percent of SURPC7 and 77.8 percent of SURP8 estimates fell outside of plus or minus 15 percent of one standard deviation of earnings and earnings changes.
30. Many practitioners consider an earnings gain of 6–9 percent as average and 12–15 percent or more to be in the growth category. Thus, surprises of the magnitude shown make a high-growth company indistinguishable from an average-growth company.
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33. Support for this research was provided by the David Dreman Foundation. The authors thank W. Van Harlow, Richard Zeckhauser, Professor Domenic Cicchetti, Professor Mitchell Stern, Professor Nelson Woodard, and anonymous referees for their assistance in the preparation of this paper. The authors also thank the Abel Noser Corporation for the use of the Abel Noser data base.

Why So Much Error in Analysts' Earnings Forecasts?

Vijay Kumar Chopra

Wall Street analysts tend to be too optimistic about the earnings prospects of companies they follow. The average consensus 12-month EPS growth forecast is 17.7 percent, which is more than twice the actual growth rate. In aggregate, forecasts are 11.2 percent above actual earnings at the start of a year and are revised downward continuously in the course of the year. For the full study period reported here, the percentage of 12-month earnings estimates revised downward exceeded the percentage revised upward, on average, by 4.4 percent every month. Since 1993, however, the quality of analyst forecasts seems to have improved. This article provides an intuitive explanation of the change and suggests ways in which analysts can use the explanation to improve portfolio performance.

Use of earnings estimates is an integral part of equity valuation by fundamental and quantitative analysts, and the estimates have even become an integral part of financial reporting in the popular press. The behavior and uses of earnings estimates have been widely studied. I/B/E/S International has published an excellent bibliography of earnings expectation research (Brown 1996). Studies that have shown that analysts tend to overestimate earnings include Clayman and Schwartz (1994), Dreman and Berry (1995), and Olsen (1996). Clayman and Schwartz attributed the positive bias to analysts' tendency to "fall in love" with their stocks. In addition, they proposed that investment banking relationships of investment houses and the prospect of being cut off from access to company managers make issuing negative or critical reports on companies difficult for analysts. Dreman and Berry examined quarterly earnings estimates and found that the average forecast errors tend to be high; in their study, only a small percentage of estimates fell into an acceptable error range. Olsen ascribed the positive bias and lack of accuracy in earnings estimates to herding behavior among forecasters. Francis and Philbrick (1993) argued that analysts make optimistic forecasts to maintain relationships with company managers.

The data for the studies reported here are from the I/B/E/S Global Aggregates database, which aggregates bottom-up analyst earnings forecasts to create forecasts at the market level. The specific forecasts analyzed were for the earnings of the S&P 500 Index. I/B/E/S uses market-capitalization weights to combine the mean earnings forecasts for each company in the S&P 500 into an index of earnings estimates. The data are available on a monthly basis beginning with January 1985; the cutoff point for this study is December 30, 1997.

Forecast Changes during a Year

This study focused on how the forecasts for the S&P 500 earnings for the current fiscal year vary over the course of the year. **Figure 1** shows the "calendarized" current fiscal year (Calendar FY1 in I/B/E/S terminology) forecasts and actual earnings per share for the entire study period, January 1985 through December 1997.[1] Because of the delay in reporting earnings, the actual earnings are not known until after the year has ended. To make sure that all companies have reported, I used the actual earnings for a calendar year from the I/B/E/S computation made in July of the following year. Therefore, the July 1996 calculation of calendarized 1995 earnings is taken to be the actual earnings for calendarized 1995.

The calendarized actual earnings follow a stair-step pattern. The long-term upward trend and the cyclicality in actual earnings are both evident from Figure 1: Earnings tend to increase over the long run. The cumulative annualized growth rate in earnings for the period is 8 percent, but earnings

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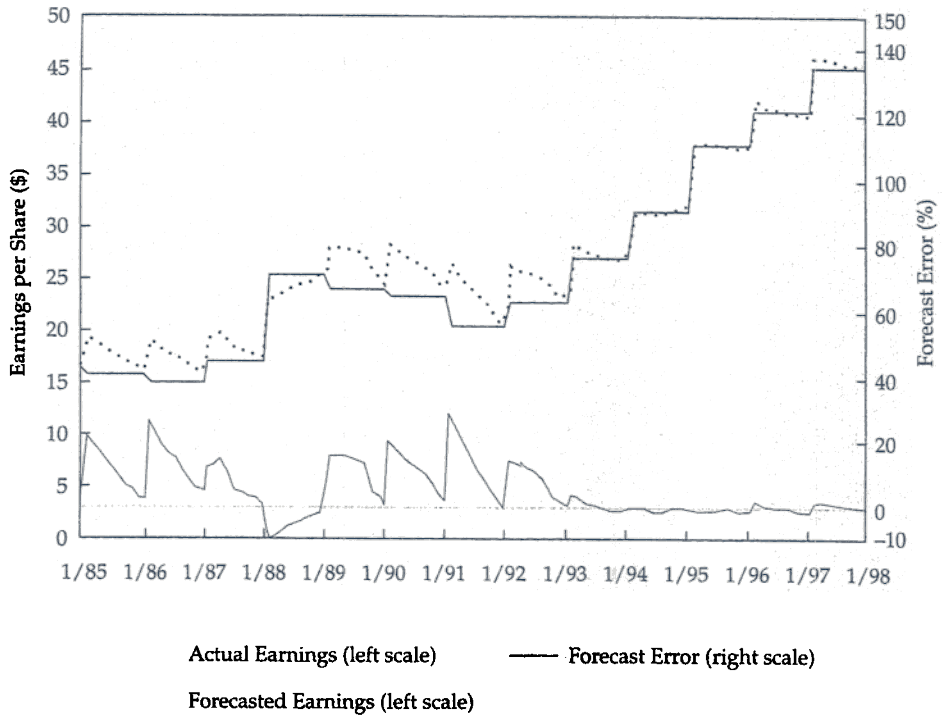
Figure 1 Calendarized FY1 Actual Earnings, Forecasted Earnings, and Forecast Errors for the S&P 500: 1985–97



have declined in some periods, such as 1986 and 1989–1991. The earnings recovery since 1992 has produced a steady step-up pattern.

In general, Figure 1 shows that earnings forecasts are very optimistic at the start of the year and decline toward actual values as the year progresses. The decline in full-year forecasts occurs as quarterly numbers are released and an increasing portion of the fiscal-year earnings becomes known. In addition, as the year progresses, company managers comment on the outlook for their companies in future quarters and analysts gather additional information that may lead them to revise their estimates. On rare occasions, analysts underestimate earnings, such as in 1988. For most years, however, analysts revise their initial estimates downward. Future research will have to separate the effect of time from the effect of better visibility for the late quarters of each year.

On average, the Street overestimated current-year earnings by 6.1 percent in the 1985–97 period. In some periods, such as around February 1991, the overestimation was as high as 30 percent, and in other periods, such as February 1988, earnings were underestimated by more than 8 percent. The average overestimation in the 1985–92 period was 9.4 percent.

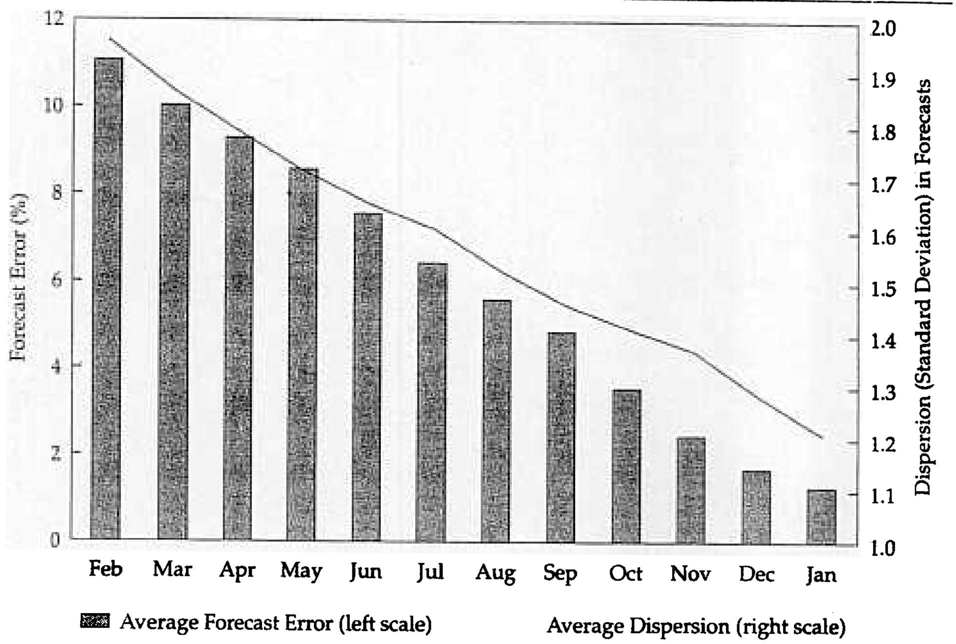
Since 1993, analyst forecasts have been much closer than in the past to actual earnings. The average forecast error since January 1993 has been remarkably small, an average overestimation of less than 1 percent.

