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Do Security Analysts Overreact?

By WERNER F. M. DE BONDT AND RICHARD H. THALER*

It has long been part of the conventional wisdom on Wall Street that financial markets “overreact.” Both casual observation and academic research support this view. The October crashes of 1987 and 1989 reinforce the research by Robert Shiller and others that suggests that stock prices are too volatile. Also, Shiller’s 1987 survey evidence reveals that investors were reacting to each other during these crashes, rather than to hard economic news. A similar conclusion is reached by Kenneth French and Richard Roll (1986) who find that prices are more volatile when markets are open than when they are closed.

Our own prior research (1985, 1987) argued that mean reversion in stock prices is evidence of overreaction. In our 1985 paper, we showed that stocks that were extreme “losers” over an initial three- to five-year period earned excess returns over the subsequent three to five years. In the 1987 paper, we showed that these excess returns cannot easily be attributed to changes in risk, tax effects, or the “small firm anomaly.” Rather, we argued that the excess returns to losers might be explained by biased expectations of the future. We found that the earnings for losing firms had fallen precipitously during

the formation period (while they were losing value), but then rebounded strongly over the next few years. Perhaps, we speculated, “the market” did not correctly anticipate this reversal in earnings. This hypothesis, of excessive pessimism about the future prospects of companies that had done poorly, was suggested by the work of Daniel Kahneman and Amos Tversky (1973). They found that people’s intuitive forecasts have a tendency to overweight salient information such as recent news, and underweight less salient data such as long-term averages.

Of course, there are many reasons to be skeptical that actual investors (stock market professionals) are subject to the same biases as student subjects in laboratory experiments. Definitely, the market professionals are experts in their field, they have much at stake, and those who make systematic errors may be driven out of business. Therefore, we present here a study of the expectations of one important group of financial market professionals: security analysts who make periodic forecasts of individual company earnings. This is an interesting group to study on three counts. First, other investigators have repeatedly found that earnings forecasts (and forecast revisions) have an important influence on stock prices (Philip Brown et al., 1985). Second, past work suggests that analysts are rather good at what they do. For example, analyst forecasts often outperform time-series models (see Robert Conroy and Robert Harris, 1987). Finally, the precision of analyst expectations represents a natural upper bound to the quality of the earnings forecasts of less sophisticated agents. After all, most investors do not have the time or the skill to produce their own predictions and, accordingly, they buy (rather than sell) earnings forecasts. Thus, for all of the above reasons, it is particularly interesting to see

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whether market professionals display any of the biases discovered in studies of nonexpert judgment.

We specifically test for a type of generalized overreaction, the tendency to make forecasts that are too extreme, given the predictive value of the information available to the forecaster. This tendency is well illustrated by an experiment conducted by Kahneman and Tversky. Subjects were asked to predict the future grade point average (GPA) for each of ten students on the basis of a percentile score of some predictor. Three predictor variables were used: percentile scores for GPA, for a test of mental concentration, and for a test of sense of humor. Obviously, a percentile measure of GPA is a much better predictor of actual GPA than is a measure of mental concentration which, in turn, is much more reliable than information on sense of humor. Therefore, subjects should give much more regressive forecasts in the latter two conditions, that is, the forecasts should be less variable. The results indicated that people were not nearly sensitive enough to this consideration. Subjects that were given a nearly useless predictor (the "sense of humor" condition) made predictions that were almost as extreme in variation as those given a nearly perfect predictor (the "percentile GPA" condition). This pattern leads to a systematic bias: forecasts that diverge the most from the mean will tend to be too extreme, implying that forecast errors are predictable.

This study asks whether security analysts display similar biases. Our focus is on forecasted changes in earnings per share (EPS) for one- and two-year time horizons. We study two questions. The first is whether forecast errors in EPS are systematically linked to forecasted changes. In particular, are the forecasts too extreme? Are most forecast revisions "up" ("down") if the analysts initially projected large declines (rises) in EPS? Clearly, under rationality, neither forecast errors nor forecast revisions should ever be predictable from forecasted changes. The second question is whether the bias in the forecasts gets stronger as uncertainty grows and less is (or objectively can be) known about the future.

Several of the regressions reported below are of the form $AC = \alpha + \beta FC$, where AC is the actual change and FC is the forecasted change. The null hypotheses of rational expectations is that $(\alpha, \beta) = (0, 1)$. The two alternative behavioral hypotheses sketched above are:

H1. Forecasted changes are too extreme, so actual changes are less (in absolute value) than predicted: $\beta < 1$.

