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Naive Investors, Earnings Announcements, and Stock Price Movements

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SYNOPSIS AND INTRODUCTION:

This paper addresses the issue of whether investors with "naive" earnings expectations (i.e., earnings forecasts that are systematically less accurate than other publicly available predictions) have sufficient market power to affect common stock prices. The results clearly indicate that when security analysts predict quarterly earnings increases (decreases), from the same fiscal quarter of the prior year, that the abnormal return around the upcoming earnings announcement tends to be positive. When the data are formed into 50 portfolios, about 66% of the abnormal return variation around earnings announcements is explained by the predicted earnings change. This is surprising since the forecasts used are dated from one to thirteen weeks *before* the earnings announcement.

These results strongly suggest that a significant portion of the price response to earnings announcements is attributable to investors who hold naive beliefs. This paper extends previous research in at least two ways. First, the tests presented here are the most parsimonious to date (i.e., they require the fewest assumptions and parameter estimates) and may be, therefore, more convincing and comprehensible than prior tests. Further, they provide evidence of a stock market that exhibits a greater degree of naivete than previously documented in papers such as Hand (1989, 1990) and Bernard and Thomas (1990).

Hand (1989) and Bernard and Thomas (1990) point out that the financial press directs atttention to the comparison between quarterly earnings that are currently being made public and those announced for the same fiscal quarter of the preceding year. This latter value, earnings of the same fiscal quarter of the preceding year, is also known as the seasonal random walk (SRW) forecast. Each paper suggests that the media's focus on the SRW forecast may indicate that it is important to investors.[1]

Hand (1990) proffers a model where stock prices are sometimes set by investors using the SRW model (or another similarly naive model). He examines the case of debt-for-equity swaps and finds evidence consistent with his hypothesis. Specifically, at the time of the earnings announcement following the swap, he finds a stock-price reaction to the non-economic component of earnings attributable to the swap.

Bernard and Thomas (1990) correlate the signs and magnitudes of future price reactions around earnings announcements to the autocorrelation structure of SRW forecast errors. They show that returns around earnings announcements are partially predictable by analyzing past time-series forecast errors.

This paper goes beyond prior findings by showing that even when analysts go so far as to digest the information reflected in previous time-series forecast errors and translate that information directly into a published earnings forecast, the market is *still* surprised when earnings turn out to be what the analysts expected. In this sense, the paper provides a more stark documentation of market naivete than suggested by previous research.

The rest of the paper is organized as follows. The next section develops a method of testing for the influence of naive investors on stock prices. Section II describes the data and the research method. The third section presents and discusses the empirical results. The final section summarizes and concludes.

Key Words: *Analysts' forecasts, earnings, efficient market hypothesis, naive investors.*

I. Development of Hypothesis

In this section a hypothesis is proposed to determine if investors who have systematically failed to update their earnings expectations from last year's figure have sufficient market power to affect stock prices at the time of earnings announcements.

Bernard and Thomas (1990) point out that if some investors use a model that is not the most accurate available, their forecast error can be decomposed into unpredictable and predictable components. For example, the SRW forecast error can be dichotomized as follows:

$$E - \hat{E}_N = (E - \hat{E}_A) + (\hat{E}_A - \hat{E}_N) \tag{1}$$

where

$E \equiv$ quarterly earnings per share (EPS),

$\hat{E}_N \equiv$ seasonal random walk (naive) EPS forecast, and

$\hat{E}_A \equiv$ analysts' EPS forecast.