Overestimations typically correct in the course of a year. **Figure 2** shows the decline toward reality of analyst optimism. On average, earnings are overestimated by about 11.2 percent at the start of the fiscal year. (The largest forecast errors occur in February because of the I/B/E/S convention of rolling over a calendar year at the end of January instead of at the end of December.) The overestimation declines to 8.7 percent three months later. Another quarter later, the estimate declines to only 6.6 percent above the actual. By the end of the third quarter, the overoptimism is only 3.6 percent. With attention shifting to the next fiscal year, the final overestimation is only slightly more than 1 percent on average. (Complete convergence does not occur at year end because of the delay in reporting earnings.)

The pattern of declining overestimation was more pronounced before 1993; in the pre-1993 period, the average forecast errors in February were almost 17 percent. At the end of July, they were still well over 10 percent. Since 1993, the error has been as low as 2 percent in February, fading to small negative values from September on.

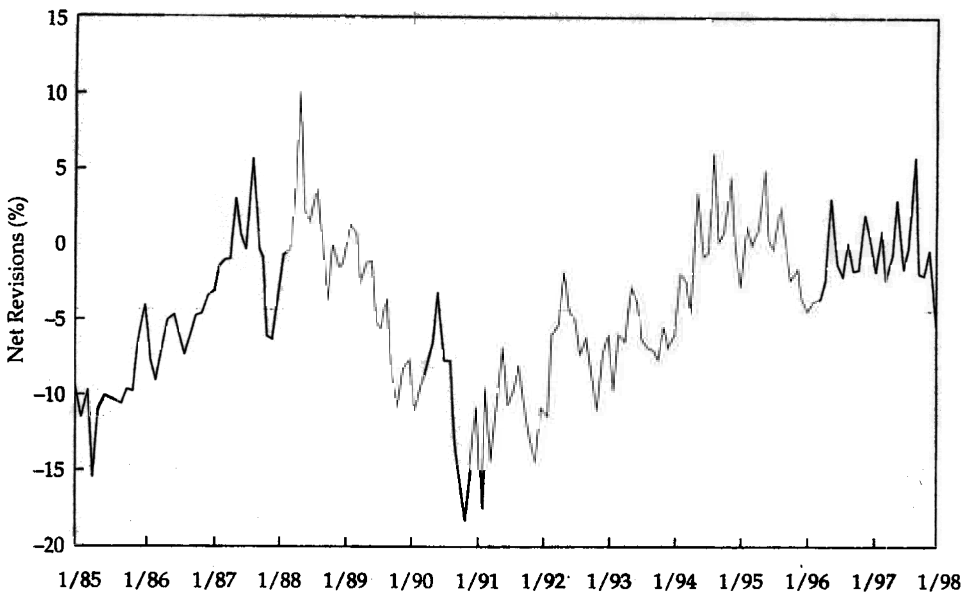
Another perspective on analyst optimism can be gained by looking at the percentage of estimates of 12-month-forward earnings that are revised upward or downward every month.[2] **Figure 3**

Figure 2. Analyst Overoptimism and Dispersion in EPS Estimates: Monthly Pattern, Averages for 1985–97



Note: Estimates are from February of a calendar year to January of the following year because of the I/B/E/S February rollover. The initial estimate for Calendar FY1 is made in February, and the final estimate is made in January of Calendar FY2.

Figure 3. Net EPS Estimate Revisions



shows the net positive revisions of 12-month-forward earnings.[3] This series is volatile, but its overall trend is important. Most of the net revisions are negative, which is to be expected; analysts are constantly adjusting their estimates downward because the initial estimates are too optimistic. The average net revision for the entire period, indicated by the shaded line in Figure 3, is –4.4 percent—that is, the percentage of estimates revised downward exceeds the percentage revised upward by 4.4 percent each month. Since 1994, however, net revisions have been close to zero, which confirms the other evidence that analyst forecasts have improved in accuracy since that time.

*

Consider now another interesting aspect of analyst forecasts—the degree of disagreement among the estimates. Figure 2 shows the decline in the dispersion of estimates over the course of a typical year. The dispersion is greatest in February and declines systematically to its lowest value the following January. This decline can be attributed to quarterly earnings releases and the resulting increase in the visibility of the company's prospects. For the whole study period, dispersion in estimates at the level of the S&P 500 exhibits the sawtooth pattern shown in **Figure 4**. Analyst estimates of Calendar FY1 earnings show the greatest disagreement at the start of the year. As companies report interim quarterly results, the proportion of the fiscal year for which earnings have to be forecasted declines, which reduces the divergence in Calendar FY1 estimates as the year proceeds. This pattern has been particularly strong since 1988 and does not show any signs of fading in recent years. Although analysts may have gotten better at estimating the year's overall level of earnings, the disagreement among analysts over earnings estimates has not diminished over the years.

Forecasted versus Actual EPS Growth

Analysts' earnings growth rate forecasts provide another perspective on the overoptimism evident in their forward estimates of EPS. **Figure 5** shows the rolling 12-month-forward actual and forecasted growth in S&P 500 earnings. For example, the 12-month forecasted growth rate in March 1986 was 16.6 percent whereas the actual growth rate for the subsequent 12 months was –2 percent.

Figure 5 provides three key insights into analyst behavior. First, earnings growth forecasts are always positive. The forecasts lie roughly in the 10–30 percent range, with an average of 17.7 percent, whereas actual growth averages 8.6 percent, almost 9 percent below the forecasts on an annual basis. Therefore, on average, analysts' forecasts are double the actual growth rate in earnings.

Second, actual earnings growth rates vary a lot more than the forecasted rates. Actual earnings growth varies between –15 percent and 40 percent, whereas the forecasts lie within a much narrower range, 10–30 percent. The standard deviation of forecasted growth rates is only 5.4 percent, compared with a 12 percent standard deviation for actual earnings growth rates. Note that, in aggregate, analysts never forecast an absolute decline in earnings, but actual earnings have fallen for extended periods of time (e.g., January 1985 to June 1986, which coincided with a rapid decline in the pace of economic activity and a collapse in the price of oil, and again from January 1989 through June 1991, which was a time of brief economic recession).

Third, Figure 5 shows that, as with EPS levels, actual and forecasted EPS growth rates have been much closer since January 1993. **Table 1** summarizes the forecasting behavior of analysts for the

Figure 4. Dispersion in Analyst EPS Estimates over Time

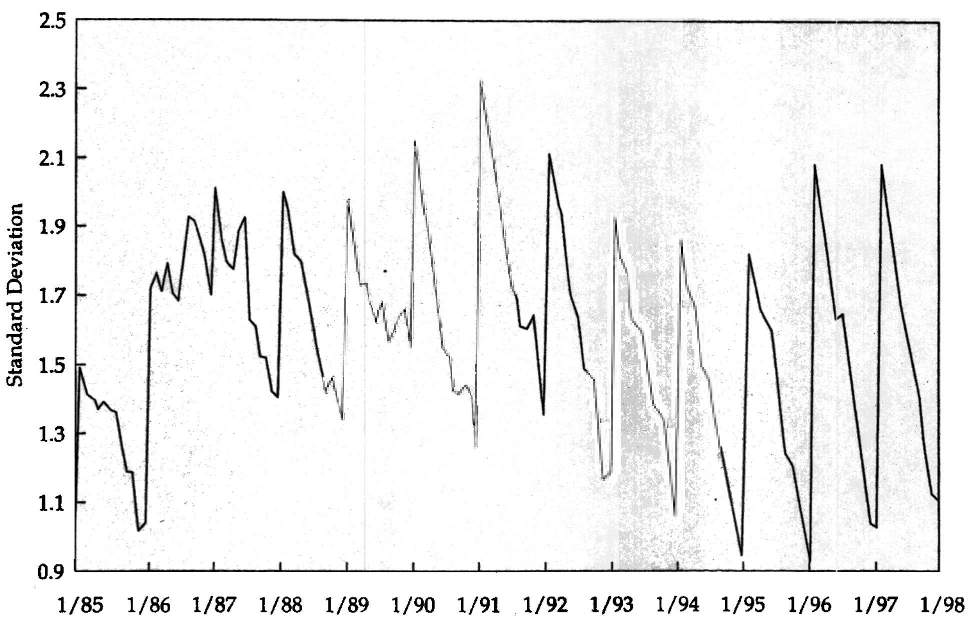
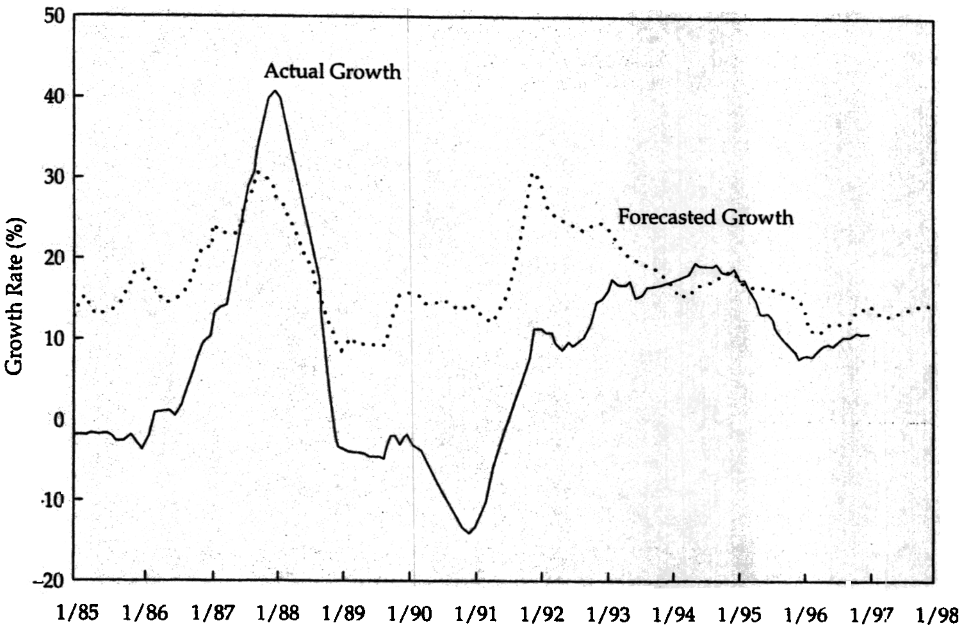