H2. The estimated β for the two-year forecasts is less than the β for the one-year forecasts.

The next two sections describe the data and the empirical results. We find considerable support for the behavioral view. We then briefly discuss the sources of the systematic forecast error.

I. Data

The analysts' earnings forecasts are taken from the Institutional-Brokers-Estimate-System tapes (IBES) produced by Lynch, Jones & Ryan, member of the New York Stock Exchange. We study forecasts between 1976 and 1984. Lynch, Jones & Ryan contacts individual analysts on a regular basis and computes summary data such as means, medians, or standard deviations. The summary data that we analyze are sold to institutional investors. Updates are available each month but here we only work with the April and December predictions of EPS for the current as well as the subsequent year. The April forecasts are approximately one- and two-year forecasts since we only consider companies with a fiscal year ending in December. For these firms, actually realized earnings are typically announced sometime during the first few months of the following calendar year.

We match the earnings forecasts for each company with stock returns and accounting numbers. The returns are provided by the Center for Research on Security Prices (CRSP) at the University of Chicago. The accounting data are listed on the annual industrial (main and delisted) COMPU-STAT files, sold by Standard & Poor's. Since all data sources contain full historical records, no survivorship biases affect the

sample selection. Care is taken to adjust for stock splits and stock dividends so that all current and past returns, earnings figures, and forecasts are expressed on a comparable basis. When necessary, forecasts of fully diluted EPS are converted to forecasts of primary EPS (excluding extraordinary items).

While some IBES data are available for approximately 2300 to 2800 companies each year, our annual sample contains many fewer observations. For example, for the one-year forecasts, the number varies between 461 and 785. This follows from the data selection criteria that we use. Companies only qualify if they have 1) records on IBES, CRSP, and COMPUSTAT; 2) returns on CRSP for three years prior to the forecast month; 3) EPS numbers on COMPUSTAT for ten years prior to the forecast month; 4) a December fiscal year; 5) the data needed to compute the variables in the regressions described below. Despite the stringent data requirements, our sample (in firm-years) is the largest we know of that has been used to study the rationality of earnings forecasts (compare Edwin Elton et al., 1984).

II. Methods and Results

Much of the regression analysis is based on three sets of variables: forecasted changes in EPS ($FC1$, $FC2$, and $FC12$), actual changes in EPS ($AC1$, $AC2$, and $AC12$), and forecast revisions ($FR1$, $FR2$, and $FR12$). The "consensus" one and two-year forecasts of earnings per share ($FEPS(t)$ and $FEPS(t+1)$) that we study are defined as the cross-sectional means or medians of analyst forecasts reported in April of year t ($t=1976\dots1984$). Forecasted changes are then computed as $FC1(t) = FEPS(t) - EPS(t-1)$, $FC2(t) = FEPS(t+1) - EPS(t-1)$, and $FC12(t) = FEPS(t+1) - FEPS(t)$, where $EPS(t)$ represents actually realized earnings per share. We compute actual earnings changes in a way that is similar to the forecasted changes. For example, $AC1(t) = EPS(t) - EPS(t-1)$. Eight-month forecast revisions ($FR1$) subtract the April forecast of $EPS(t)$ from the equivalent forecast in December. Twenty-month forecast revisions ($FR2$) are

TABLE 1—TESTS FOR THE RATIONALITY OF EARNINGS PER SHARE FORECASTS

Equation	Variables	Constant	Slope	Adj. R^2
1	$AC1, FC1$	-.094 (-3.7)	.648 (-21.7)	.217 [5736]
2	$FR1, FC1$	-.120 (-6.7)	-.181 (-15.6)	.041 [5736]
3	$AC2, FC2$	-.137 (-2.3)	.459 (-19.5)	.071 [3539]
4	$FR2, FC2$	-.192 (-3.9)	-.381 (-16.8)	.074 [3538]
5	$AC12, FC12$	.153 (2.4)	-.042 (-16.9)	.000 [3520]
6	$FR12, FC12$	.348 (19.4)	-.439 (-25.3)	.153 [3562]

Note: All variables are as defined in the text. The dependent variable is listed first. T -values appear in parentheses beneath the regression coefficients and test whether they differ from zero. However, for the slopes of equations 1, 3, and 5, the t -statistics test whether the coefficients differ from one. Note that the number of observations is given in brackets in the far right-hand column.

the difference between the December forecast in year $t+1$ and the April forecast of $EPS(t+1)$. Similarly, $FR12$ subtracts the April $FC12(t)$ from the equivalent $FC12(t)$ in December of year t .