The first term on the right side of equation (1) is the unpredictable component of the SRW forecast error and the second term is the predictable component. The second term is predictable because the SRW forecast (earnings for the same fiscal quarter of the preceding year) is known and analysts' forecasts are available to a large number of investors. For example, the *Value Line Investment Survey*, which is available in many public libraries, provides fairly timely EPS forecasts for about 1,700 firms. The second term is interesting because analysts are systematically more accurate than the SRW model.[2] If investors who use (or behave as if they use) the SRW model affect stock prices, then the abnormal return around an earnings announcement can be written as a function of the two components.

$$AR = \alpha_0 + \alpha_1 \left(\frac{E-\hat{E}_A}{D} \right) + \alpha_2 \left(\frac{\hat{E}_A-\hat{E}_N}{D} \right) \tag{2}$$

where

AR ≡ the abnormal return around the earnings announcement and

D ≡ a deflator, such as share price prior to the earnings announcement or the absolute value of $\hat{E}_N$.[3]

It is well known that α_1 is positive (when analysts' forecast error is used in a simple regression) and it is easily shown that the test of $\alpha_2>0$ is equivalent to the test of $\delta_2>0$ in the following model:

$$AR = \delta_0 + \delta_1 \left(\frac{E-\hat{E}_A}{D} \right) + \delta_2 \left(\frac{E-\hat{E}_N}{D} \right) . \tag{3}$$

This is the model tested by Hughes and Ricks (1987) and Brown et al. (1987). It does not allow for a distinction between the influence of naive investors and other possible explanations for δ_2 being positive. For example, if $(E-\hat{E}_A)/D$ is measured with error and $(E-\hat{E}_N)/D$ is correlated with that error, δ_2 could be significantly different from zero even if investors with naive expectations do not influence prices. Related to equation (2), this means that in an efficient market α_2 may be non-zero due to, for example, bias resulting from measurement error in the other independent variable. Removal of the first regressor, therefore, gives a clear test of market efficiency.

$$AR = \gamma_0 + \gamma_1 \left(\frac{\hat{E}_A-\hat{E}_N}{D} \right) . \tag{4}$$

If prices are affected only by informed investors, γ_1 will equal zero. This is true because $(\hat{E}_A-\hat{E}_N)/D$ is known by informed investors prior to the earnings announcement and, therefore, must not be correlated with their true forecast error. Since $(\hat{E}_A-\hat{E}_N)/D$ is old news at the time of the earnings announcement, it should not, in an efficient market, be correlated with price movements that occur at that time (captured by AR).

Since returns are explained by a single independent variable, $(\hat{E}_A-\hat{E}_N)/D$, random errors in measuring any component of that variable unambiguously bias γ_1 towards zero (see Johnston [1984] p. 430). That is, if naive investors affect prices, then informed investors' ability to predict returns declines as noise is added to either $\hat{E}_A$ or $\hat{E}_N$. Therefore, problems such as recording errors and the use of aged forecasts bias the tests of this paper towards falsely failing to reject the null hypothesis. Specifying an inappropriate functional form for the relation or failing to account properly for analysts' utility functions have a similar effect.[4]

II. Data and Research Method

Data

To be included in the sample a firm-quarter must meet the following criteria: 1) current quarter EPS, announcement date, and prior year's EPS for the same fiscal quarter, must be available on quarterly Compustat; 2) an analysts' forecast of current quarter EPS (dated between one and thirteen weeks prior to the earnings announcement) must be available on either a previously hand-collected data set of Value Line forecasts (1982-1987) or from Institutional Brokers Estimate System, Inc. (IBES) (1984-1990); and 3) returns and price data must be available on the Center for Research in Security Prices (CRSP) NYSE/AMEX Daily Return File.

The sample consists of 20,551 firm-quarters over the April 1982 through September 1990 period. The number of observations per year varies primarily due to availability of analysts' forecasts, with 1986 (1982) having the most (least) with 3,223 (1,062). Also due to data availability constraints, firms in the sample tend to be larger than average. Over half (51.7%) of the observations are for firms in one of the three largest NYSE-AMEX size deciles based on market capitalization of equity. Only 7.4% of the sample are in the smallest three size deciles. The mean (median) lag between the forecast date and the earnings announcement is 22.4 (18) trading-days.[5]