Figure 5. Forecasted versus Actual EPS Growth Rates



Note: The actual growth rates end in December 1996, whereas the forecasted growth rates are available through the end of 1997 because the actual growth rate is not known until 12 months after a given month-end. For example, the actual growth rate for March 1986 comes from March 1987 data.

Table 1. Twelve-Month-Forward Forecasted and Actual Earnings Growth Rates: Summary Statistics

Period/Statistic	Forecasted Growth Rate	Actual Growth Rate	Difference in Rates
January 1985 to December 1996			
Mean			9.1%
Standard deviation			9.3
Maximum			28.7
Minimum			–13.1
January 1993 to December 1996			
Mean	16.5		2.1
Standard deviation	3.2		2.8
Maximum	24.3		8.3
Minimum	10.9		–2.9

Note: The difference between forecasted and actual growth rates is a new series. The last column shows the mean, standard deviation, maximum, and minimum for this series.

whole study period and the post-1993 periods. The average forecasted growth rate of 16.5 percent since January 1993 reported in Table 1 is only about 2 percent higher than the actual increase of 14.4 percent. The standard deviations have also been closer, at 3.2 for the forecast versus 3.9 for the actual.

The correlation between average forecasted and actual EPS growth rates for the total period is 0.67, which indicates that analysts have done a moderately good job of capturing changes in EPS growth rates over time. The correlation for the 1993–97 period was 0.70.

Does the recent convergence between analyst forecasts and actual EPS indicate a sudden increase in analyst forecasting ability? Possibly, but the more likely explanation is that analysts have continued to predict optimistic growth rates but those predictions turned out to be in line with actual rates that were high by historical standards. That is, because of restructurings during the previous decade, when the economy started strengthening in 1992, earnings per share grew strongly to match the usual analyst optimism. This explanation is supported by a comparison of rates since January 1993 with rates for the whole period. The forecasted growth rates are very close, 16.5 for the recent period and 17.7 for the whole period, which indicates that analyst optimism did not decline; the actual growth rate for the recent period, however, was almost 6 percentage points higher than growth for the whole period. In short, the actual growth rate for January 1993 through December 1997 has been close to the long-term average growth forecast in what has been one of the longest economic expansions in the history of the United States.

Economic Growth and Earnings Growth

At the aggregate level, company earnings are likely to be tied to the state of the economy. Strong economic growth should, therefore, lead to strong growth in EPS, and indeed, a comparison of growth in industrial production with earnings growth for the S&P 500 supports that expectation.[4]

Figure 6 provides plots of the year-on-year growth in industrial production and the year-on-year growth in actual earnings. Earnings growth lags industrial production growth by between 9 and 18 months, with an average of about 12 months. In order to highlight the close link between growth in industrial production and EPS growth, the earnings growth has been shifted back by 12 months; that is, for example, the June 1996 growth in industrial production is the growth for June 1995 to June 1996 and the June 1996 earnings growth is the growth from June 1996 to June 1997.

Figure 6 suggests that investment analysts could predict aggregate earnings using industrial production data. The correlation between the growth of the two series is 0.77. When industrial production is lagged by one additional month to account for the late release of the data, the correlation is still very high, 0.73. In comparison, the correlation between forecasted and actual earnings growth rates has been averaging 0.67.

An exploration of the link between the strength of the economy and earnings growth estimates will shed considerable light on why earnings estimates are consistently off the mark and why they have been closer to actual earnings since 1993. **Figure 7** shows the year-on-year growth in industrial production and plots the error in the 12-month-forward earnings growth forecast (the difference between the 12-month-forward forecasted earnings growth and actual earnings growth). The clear inverse relationship between the two series indicates that forecast errors are greatest when industrial production growth is at a peak or trough. Furthermore, when industrial production growth accelerates, forecast errors decline, and when industrial production decelerates, forecast errors increase. When growth in industrial production accelerates, earnings grow strongly and the gap between the optimistic growth forecasts and actual earnings growth narrows, which results in more-accurate forecasts. When growth in industrial production decelerates, earnings growth declines

Figure 6. Industrial Production Growth and Aggregate EPS Growth

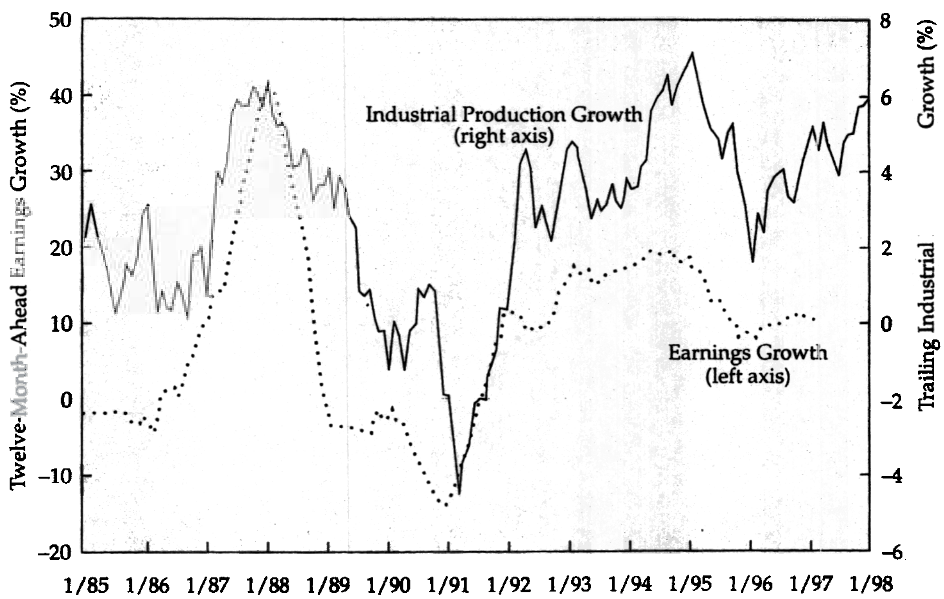
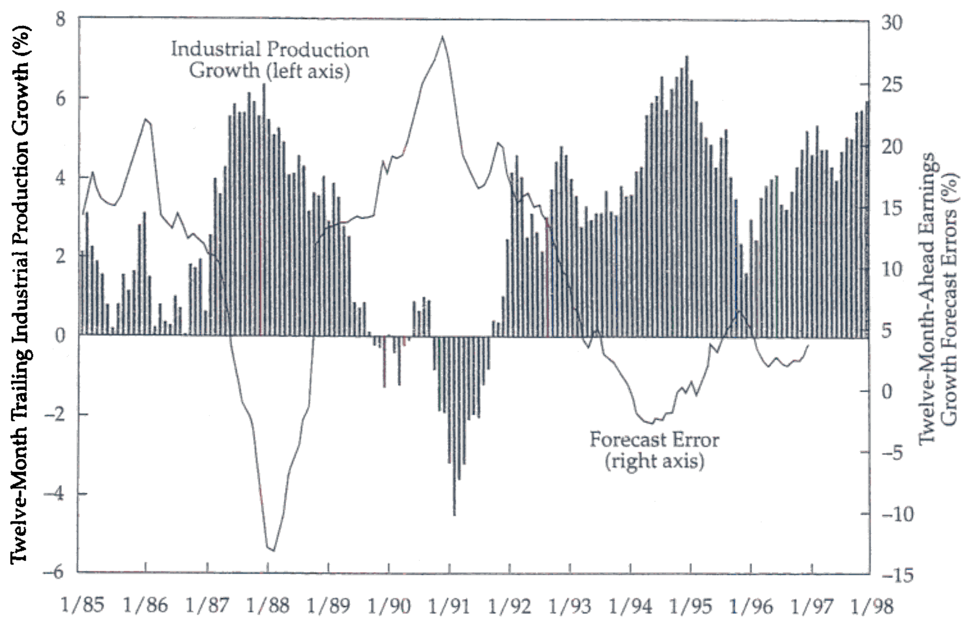