The regressions in Table 1 use mean consensus forecasts. All variables are normalized by the standard deviation of earnings per share between years $t-10$ and $t-2$.¹ Even though we also ran the regressions year by year, the results in Table 1 are based on the pooled samples. There are three main findings. Forecasts are too optimistic, too extreme, and even more extreme for two-year forecasts than for single-year predictions.

Equation 1 refers to the one-year forecasts. We regress the actual change in earnings on the April forecasted change. The intercept is significantly negative, indicating that the forecasts are too optimistic. This

¹We also tried other normalization procedures, such as dividing by company assets per share at the end of year $t-1$, the stock price on the last trading day of year $t-5$, or the standard deviation of EPS between $t-5$ and $t-2$. Results are qualitatively the same for all methods.

excessive optimism also appears in equation 3 for the two-year forecasts. The negative intercepts in equations 2 and 4 reveal that there is a general tendency for forecasts to be revised downwards between April and December.

The finding of unrealistic optimism seems consistent with the experimental research of Neil Weinstein (1980) and others who find such biases in the expectations of individuals in everyday life. However, we do not want to push this argument too far for two reasons. First, if we consider the nine individual year-by-year regressions, the intercepts are positive four times. Second, optimism bias also has a plausible agency interpretation. Many analysts work for brokerage houses that make money by encouraging trading. Since every customer is potentially interested in a buy recommendation, while only current stockholders (and a few willing to go short) are interested in sell recommendations, optimistic forecasts may be preferable. Indeed, it is well known that buy recommendations issued by brokerage houses greatly exceed sell recommendations.

All six regressions in Table 1 present evidence supporting the hypothesis that forecasts are too extreme. Ignoring the constant term in equation 1, actual EPS changes average only 65 percent of the forecasted one-year changes. For the two-year forecasts (equation 3), this statistic falls to 46 percent.² In the year-by-year regressions equivalent to equations 1 and 3, the slope coefficients are less than one every single time.

Note that equations 1 and 3 could be rewritten with the forecast errors ($AC1 - FC1$ and $AC2 - FC2$) on the left-hand side and with the forecasted changes as the regressors. The new slope coefficients then equal the *betas* in Table 1 *minus one*, while the *t*-statistics remain the same. The new

slopes have a straightforward interpretation: The larger the forecasted changes, the larger is the forecast error in the opposite direction. The R^2 s of these regressions are .076 and .097.

The previous findings all suggest that forecast revisions should also be predictable from forecasted changes, and indeed they are, as shown in equations 2 and 4. In these regressions, rationality implies that β should be equal to zero. In actuality, the slopes are significantly negative. By December, the average reversal of the one-year forecasts made in April equals 18 percent of the original predicted changes. For the two-year forecasts, the reversal amounts to 38 percent.

As expected, the results are stronger for the two-year and second year forecasts. The two-year results are clearly driven by the predicted changes for the second year (see equations 5 and 6). With the R^2 for equation 5 equal to zero, actual changes are simply unrelated to forecasted changes in EPS from year t to $t+1$. On average, any nonzero prediction, either positive or negative, is pure error. By December, the analysts have reversed their April forecasted changes for the second year by 44 percent.

In sum, the above results are consistent with generalized overreaction. However, a different interpretation is based on the problem of errors in variables. If our measure of forecasted changes in earnings contains error, then the slope coefficients are biased downward. In evaluating this argument, one should consider the most likely sources of error. One possibility is IBES data entry errors. Following Patricia O'Brien (1988), we removed any data points for which the predicted change in EPS or the forecast revision was greater than \$10. The results in Table 1 reflect this error screen. In addition, we also recomputed regressions 1 and 3 using a smaller sample of firms for which the consensus forecast is based on the individual predictions of three analysts or more. For this subset, we then used the median forecasted earnings change as the regressor. The β s increased but were still significantly less than one.