Research Method

The model tested is equation (4). The null hypothesis, therefore, is no systematic relation between $(\hat{E}_A - \hat{E}_N)/D$ and the abnormal returns around the earnings announcement. If naive investors affect prices, however, we expect to reject the null hypothesis in favor of a positive relation between $(\hat{E}_A - \hat{E}_N)/D$ and the returns around earnings announcements. Since $(\hat{E}_A - \hat{E}_N)/D$ may be viewed as the (deflated) predicted change in earnings from the same fiscal quarter of the preceding year (or the predicted SRW error),

$$PRED \equiv \frac{\hat{E}_A - \hat{E}_N}{D} \quad . \tag{5}$$

PRED's calculation is straightforward. $\hat{E}_A$ equals the most recent quarterly EPS forecast from Value Line or, if the Value Line forecast is not available, the most recent mean forecast from the IBES History Tape.[6] $\hat{E}_N$ is the EPS reported by the firm for the same fiscal quarter of the previous year. Both sets of forecasts are adjusted for stock splits and stock dividends. For tests where D is necessary, it is the stock price two weeks prior to the earnings announcement. (See footnote 3).

Abnormal returns are calculated using the size control portfolio approach used by Foster, Olsen, and Shevlin (1984) and Dimson and Marsh (1986). The estimated abnormal return is a firm's raw return minus the return of the NYSE/AMEX size decile portfolio of which the firm is a member at the beginning of the calendar year. Firm size is measured as the market value of common equity. The reaction to the earnings announcement is assumed to be captured by the abnormal return on the *Compustat* report date plus the abnormal return on the previous day (see Patell and Wolfson [1984]). As in equation (4), this two-day abnormal return is designated AR.

III. Empirical Results

Regression Tests

The first set of results is generated by performing OLS regression tests of equation (4). Recall the null hypothesis is $\gamma_1=0$ and the alternative hypothesis is $\gamma_1>0$. A finding of $\gamma_1>0$ is not consistent with traditional notions of market efficiency. It is consistent, however, with the conjecture (and results) of Hand (1990) and Bernard and Thomas (1990) that investors with naive earnings expectations have sufficient market power to influence stock prices. The results of the regression estimation for three different model specifications are presented in Table 1.

[Insert Table 1 About Here]

The first column results refer to a regression test where PRED is represented by a coded score based on the PRED decile of the observation. In other words, the sample is ranked on PRED and divided into ten deciles and each decile is assigned a coded score to replace PRED. This specification reduces the effects of outliers and possible non-linearities in the relation (see Bernard and Thomas [1990]). To aid in economic interpretation, the scores are equally spaced from -0.5 (lowest decile) to +0.5 (highest decile). As discussed in Affleck-Graves and Mendenhall (1992), this coding method has two desirable properties. First, the intercept can be interpreted as the mean abnormal return for a hypothetical median observation between the two middle deciles and should be close to zero. Second, the regression slope coefficient γ_1 indicates the average difference in abnormal returns between observations in the highest and lowest PRED deciles. The hypothesis that $\gamma_1=0$ is rejected at conventional levels. Further, the 0.011 coefficient is interpreted as an expected 1.1% mean difference in the two-day abnormal return between the top and bottom PRED deciles. Recall that PRED is based only on information that is available at least one week before the abnormal return cumulation period begins and should, therefore, be unrelated to the abnormal return around the earnings announcement.

The second column presents results after replacing both variables (AR and price-deflated PRED) by their ranks within the sample minus the median rank (e.g., for the observation with the lowest PRED, PRED = -10,275; for the highest observation PRED = +10,275). Subtracting the median rank causes the median observation of each variable to have a converted rank of zero. The intercept, which is the expected abnormal return rank for the median PRED observation, therefore has an expected value of zero. Again, the null hypothesis of γ_1=0 is rejected at traditional levels. The coefficient of 0.096 implies that an observation with a PRED rank about ten places higher than another observation is expected to be about one abnormal return rank higher. The observation with the top PRED rank is expected to have an abnormal return rank 1,973 (20,550 X 0.096) places higher than the observation with the lowest PRED rank.