Figure 7. Industrial Production Growth and Errors in EPS Growth Forecasts



(with a 12-month lag) and the gap between the optimistic forecasts and actual earnings growth widens, which results in inaccurate forecasts. When industrial production growth is at its peak, the forecast errors overshoot on the downside and are large but negative. An example is the fourth quarter of 1987 through the first quarter of 1988. On the other hand, when the growth in industrial production started declining in January 1988 from 6.4 percent down to −4.5 percent in March 1991, the forecast errors went from −13 percent to almost 29 percent.

In light of this evidence on growth in the economy and analysts' forecasts, the aggregate behavior of analysts can be described as follows: They are normally very optimistic. When economic growth strengthens, actual earnings accelerate toward the normally optimistic forecasts, so forecast errors decline. If economic growth is very strong, earnings rise well beyond the forecasts, so analysts end up underforecasting earnings for a while. When the economy slows down, earnings start declining but the analysts' optimism prevents them from reducing their estimates far enough. Therefore, the size of forecast errors increases. If forecast errors are negative when the economy starts to slow down, as in January 1988, the errors become less negative at first; then, as the economy continues to decelerate and moves into a recession, the forecast errors move into the positive range and continue to grow. In December 1990, the errors hit a peak of almost 29 percent.

This behavior implies that analysts are likely to be most accurate in an environment of continuing strong economic growth, when earnings growth will approach the analysts' usually bullish forecasts—as has been the case since early 1992. The worst economic environment for aggregate analyst forecasts is one of an accelerating or decelerating economy, and the faster the pace of acceleration or deceleration, the greater the deviation between forecasts and actual earnings growth. The bottom line is that analysts will continue to forecast inaccurately as long as business cycles exist.[5]

Investment Implications

Users of EPS estimates will clearly benefit from recognizing the extent of analyst optimism. Valuation models that rely on earnings forecasts are likely to be biased, but if the extent of optimism is similar across industries and sectors, these valuation models will still be useful in evaluating stocks relative to each other.

The finding that forecast errors vary systematically with the business cycle suggests that analysts may focus too much on firm-specific issues and not enough on the overall macroeconomic environment. Portfolio managers could improve portfolio performance, therefore, by adjusting consensus earnings for systematic biases in forecasts.

One of the uses of aggregate estimate data is in global asset allocation, and conventional asset allocation approaches rely on comparing earnings yields with interest rates. Emanuelli and Pearson (1994) described an approach to global asset allocation that relies on estimate revisions. Recognizing that biases in earnings forecasts are linked to the business cycle and adjusting earnings forecasts to reduce the bias will improve the performance of such global asset allocation strategies.

Conclusion

Analysts' forecasts of EPS and growth in EPS tend to be overly optimistic. Calendarized earnings estimates overstate actual earnings by about 11 percent at the start of the year. These estimates are revised downward monotonically as a typical year unfolds. On average, the percentage of 12-month earnings estimates revised downward exceeds the percentage revised up by 4.4 percent a month. Analyst forecasts of 12-month earnings growth rates average 17.7 percent, more than twice the actual growth rate in the past 13 years.

Industrial production is a good predictor of earnings growth for a year in the future; the correlation is 0.77 percent. The analyst forecast for aggregate EPS growth is also a good predictor of actual growth (with a correlation of 0.67), but the forecasted growth rates are generally too optimistic and lie in a narrow (10–30 percent) range whereas the actual growth rates have varied from –10 percent to 40 percent.

Analysts' usual optimism, their tendency to forecast in a narrow and comfortable range, and the business cycle prove to be the bane of their forecasts. Acceleration or deceleration in economic growth tends to catch analysts off-guard. The forecasts are most accurate in an environment of continued strong growth, such as the one the U.S. economy has been in since 1992. Therefore, although the quality of forecasts has improved since 1992, it will deteriorate if and when the U.S. economy slows down and reverts to its historical cyclical pattern.

Notes

I/B/E/S uses the "Compustat rule" to calendarize company-level data prior to aggregation. Data for fiscal years ending between January and May are included in the aggregate for the prior calendar year. Data for the fiscal years ending between June and December of the current calendar year are included in the current calendar-year aggregate (Calendar FY1). For example, data for a company with a fiscal year ending in March 1996 are in the 1995 aggregate; data for a company with a fiscal year ending August 1996 are in the 1996 aggregate. I/B/E/S applies a February "rollover"; that is, when the calendar year ends and a new calendar year begins, the data for Calendar FY1 should shift or roll over from the year just ended to the new year, but I/B/E/S lags the shift by one month. Therefore, the current calendar year is not considered Calendar FY1 until February. The rationale for the lag is, presumably, that a majority of the companies with fiscal years ending in December do not report by the end of January.

2. I/B/E/S calculates 12-month-forward estimates for a company by prorating the current and next fiscal year estimates using the formula [(a/12)(Current fiscal year EPS] + [(12 – a)]/[12(Next fiscal year EPS)], where a is the number of months remaining in the current year. I/B/E/S then aggregates 12-month-forward company estimates to the index level.
3. Net revisions are defined as (Number of estimates revised upward – Number of estimates revised downward)/Total estimates, over the preceding four weeks, in percentage terms.
4. I used industrial production as a measure of economic activity instead of GDP because of the monthly availability of production data. Using GDP produced qualitatively similar results.
5. This link between forecast errors and the business cycle contrasts with the findings of Dreman and Berry, who found that forecast errors are not meaningfully affected by the business cycle.

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Improving Analysts' Negative Earnings Forecasts

Kirt C. Butler and Hakan Saraoglu

In contrast to positive earnings forecasts, the negative earnings forecasts of security analysts are grossly optimistic. We adjusted negative earnings forecasts downward by varying amounts and evaluated forecast performance according to (1) forecast accuracy relative to the consensus, (2) the frequency of being closer to actual earnings than the consensus, and (3) the frequency with which adjusted forecasts underestimate actual earnings, thereby jeopardizing the analyst's relations with corporate managers. Relative forecast accuracy and the probability of beating the consensus are improved, without an inordinate increase in the probability of underestimating earnings, by adjusting negative forecasts downward by a small amount.

In his review of the academic research on security analysts' forecasts of earnings, Brown (1993) concluded that analysts' earnings forecasts are positively biased. Documented positive biases include forecasts provided by a company's broker (Carleton, Chen, and Steiner 1998) or investment banker (Dugar and Nathan 1995),[1] forecasts of companies with less-predictable earnings (Das, Levine, and Sivaramakrishnan 1998), forecasts of companies in financial distress (Moses 1990; Klein 1990), and forecasts of companies reporting negative earnings (Clayman and Schwartz 1994; Dowen 1996).

The question of whether or not this forecast bias is intentional has been the focus of several recent studies. One proposed cause of bias is that analysts do not strive for earnings forecast accuracy in all circumstances because, among other tasks, they must generate commissions (Hayes 1998) and maintain good relations with company managers (Francis and Philbrick 1993). Another proposal is that analysts' earnings forecasts are biased by the tendency of analysts to herd with other analysts (Olsen 1996; Hong, Kubik, and Solomon 1998). Pressures toward optimism are especially strong for companies that report bad news or are viewed unfavorably by analysts. Francis and Philbrick found that analysts' earnings forecasts tend to be optimistic for stocks on the analysts' sell or hold lists. McNichols and O'Brien (1997) reported that analysts tend to add coverage of companies they view favorably and drop companies they view unfavorably, which results in a censoring of the lower tail of the distribution of forecasts.