A second potential source of error stems from the fact that the forecasts on the IBES

²The two-year regressions are open to criticism because the sampling interval (one year) is shorter than the forecast interval (two years) creating a nonindependence across data points. To remove this problem, we break the sample in two, and replicate equation 3 using forecasts just from every other year, so that the time periods are nonoverlapping. Results are comparable.

tape may be stale. In fact, O'Brien finds that the average forecast in the IBES sample is 34 days old. Stale forecasts are troublesome if the forecasters do not know the earnings for year $t-1$ when they make their predictions for year t . For example, a forecaster who thinks that year t earnings will remain unchanged from year $t-1$ will appear to be predicting a change in earnings if his estimate of $t-1$ earnings is wrong. We cannot completely rule out this interpretation of the results but we selected April as the month to study with an eye toward minimizing the problem. We chose the longest possible forecast horizon where we could still be reasonably confident that the forecasters would know the previous year's earnings. The April forecasts are issued in the third week in April so that, by O'Brien's estimate, the average forecast was made in mid-March. At this point, the analysts should either know the past year's earnings exactly or have a very good estimate. Thus it seems unlikely that such a large bias could be produced by errors of this type.

Another reason for confidence in the results reported here is that others have obtained similar results in previous studies of professional forecasters, both security analysts and economists. Using just the 1976-78 years of the IBES data, Elton et al. estimated regressions similar to ours, and obtained slope coefficients less than one in each year. In a study of exchange rate expectations, Kenneth Froot and Jeffrey Frankel (1989) also found evidence consistent with overreaction or, what they call, "excessive speculation." Forecast errors are regressed on forecasted changes in exchange rates. The slope coefficients which, under rationality, should equal zero, are always significantly different from zero. When an instrumental variables technique is used to correct for errors-in-variables, the results do not change. Finally, David Ahlers and Josef Lakonishok (1983) study economists' forecasts of ten macroeconomic variables, using the Livingston data set. In regressions similar to our equation 1, they find slope coefficients significantly less than one for each of ten variables being forecast. In other words, predicted changes

were more volatile than actual changes, consistent with overreaction.³

We have documented generalized overreaction. However, an interesting question remains: What causes excessive optimism or pessimism in earnings forecasts? We considered several variables that might explain EPS forecast errors. Two variables that are of interest in light of our previous work include a measure of market valuation, MV/BV , the ratio of the market value of a company's equity to its book value (at the end of year $t-1$), and earnings trend (the growth rate of earnings over the years $t-6$ to $t-2$). Both variables were significantly related to forecast error in the expected direction, that is, excessive optimism for high MV/BV and high earnings growth firms, and excessive pessimism for firms low on these measures. Unfortunately, neither factor explained much of the variation in the forecast errors.

III. Conclusion

Formal economic models of financial markets typically assume that all agents in the economy are rational. While most economists recognize that, in fact, not everyone is fully rational, the existence of an irrational segment of the economy is often dismissed as irrelevant with the claim that there will be enough rational arbitrageurs to assure that rational equilibria will still obtain. Whatever the theoretical merits of this position (for a critique, see Bradford De Long et al., 1990; Thomas Russell and Thaler, 1985), an interesting empirical question is whether the presumed smart money segment actually can be identified. This paper investigates one possible source of rationality in financial markets, namely security analysts.

³As mentioned above, analysts may have incentives to make biased forecasts in order to stimulate trading by customers. Our discussant, Andrew Lo, suggested that these agency problems could produce an overreaction bias as well as an optimism bias. Whether or not this argument is plausible, the fact that the overreaction bias is observed for forecasters in domains in which the agency problem is not present suggests that the bias is produced by cognitive errors rather than faulty incentives.

ble source of rationality in financial markets, namely security analysts.

The conclusion we reach from our examination of analysts' forecasts is that they are decidedly human. The same pattern of overreaction found in the predictions of naive undergraduates is replicated in the predictions of stock market professionals. Forecasted changes are simply too extreme to be considered rational. The fact that the same pattern is observed in economists' forecasts of changes in exchange rates and macroeconomic variables adds force to the conclusion that generalized overreaction can pervade even the most professional of predictions.

The proper inference from this, we think, is to take seriously the behavioral explanations of anomalous financial market outcomes. When practitioners describe the recent October crashes as panics, produced by investor overreaction, perhaps they are right. After all, are not these practitioners the very same "smart money" that is supposed to keep markets rational?

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