As is normal with large scale pooled cross-sectional regressions, the R-squareds for the first two specifications are small. A third test is performed to determine how much of the cross-sectional variation in returns around earnings announcements can be explained when: (1) a recent development regarding the functional form between earnings surprises and abnormal returns is utilized; and (2) observations are grouped to diversify away the unsystematic effects of factors unrelated to the association of interest.

Freeman and Tse (1992) provide motivation for a nonlinear price response to earnings surprises. They also provide empirical results indicating that an inverse tangent (arctan) function is more descriptive of the earnings-return relation than linearity. Following them, I estimate the coefficients a_0, a_1 and a_2 of the following equation using the Gauss-Newton iterative method on the entire sample:

$$AR = a_0 + a_1 \arctan(a_2 \cdot PRED) \tag{6}$$

The results of this test on individual observations are similar to those of the two specifications presented (e.g., 0.82% of the variance of AR is explained). When the data are formed into fifty portfolios on the basis of AR, however, and equation (4) is re-estimated after replacing AR with its portfolio mean and replacing PRED with the portfolio mean of arctan ($\hat{a}_2$ PRED), the R-squared exceeds 66%.[7] The results are presented in the third column of Table 1. Because PRED has been converted to an arctangent, further economic interpretation of the results is difficult. Figure 1 shows the OLS plot of equation (4) after the transformation. These results make it difficult to reject the economic significance of the PRED variable in predicting returns around future earnings announcements and are consistent with a market where the information in published analysts' forecasts is not reflected in stock prices.

It may be of some interest to note that analysts appear to be very good at predicting which firms will have large positive abnormal returns around the upcoming earnings announcement, but are not so competent at predicting large negative responses. The portfolio consisting of those observations with the highest ARs (about 13% on average) is also the portfolio with the highest predicted earnings change from last year. The portfolio consisting of the firms with the smallest (most negative) AR (about -13%) is not the portfolio with the smallest predicted earnings change and is represented by the point lying furthest from the regression line. An investigation as to the reason for this asymmetry is beyond the scope of this paper.

Comparison of Subsamples

This section tests PRED's ability to predict abnormal returns around upcoming earnings announcements by comparing the abnormal return characteristics of subsamples based on PRED. These results are summarized in Table 2.

[Insert Table 2 About Here]

Panel A shows the comparison of mean returns of the top and bottom one-half firms as ranked by PRED. Panel B compares the top decile to the bottom decile.

Panel A shows that the difference in mean AR between the HIGH and LOW PRED partitions is 0.64% [0.29-(-0.35)]. Tests of the significance of this difference are unnecessary since the mean AR of the HIGH (LOW) PRED group is significantly greater (less) than zero. Also presented are the median AR of each group, the percentage of observations for which AR is positive, the p-value of a binomial test that the fraction of positive abnormal returns is fifty percent, and the p-value of the null hypothesis that the signed rank is zero. The results of the binomial tests and the signed rank tests are consistent with the mean tests. Panel B presents the results for the highest and lowest PRED deciles. Conclusions from these tests are the same as those discussed for Panel A. Notice that the difference in AR for the two extreme deciles is 1.30 [0.54-(-0.76)] which is consistent with, but slightly larger than, the 1.1% predicted by the regression results displayed in the first column of Table 1.

In order to reject the null hypothesis it is not necessary that these two-day abnormal returns be deemed economically large, or exceed some benchmark such as estimated transaction costs. Those issues miss the fundamental point of this line of research--why are investors willing to trade at one price on one day and willing to trade at a predictable and systematically different price two days later? Why don't the sellers (buyers) of those stocks expected to have price increases (decreases) wait for the earnings announcement? The results here represent a violation of at least one definition of market efficiency--that prices are unbiased estimates of future prices minus a fair return. The primary interest in these results is not their direct implications for portfolio management (although portfolio managers who plan to trade can benefit directly by knowing whether to wait for the earnings announcement), but rather that they cannot be predicted by any existing return generating model. The very short (2-day) return window used here makes the results virtually immune to the problems of model misspecification (see Fama [1991]).