We extend Clayman and Schwartz's and Dowen's observation that analysts tend to overestimate the earnings of companies reporting negative earnings. We show that, whereas the earnings of companies reporting positive earnings are fairly accurately forecasted by security analysts, analyst forecasts for companies reporting negative earnings are grossly overoptimistic. Furthermore, when a consensus forecast is negative in sign, it usually overestimates actual earnings.

We incrementally decreased negative earnings forecasts and assessed the resulting forecast performance along three dimensions: (1) the change in forecast accuracy relative to the consensus estimate, (2) the probability of beating the consensus, and (3) the probability of underestimating actual earnings.

Figure 1 contains a plot of actual annual earnings per share (EPS) against forecasted annual earnings per share (FEPS) based on median consensus forecasts reported during November for a sample of 4,250 observations in the 1984–91 period. (Throughout, "earnings" and "EPS" refer to the earnings-to-price ratio, E/P. We provide a description of the sample in a later section.) A casual inspection of Figure 1 suggests that positive earnings outcomes tend to be clustered around a 45-degree line through the origin, as one would expect of rational forecasts. The forecasts associated with negative earnings outcomes, on the other hand, are clearly overoptimistic. Indeed, rarely do negative earnings outcomes exceed the consensus forecast and fall above the 45-degree line.

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Figure 1. Actual EPS versus Forecasts of EPS, 1984–91

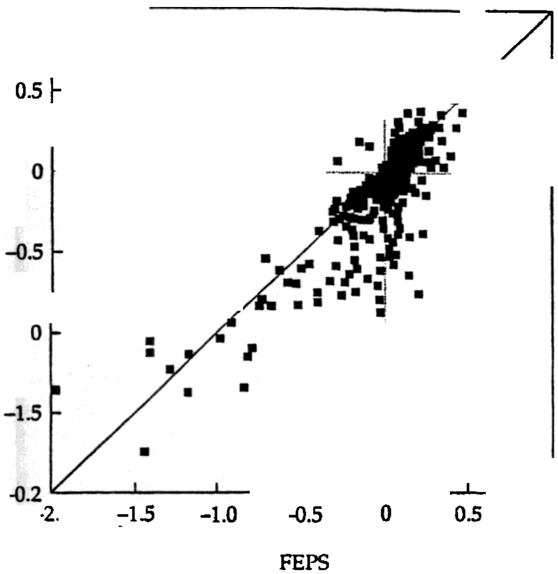


Table 1 presents the percentage of cases in which forecasts overestimated actual earnings in the sample period; the data are presented on a year-by-year basis, and observations are categorized according to the sign of actual earnings and the sign of the consensus forecast. Forecasts of positive earnings outcomes do not appear to be inaccurate in any systematic way, but forecasts of negative earnings overestimate actual earnings in each of the sample years in Table 1. The upper right quadrant of Figure 1 (EPS ≥ 0 and FEPS ≥ 0) corresponds to the positive-earnings/positive-forecast category in the center of Table 1. The forecasts in this quadrant appear to be unbiased and efficient. In contrast to that quadrant, more than 75 percent of forecasts in the lower left quadrant (EPS < 0 and FEPS < 0) are overoptimistic. The cluster of observations scattered in the lower right quadrant of Figure 1 reflects a tendency of analysts to report positive forecasts when actual earnings end up being negative.

The upper left and lower right quadrants of Figure 1 are also asymmetrical. In only a handful of cases did analysts make the error of forecasting negative earnings when actual earnings turned out to be positive (which placed them in the upper left quadrant). Of the 258 negative forecasts, only 14 earnings outcomes (or about 5 percent of the sample) were positive. Many more analysts made the opposite error of forecasting positive earnings when actual earnings turned out to be negative. As many as 206 of the 450 forecasts associated with negative earnings outcomes were positive, and about 87 percent of those forecasts were higher than actual earnings. Negative forecasts, as a whole, overestimated actual earnings 71.7 percent of the time.

No one can tell *ex ante* whether a positive earnings forecast is an unbiased forecast of a positive earnings outcome drawn from the upper right quadrant of Figure 1 or a biased forecast of a negative earnings outcome from the lower left quadrant. Table 1 indicates, however, that given that a consensus forecast is negative, the forecast is overoptimistic 71.7 percent of the time. The implication is that the accuracy of negative forecasts can be improved by adjusting for forecast bias.

We assess the performance of adjustments of varying magnitude to negative earnings forecasts and develop a prescription for deciding on the size of the bias adjustment. Because the costs and benefits of over- and underadjustment differ depending on one's perspective, the choice of how far to diverge from the consensus forecast is best left to the individual. Our goal is to provide information on the likely gain in forecast performance arising from adjusting negative forecasts for analyst overoptimism so that both producers and consumers of earnings forecasts can make an informed decision about what is for them an optimal adjustment.

Data and the Forecast Adjustment

We used the I/B/E/S International detail database of annual earnings forecasts for the 1984–91 period, which contains individual security analysts' forecasts of annual primary earnings per share before extraordinary items. We matched these earnings forecasts with the corresponding earnings figures from Standard & Poor's Compustat Full Coverage Annual database.[2] We kept observations if the following conditions were satisfied:

- three or more forecasts of primary EPS reported to I/B/E/S during November for December fiscal year-end companies and
- share price greater than $2.00 from the previous December on Compustat.

We divided forecasted and actual earnings per share for each company by beginning-of-year share price in order to scale for cross-sectional differences in the level of earnings and share price.

We then constructed median consensus forecasts for each sample company and year from the November forecasts. Median consensus forecasts were chosen rather than mean forecasts because of O'Brien's (1988) finding that median earnings forecasts exhibit the smallest bias of competing consensus forecast measures. The filter on share

Table 1. Predictions of Earnings per Sha

		FEPS < 0				FEPS ≥ 0				Total			
Earnings	Year	N	Percent Over	Mean EPS	Average Bias	N	Percent Over	Mean EPS	Average Bias	N	Percent Over	Mean EPS	Average Bias
				0.007906	0.033762	443	53.27	0.100256	−0.003232[a]	445			
						420	53.81	0.077877	−0.004030[a]	420			
				0.050331	0.070199	457	47.92	0.073917	−0.002453[a]	458			
				0.078311	0.221718	510	47.45	0.086444	−0.001119	513			
				0.010526	0.013158	540	44.63	0.091539	−0.001144	541			
				0.000779	0.032409	457	51.20	0.077631	−0.003195[a]	458			
				0.063812	0.124655	461	55.61	0.085385	−0.004017[a]	564			
				0.017386	0.033043	398	50.75	0.059805	−0.003625[a]	401			
				0.039712	0.094396[a]	3,786	50.50	0.082303	−0.002797[a]	3,800			
EPS < 0	1984	21	80.95	−0.371333	−0.101611	16	100.00	−0.106710	−0.164902[a]	37	89.19	−0.256901	−0.128980[a]
	1985	20	85.00	−0.201959	−0.120343[a]	29	100.00	−0.098461	−0.154834[a]	49	93.88	−0.140705	−0.140756[a]
	1986	40	60.00	−0.261952	−0.081119[a]	35	100.00	−0.118035	−0.159977[a]	75	78.67	−0.194791	−0.117919[a]
	1987	33	84.85	−0.311831	−0.080461[a]	12	100.00	−0.115261	−0.162730[a]	45	88.89	−0.259412	−0.102400[a]
	1988	25	72.00	−0.157202	−0.043477[a]	20	100.00	−0.066905	−0.128203[a]	45	84.44	−0.117070	−0.081133[a]
	1989	30	80.00	−0.189943	−0.044111[a]	19	100.00	−0.086157	−0.147544[a]	49	87.76	−0.149700	−0.084218[a]
	1990	32	81.25	−0.423199	−0.153461[a]	39	100.00	−0.110759	−0.178691[a]	71	91.55	−0.251577	−0.167320[a]
	1991	43	72.09	−0.199233	−0.062728[a]	36	100.00	−0.103797	−0.149874[a]	79	84.81	−0.155743	−0.102440[a]
	All	244	75.82	−0.263702	−0.083848[a]	206	100.00	−0.102468	−0.157342[a]	450	86.89	−0.189893	−0.117492[a]
Total	1984	23	73.91	−0.338356	−0.089840	459	54.90	0.093042	−0.008867[a]	482	55.81	0.072456	−0.012731[a]
	1985	20	85.00	−0.201959	−0.120343[a]	449	56.79	0.066487	−0.013770[a]	469	58.00	0.055040	−0.018315[a]
	1986	41	58.54	−0.254335	−0.077428[a]	492	51.63	0.060262	−0.013659[a]	533	52.16	0.036062	−0.018564[a]
	1987	36	77.78	−0.279319	−0.055280[a]	522	48.66	0.081807	−0.004834[a]	558	50.54	0.058508	−0.008089[a]
	1988	26	69.23	−0.150751	−0.041299	560	46.61	0.085880	−0.005681[a]	586	47.61	0.075381	−0.007262[a]
	1989	31	77.42	−0.183791	−0.041643[a]	476	53.15	0.071094	−0.008957[a]	507	54.64	0.055509	−0.010956[a]
	1990	35	74.28	−0.381456	−0.129622[a]	600	40.17	0.072636	−0.015371[a]	635	59.37	0.047607	−0.021668[a]
	1991	46	67.39	−0.186106	−0.056482[a]	434	54.84	0.046234	−0.015757[a]	480	56.04	0.024064	−0.019660[a]
	All	258	71.71	−0.247238	−0.074176[a]	3,992	53.06	0.072768	−0.010772[a]	4,250	54.19	0.053342	−0.014621[a]

[a]The null hypothesis, H_0: Average bias = 0, is rejected by a t-test at the 5 percent level of significance.

price (> \$2/share) eliminated 22 observations (about 0.5 percent of the sample). A large number of these companies were companies in financial distress with depressed stock prices and large negative earnings outcomes, for which E/Ps are not meaningful.

Overoptimism in negative earnings forecasts (EPS < 0) manifests itself in Table 1 as a negative bias (where BIAS = EPS – FEPS) ranging from 4.35 percent to 15.35 percent of share price for annual samples and averaging 7.42 percent of share price for the pooled sample. Both consumers and producers of earnings forecasts should be able to obtain better forecasts by lowering the negative consensus forecasts farther. Thus, we carried out the following adjustment:

$$AFEPS_{i,t} = FEPS_{i,t} - ADJ_{i,t}, \tag{1}$$

where

$AFEPS_{i,t}$ = adjusted forecast for company i in fiscal year t

$FEPS_{i,t}$ = unadjusted earnings forecast for company i in fiscal year t

$ADJ_{i,t}$ = adjustment factor ($ADJ_{i,t} > 0$) as a percentage of share price for company i in fiscal year t

If the penalties associated with forecast errors are not symmetrical around actual earnings, then individuals will want to adjust consensus forecasts by an amount that varies from the expected bias.

Measures of Analyst Forecast Performance

We used the following three measures of forecast performance to evaluate forecast adjustments of varying magnitudes: (1) the change in forecast accuracy relative to the consensus, as measured by mean square forecast error, (2) the frequency of being closer to actual earnings than the consensus forecast, and (3) the frequency with which adjusted forecasts underestimate actual earnings and thereby jeopardize the analyst's relations with corporate managers.

The performance of earnings forecast adjustments must be evaluated by individual users. If security analysts are deliberately adding bias to their beliefs, whether to maintain good relations with managers or to remain close to the herd, they can use our results as a framework to reevaluate their forecasts while keeping an eye on the criteria by which their performance is assessed. Investors with a need for accuracy in their earnings forecasts can use our results to improve forecast accuracy.

Relative Forecast Accuracy. Consumers of earnings forecasts, such as individual investors and fund managers, use forecasts of current and future earnings to form expectations about security values. Consequently, consumers of earnings forecasts are concerned with the magnitude of actual earnings and would like the earnings forecasts they receive to be unbiased and efficient. Unbiased and efficient forecasts would be neither too high nor systematically too low and would be distributed as tightly as possible around actual earnings. Therefore, a good measure of forecast performance for consumers of earnings forecasts is the mean squared forecast error.

In order to measure the accuracy of our adjusted earnings forecasts relative to unadjusted consensus forecasts, we computed mean squared forecast errors before adjustment (MSE) and after adjustment (AMSE) according to

$$\text{MSE} = \left(\frac{1}{n}\right)\left[\sum_{i=1}^{n}(EPS_{i,t} - FEPS_{i,t})^2\right] \tag{2}$$

and

$$\text{AMSE} = \left(\frac{1}{n}\right)\left[\sum_{i=1}^{n}(EPS_{i,t} - AFEPS_{i,t})^2\right], \tag{3}$$

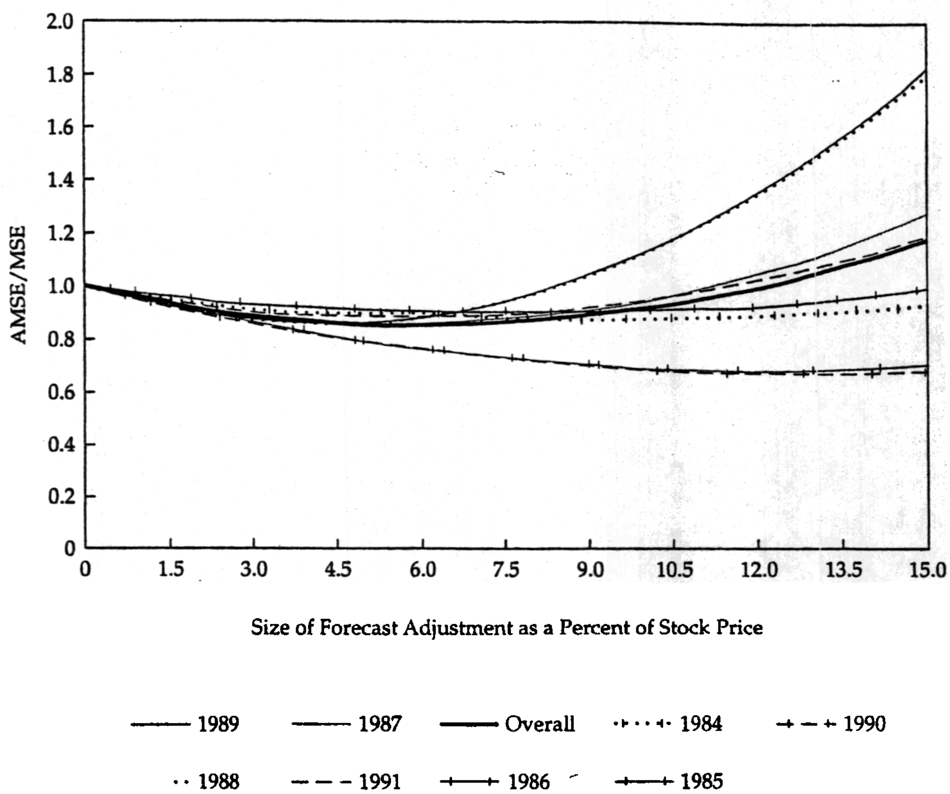
where n is the number of negative forecasts in a particular sample. The performance of adjusted forecasts relative to unadjusted forecasts is measured by the ratio:

$$\text{Relative forecast accuracy} = \text{AMSE/MSE}. \tag{4}$$

This measure of forecast performance will be of interest to both producers and consumers of earnings forecasts.

Figure 2 contains plots of the observed improvement in MSE (Equation 4) against the magnitude of the forecast adjustment in each of the years 1984–1991 and over the pooled 1984–91 sample (the dark line in the figure). A bias adjustment of about 6 percent of share price results in the best forecast accuracy in the negative forecast sample pooled across all sample years. This percentage adjustment corresponds to an earnings forecast adjustment of \$6 on a \$100 share of stock. This result is fairly close to the mean bias of 7.4 percent of share price in the negative forecast sample of Table 1. With this adjustment, the squared errors of the adjusted forecasts are 85.7 percent of unadjusted forecast squared errors. Adjusted forecast accuracy begins to deteriorate in the overall sample beyond an adjustment of about 6 percent of share price. By the time forecasts have been reduced by 12 percent of share price, adjusted and unadjusted forecasts

Figure 2. Relative Forecast Accuracy, 1984–91



have nearly equal forecast accuracy in the pooled sample. At this level, adjusted forecasts are about as far below actual earnings as unadjusted forecasts are above earnings.

Within each sample year, relative forecast accuracy improves monotonically for adjustments of up to 4 percent of share price. Beyond that point, the magnitude of the optimal adjustment exhibits a good deal of year-to-year variation, as Figure 2 shows. Those years with the largest *ex post* bias in the negative forecasts sample of Table 1 (1985 and 1990) benefit the most from large forecast adjustments. Improvement in forecast accuracy during those years with the smallest bias (1988 and 1989) is correspondingly smaller. The magnitude of the forecast bias in the negative forecast samples is about 4.1 percent of share price in 1988 and 1989, and adjustments of more than this amount begin to lose their effectiveness. Nevertheless, forecast accuracy is improved relative to unadjusted forecasts for adjustments of up to 8 percent of share price in those two years. The accuracy of adjusted forecasts is superior to that of unadjusted forecasts for adjustments of up to 11 percent of share price in the remaining six years.