Factors Related to PRED's Ability to Predict Future Returns

Hand (1990) suggests that the probability that a stock's price is set by a marginal "unsophisticated" investor is inversely proportional to the fraction of shares held by institutions. His unsophisticated investor is similar in spirit to the naive investor in this paper. Two variables that should be related to the influence of naive investors are included in the data set. For the entire sample, market value of equity (size) is available and, for a subset of firms, the number of analysts who provide forecasts to IBES is also available.[8] Intuitively, larger firms and firms with greater analyst following will tend to have greater institutional interest and their prices should be affected less by investors using a naive forecast of earnings.

In addition, PRED's ability to predict future abnormal returns around earnings announcements is hypothesized to be attributable to its ability to predict future SRW forecast errors.[9] PRED's effectiveness, therefore, should depend on its accuracy, or closeness to the SRW forecast error. To capture this accuracy, the variable ACC is defined as a coded score of the absolute value of (PRED/SRWFE)-1. ACC is coded from 0 (least accurate decile) to 1 (most accurate) so that ACC is increasing in forecast accuracy.

These two factors, firm size and accuracy of PRED in predicting the SRW forecast error, are tested using the following equation:

$$AR = \delta_0 + \delta_1 PRED + \delta_2 (ACC*PRED) + \delta_3 (DEC*PRED)\ . \tag{7}$$

The coefficient δ_2 is hypothesized to be positive, indicating greater abnormal returns per unit of PRED as accuracy increases. While δ_3 is hypothesized to be negative indicating smaller abnormal returns per unit of PRED as firm size increases. Results are presented in Table 3 for the coded-decile specification of PRED (as in column 1 of Table 1). Results for other specifications are similar and inferences are unaltered.

[Insert Table 3 About Here]

Lines (1) and (2) in Table 3 indicate that each variable is highly significant in the expected direction. Line (3) shows that both variables remain highly significant when they appear in the model simultaneously. PRED's effectiveness decreases with firm size and increases with its accuracy in predicting the SRW forecast error. These results suggest that return predictability depends on the fraction of individual investors holding the stock and analyst superiority over the SRW model. It should be noted that regressions including ACC [lines (2) and (3)] are not ex ante because they require knowledge of announced earnings in order to form the SRW forecast error.

Time Period Specificity

The analysis is limited to an eight-year period because of the availability of analysts' forecasts of quarterly earnings. The results presented could be attributable to certain economic conditions that existed "on average" over this period. These conditions might not persist over time and possibly were not properly anticipated over this relatively short period.

In an attempt to address issues of time period specificity, IBES annual forecasts for the period 1976-1981 are converted to fourth quarter forecasts and appended to the data set. This is accomplished by taking the most recent IBES annual earnings forecast preceding an annual earnings announcement and subtracting the sum of the first three quarters' earnings for that fiscal year. The new data set contains observations from 1976 into 1990. This sample was divided by year and then again by the sign of PRED. For both PRED groups for each year, Table 4 presents the mean AR and the percentage of positive ARs. It also shows the difference in ARs between PRED groups for each year and the associated t-statistic.

[Insert Table 4 About Here]

Notice that every year the mean abnormal return for the positive PRED group is greater than the mean abnormal return for the negative PRED group. In 12 of the 15 years this difference is significant at the 5% level. The only years for which it is not significant occur in the 1976 to 1981 period when annual forecasts are converted to fourth quarter forecasts. These years not only have fewer observations, but some researchers believe the reporting lag of IBES was substantially greater for this early period than for more recent years (see, e.g., Cornell and Landsman [1989]). This could have a substantial impact on these results, since it is assumed that analysts' are aware of the first three quarters' earnings levels, which might not be true in some cases.[10] Finally, note that in all 15 years the fraction of observations exhibiting positive abnormal returns is higher for the positive PRED group than for the negative PRED group. It appears that the earlier results are not time period specific.