Beating the Consensus. Forecast accuracy as measured in the previous section is most prized by consumers of earnings forecast data. In contrast to consumers of earnings forecasts, forecast *producers* are judged not on forecast accuracy but on how their forecasts compare with those of other analysts. This performance measure leads to herding behavior as security analysts seek to protect their reputations by issuing forecasts that conform to the consensus, especially when forecasting hard-to-predict earnings (Olsen). In this setting, a successful security analyst is one whose forecasts are consistently closer to actual earnings than competing forecasts. Given the observed overoptimism in the negative forecast samples, analysts should be able to consistently beat consensus forecasts simply by adjusting their consensus forecasts downward by an arbitrarily small amount. More aggressive analysts might attempt larger adjustments in an effort to further improve their forecast accuracy relative to the consensus.

The measure of relative forecast accuracy in Equation 4 is based on a squared error criterion. An alternative measure of forecast accuracy is the frequency with which adjusted forecasts lie closer to actual earnings than the consensus. This frequency can be used to estimate the probability of an analyst beating the consensus forecast:

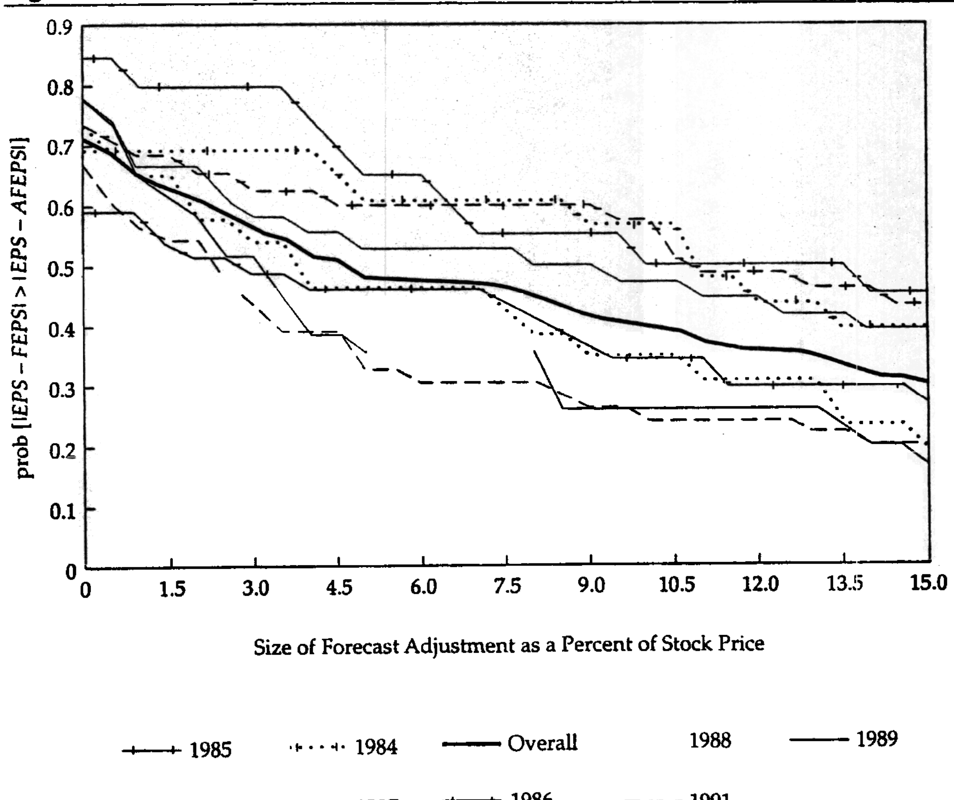
$$\text{prob[Beating the consensus]} = \text{prob}[\,|EPS_{i,t} - FEPS_{i,t}| > |EPS_{i,t} - AFEPS_{i,t}|\,]. \quad (5)$$

For the negative forecast sample, arbitrarily small downward adjustments will beat the consensus forecast by the amount shown in the "Percent Over" column under "Total" in Table 1. For example, because 71.7 percent of the total sample of negative forecast observations overestimated actual earnings, small downward adjustments to the consensus forecasts will be closer to actual earnings 71.7 percent of the time across the entire sample. As progressively larger downward adjustments are made, relative forecast accuracy will improve but the probability of beating the consensus forecast will fall below the initial level of 71.7 percent. Eventually, relative forecast accuracy will deteriorate, and the probability of beating the consensus will fall below 50 percent.

Figure 3 contains the plots of the probability of beating the consensus forecast for progressively larger downward adjustments for the yearly samples and for the pooled sample. For arbitrarily small downward adjustments ($ADJ_{i,t} > 0$), these probabilities emerge from the y-axis in Figure 3 according to the "Percent Over" probabilities in Table 1. The overall sample and each of the yearly samples begin at probabilities well over 50 percent, so it is a good bet that small downward adjustments will beat the consensus. As the size of the downward adjustment is progressively increased, the probability of beating the consensus falls. In the pooled sample, downward adjustments of up to 4.75 percent of stock price continued to yield a greater than 50 percent probability of beating the consensus. Downward adjustments of up to 2.2 percent of stock price yielded a greater than 50 percent probability of beating the consensus in each of the yearly samples. Adjusted forecasts of up to 10 percent of share price continued to beat the consensus more than 50 percent of the time in half the sample years. The years in which forecast bias was smallest tended also to be the years in which the probability of beating the consensus fell most rapidly, although the relationship between these two variables is not as pronounced as the relationship between forecast bias and changes in relative forecast accuracy in Figure 2.

"Politically Correct" Earnings Forecasts. Several recent studies have suggested that analyst overoptimism arises from a deliberate attempt to maintain good relations with company managers (Francis and Philbrick), especially for companies in financial distress (Klein; Clayman and Schwartz).

Figure 3. Probability of Beating the Consensus, 1984–91



Managers are most sensitive to negative publicity during financial distress, and an analyst issuing an unfavorable earnings forecast risks losing access to company managers and their inside knowledge of company performance. If good relations with management are more important than forecast accuracy, then a politically correct forecast will result that is more generous than is warranted by the facts.

An analyst adjusting negative consensus forecasts downward, according to Equation 1, will want an estimate of the probability of being exposed to critical scrutiny by management. Our estimate of the probability of "overadjusting" an earnings forecast is the frequency with which a forecast adjustment of a given size results in earnings overestimates in our sample:

$$\text{prob}\,[\text{Overestimating earnings}] = \text{prob}\,[EPS_{i,t} < AFEPS_{i,t}]. \quad (6)$$

Analysts who fear being penalized for underestimating earnings can use the probability

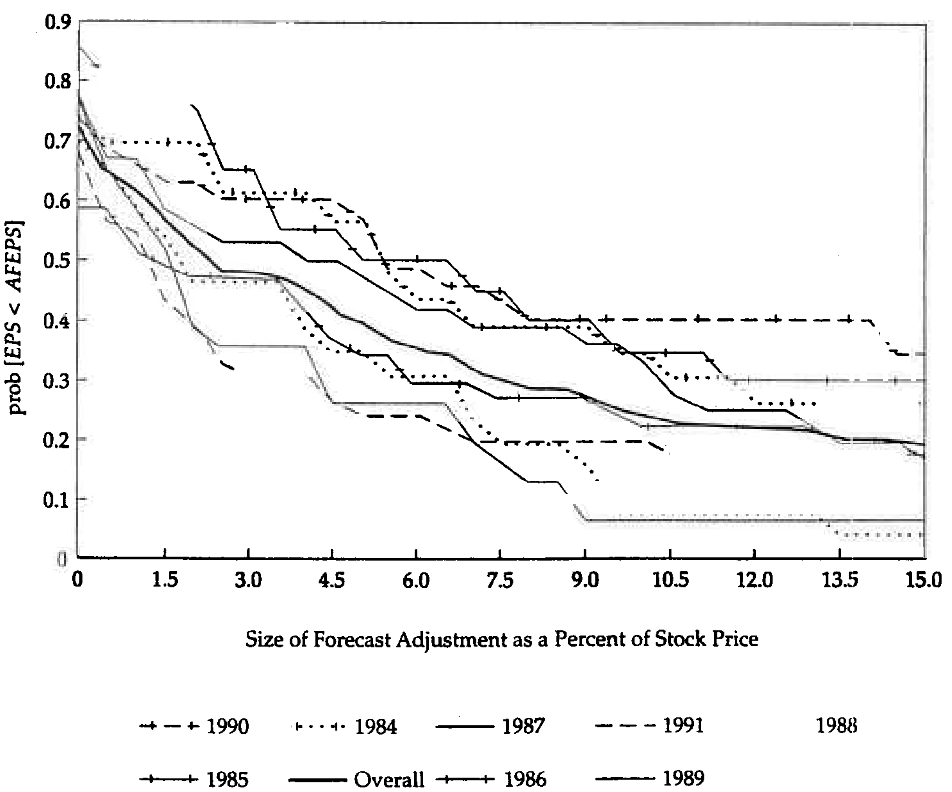
$$1 - \text{prob}\,[EPS_{i,t} < AFEPS_{i,t}]$$

as an estimate of their exposure to this risk. For example, because unadjusted forecasts overestimated actual earnings 71.7 percent of the time in the pooled sample, the risk of underestimating earnings is 28.3 percent. Progressively larger adjustments for overoptimism increase the probability of underestimating earnings. At a probability of 0.5, adjusted forecasts are as likely to be too high as too low.