IV. Summary and Conclusions

Previous research suggests that investors with naive earnings expectations, that may be represented by the seasonal random walk (SRW) model, affect stock prices. If this is true, and better contemporaneous forecasts of earnings are available (e.g., analysts' forecasts), then the returns around upcoming earnings announcements should be predictable. Previous research shows that analysts' forecasts of quarterly earnings are more accurate than SRW forecasts. Therefore, if investors with naive beliefs affect common stock prices, the abnormal return around earnings announcements should be positively correlated with the difference between analysts' forecasts and SRW forecasts. Results presented in this paper document that this positive correlation existed consistently over the 1976 to 1990 period.

This paper extends previous research in at least two ways. First, the tests employed do not require the estimation of any statistical parameters and therefore are not dependent on researcher judgement. This may make the results more convincing and comprehensible.

Further, the results provide a more stark documentation of stock market naivete than currently exists in the literature.

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FOOTNOTES

[1]Hand (1989) and Bernard and Thomas (1990) do not explicitly conjecture the direction of causality. At least three possibilities present themselves: (1) investors use the SRW forecast because it is available in the financial press; (2) the financial media provide SRW forecasts because many members of their audience (investors) use them; and/or (3) investors and the financial press focus on the SRW forecast for some of the same (unobservable) reasons.

[2]For the data set used in this paper, analysts are more accurate than the SRW model for 68.8% of the observations, while the SRW model is more accurate 29.3% of the time. About 2% of the time the forecasts are identical.

[3]It is necessary to deflate earnings forecast errors (and components of errors) to control for share size. Many deflators such as past or predicted earnings, the standard deviation of past earnings, and recent share price have been used in prior research. The implications of the results presented in this paper are not sensitive to the choice of deflator.

[4]It is possible that γ_1 in equation (4) may be positive because of its indirect effect on returns via its relation with analysts' forecast errors. That is, if $(\hat{E}_A-\hat{E}_N)/D$ is positively correlated with analysts' forecast errors ($[E-\hat{E}_A]/D$), which are known to be positively correlated with the returns around earnings announcements, this could induce a positive correlation between $(\hat{E}_A-\hat{E}_N)/D$ and AR. In other words, omitting the analysts' forecast error from equation (4) may bias γ_1 upward. Although this would raise the new question of why $(\hat{E}_A-\hat{E}_N)/D$ is able to predict analysts' forecast errors, it would render the naive-investor interpretation inappropriate. Fortunately, the issue may be resolved by examining the correlation between $(\hat{E}_A-\hat{E}_N)/D$ and analysts' forecast errors. The Pearson product-moment (Spearman rank-order) correlation is *negative* 0.12 (*negative* 0.01). This indicates that any bias in γ_1 from omitting the analyst forecast error from equation (4) is downward. I verified

this by replicating the regression tests of this paper after adding the analysts' forecast error as an independent variable.

[5]The mean and median lag between earnings forecasts and announcements should be interpreted with care. For Value Line, the forecast date is defined as the publication date, which is the day Value Line expects its subscribers to receive the report [See Stickel (1985, p. 124)]. The actual forecast formation date occurs somewhat earlier, but is unknown. The IBES forecast date is the third Thursday of the "Statistical Period" (which consists of a calendar year and month) on the IBES History Tape. Since the IBES mean is an aggregate of forecasts from different sources, a single lag between forecast and announcement does not exist. (For a discussion of the IBES forecast lag, see Cornell and Landsman [1989].)