Figure 4 contains plots of changes in the probability of overestimating earnings for incremental adjustments of 0 to 15 percent of share price. In the pooled sample, the probability of overestimating earnings falls to 0.5 for downward forecast adjustments of about 2.2 percent of share price. The yearly samples fall to a 0.5 probability for adjustments of between 1.2 percent (1986 and 1991) and 5.5 percent (1984 and 1990) of share price. Beyond 5.5 percent of share price, the probability of underestimating earnings exceeds that of overestimating earnings in each yearly sample.

Recommendations for Earnings Forecast Adjustments. Summarizing the results in Figures 1–4, we find that adjustments of up to 1 percent of share price result in improved forecast accuracy, a high probability of beating the consensus forecast, and little increase in the probability of underestimating actual earnings. Forecast adjustments of 1–2 percent of share price consistently beat consensus forecasts and continue to improve forecast accuracy, although the risk of underestimating earnings

Figure 4. Probability of Overestimating Earnings, 1984–91



increases. Relative forecast accuracy continues to improve for adjustments of up to 5 percent of share price. Although the probability of beating the consensus is still, on average, greater than 0.5 for adjustments of up to 5 percent of share price, the extent to which forecasts can be adjusted and still beat the consensus more than half the time exhibits a good deal of year-to-year variation. The maximum adjustment before the probability of beating the consensus falls below 0.5 in our yearly samples ranged from 2 percent to 11 percent of share price. Beyond an adjustment of 2 percent of share price lies substantial risk of underestimating earnings. Forecast adjustments of up to 11 percent of share price are still likely to be more accurate than unadjusted forecasts, but by this point, the analyst has probably overshot the mark; the probability of beating the consensus and the probability of underestimating earnings are both unacceptably high.

Conclusions

Security analysts do a relatively good job of forecasting earnings that turn out to be greater than zero, but they persistently overestimate negative earnings outcomes. This overoptimism arises from an apparent reluctance on the part of security analysts to report negative earnings forecasts. When analysts do report a negative forecast, they are almost certain to be overoptimistic. In our sample of 4,250 consensus forecasts of annual earnings in the 1984–91 period, negative consensus forecasts overestimated actual earnings 71.7 percent of the time whereas positive consensus forecasts were fairly symmetrically distributed around actual earnings.

We found that small adjustments to negative earnings forecasts improve forecast accuracy. Each analyst must make an individual decision, based on the incentives and penalties each faces, about how much to adjust negative earnings forecasts. Small downward adjustments can improve forecast accuracy and the probability of beating the consensus forecast. Larger adjustments continue to improve forecast accuracy at the expense of increasing the probability of underestimating earnings and decreasing the probability of beating the consensus forecast.

If forecast accuracy is paramount, then adjustments of about 5 percent of share price are likely to prove optimal. If beating the consensus forecast is prized, then adjustments of up to 2 percent of share price will capture gains in forecast accuracy while providing the analyst with bragging rights over consensus forecasts. To the extent that a security analyst is penalized for underestimating earnings, attempting to adjust for the full extent of the bias will expose the analyst to undue criticism. Adjustments of up to 1 percent of share price are likely to keep the analyst's probability of underestimating earnings below 0.5, although the managers of individual companies might still find room to complain. Adjustments of 1 percent do not take full advantage of the potential gain in forecast accuracy but do provide a high probability of beating the consensus forecast.

Financial markets react to new information. At the time this article appears in print, the observed bias in security analysts' negative earnings forecasts will be public knowledge. Both producers and consumers of earnings forecasts will then be faced with a dilemma: If analysts follow the recommendations in this article, the forecast bias will disappear. If all analysts adjust their forecasts by the average forecast bias reported in Table 1, forecasts will, on average, underestimate actual earnings by the amount of the current forecast overestimate.

Our prediction, however, is that analysts will be slow to adopt the recommendations in this article because the institutional incentive (and penalty) structure faced by security analysts is unlikely to change overnight. Room will remain for improvement in forecast performance as long as analysts make only incremental, rather than complete, adjustments to their negative earnings forecasts. We forecast that the payoffs to adjustment in the forms of improved forecast accuracy and bragging rights over consensus forecasts will persist. As for the users of forecasts, investors must take into account the overoptimistic bias in negative forecasts before forming their expectations about the underlying stocks.

Notes

1. Lin and McNichols (1998) reported that lead- and co-underwriter analysts' earnings forecasts are generally not greater than those of unaffiliated analysts, although their growth forecasts and buy recommendations are significantly more favorable.

2. To the extent that analysts do not report "earnings before extraordinary items" to I/B/E/S, there is an empirical problem with matching earnings from Compustat with forecasts from I/B/E/S. Discussion of this errors-in-variables problem is beyond the scope of this article.

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Attachment D

From the Trenches: Analysis without analysts

Tech Soundings: Startups aim to replace sell-side analysts with stock-analysis software. Is that the future of investing?
By Lisa Meyer
September 18, 2001

In the wake of the Internet bubble bursting, investors are looking for ways to cut through hype and find good investments. The increasing demand for unbiased research has produced a handful of upstarts constructing decision-support tools that not only help banking analysts process information but also create competition for those analysts by helping individual and institutional investors determine the values of stocks. For prices ranging from a few dollars to $50 per month, Tradeworx, VectorVest, and ValuEngine.com sell software that analyzes company data and spits out stock recommendations based on the result.

Unlike sell-side analysts, these programs have no incentive to slant data. "While Mary Meeker and Henry Blodget were recommending stocks that were way overvalued, VectorVest's valuations for those same stocks were much lower," says Jeremy Bork, VectorVest's vice president of sales and marketing. The company's products employ both fundamental analysis (which seeks to measure the intrinsic value of a stock by figures like sales, earnings, and growth) and technical analysis (which assesses market value through an examination of moving averages, trading volume, and so on) to find undervalued stocks, mostly for individual investors. The company is privately held by about 15 shareholders.

Such software companies bring to the masses tools that were once available only to professionals. Tradeworx is developing software for its Web site that will generate reports, for $3 to $5, that grade stocks according to different investment strategies. The company has raised $10 million from angel investors and from OppenheimerFunds, the Individual Investor Group, and The McKenna Group. Tradeworx estimates that it will make around $1 million in 2001 from such customers as Hull Trading and Thomson Financial.

ValuEngine.com would not disclose revenues, but expects to post a profit by the end of the year. The company has received $3 million to $4 million in funding from cofounder Zhiwu Chen, who is a Yale University professor, as well as from various brokerage firms and Taiwanese companies.

"There is no conflict of interest in our advice because there is no individual analyst doing the data," says ValuEngine president Paul Henneman. "We get calls from companies saying that our analysis is unfair because it doesn't take into account an upcoming new product line. But we don't base our decisions on that."

MIXED OUTLOOK
That's a major shortfall. Being software, the products rely solely on numbers, like earnings, interest rates, and stock prices. Some institutional investors question whether these upstart companies will survive only long enough to allow outraged investors an opportunity to express their displeasure with sell-

side analyst research; such institutions believe investors will return to professional research once the market improves, partly because it's easier and faster to turn to ready-made recommendations and partly because investing will seem less risky again.

These startups also may lose business if investors who use them lack the time or knowledge to follow nonquantitative information about a particular company, like management changes and research-and-development projects. "Although their recommendations may be biased, sell-side research analysts understand companies," points out Greg Kyle, CEO of Pegasus Research International, an independent research firm.

Another uncertainty is whether the formulas governing the software actually work. "Numerous plausible investment philosophies exist, but they aren't proven," says Paul McEntire, chairman of the BearGuard Fund, which specializes in shorting stocks. Even for research analysts with every possible tool at their disposal, there's never, after all, been anything close to a foolproof way to pick stocks.

Even the startups agree that the need for analysts will not disappear. "Sometimes investors just need humans to do hand-holding and provide explanations," admits Manoj Narang, CEO of Tradeworx.

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In the wake of the Internet bubble bursting, investors are looking for ways to cut through hype and find good investments. The increasing demand for unbiased research has produced a handful of upstarts constructing decision-support tools that not only help banking analysts process information but also create competition for those analysts by helping individual and institutional investors determine the values of stocks. For prices ranging from a few dollars to $50 per month, Tradeworx, VectorVest, and ValuEngine.com sell software that analyzes company data and spits out stock recommendations based on the result.