As discussed in the previous section, the use of aged forecasts in this paper biases the tests against rejection of the null hypothesis. For the sample tested, I find little evidence of a weakening of the effect described in this paper as forecast lag increases. However, the effect is substantially reduced (but still significant) when two-quarter (versus one-quarter) ahead forecasts are used.

[6]The choice of Value Line as the default forecast is arbitrary. The tests of this paper were replicated on a sample consisting only of those observations for which an IBES forecast was available and on a sample consisting only of those observations for which a Value Line forecast was available. The results in each case are very similar to those presented and inferences are unaltered.

[7]When the portfolios are formed on the basis of PRED, the R-squared goes up to 75.20%. For comparison, the R-squared for similar tests using the contemporaneous analysts' forecast error (AFE $\equiv$ [E-$\hat{E}_A$]/P) are 88.99% when the portfolios are based on AR and 95.83% when they are based on AFE. These latter regressions do not, of course, represent an assault on market efficiency since they rely on information (i.e., announced earnings) that becomes available at the time the abnormal returns are being measured.

[8]Potter (1992) documents a positive relation between firm size and fraction of shares held by institutions.

[9]As a predictor, PRED explains 41.2% of the variability in the SRW forecast error for raw but Winsorized (at 1% of the distribution on each end) variables ($\rho = +0.64$). For the coded variables, results are similar.

[10]The somewhat weaker results obtained in the 1976 to 1981 period are apparently not attributable to a reduction in PRED's predictive ability for fourth quarter announcements. For the 20,551 observation sample used throughout the paper, the regression coefficients (t-values) that correspond to γ_1 in column (1) of Table 1 for quarters one through four are 0.011 (6.02), 0.009 (5.01), 0.014 (7.66), and 0.012 (7.56), respectively.

Table 1

Regression Tests of the Relation Between the Abnormal Stock Returns Around Earnings Announcements (AR) and Predicted Seasonal Random Walk Earnings Forecast Errors (PRED), 1982-1990.

$AR = \gamma_0 + \gamma_1 \text{ PRED} + \text{error}^a$

	(1)[b] AR on PRED Coded Decile Score	(2)[c] Rank of AR on Rank of PRED	(3)[d] Mean AR on Mean of arctan of PRED for Fifty Portfolios
γ_0	-0.000 (-1.05)	1.985 (0.05)	-0.067 (-8.79)**
γ_1	0.011 (13.17)**	0.096 (13.87)**	0.331 (9.68)**
R^2	0.84%	0.93%	66.14%

N = 20,551

[a]AR is the two-day abnormal stock returns around earnings announcements. PRED = $(\hat{E}_A\text{-}\hat{E}_N)/P$, where $\hat{E}_A \equiv$ the analysts' forecast of earnings per share (EPS), $\hat{E}_N \equiv$ the SRW forecast of EPS, and P is the stock price two weeks before the EPS forecast.

[b]For this test, the independent variable is a coded score based on the decile (-0.5=lowest, ... , 0.5=highest) of PRED within the sample.

[c]Both variables are defined as their rank within the sample minus the median rank (e.g., for the observation with the lowest abnormal return AR=-10,275; for the observation with the highest abnormal return AR=+10,275).

[d]For this specification the data are placed in fifty portfolios on the basis of AR. The dependent variable is the portfolio mean of AR. The independent variable is the portfolio mean of arctan (205.83 PRED). The coefficient of 205.83 was determined using the Gauss-Newton iterative method.

**, significant at the 0.01 level.

Table 2

Comparison of Abnormal Stock Returns Around Earnings Announcements (AR) Across Subsamples Based on Predicted Seasonal Random Walk Earnings Forecast Errors (PRED), 1982-1990.

N	GROUP[a]	MEAN AR	(T-STAT)	MEDIAN AR	% POS AR	BINOMIAL P-VALUE	SIGNED RANK P-VALUE
Panel A. Partition of Entire Sample on the Basis of PRED							
10,275	HIGH PRED	0.29	(7.02)**	0.21	53.2	.000	.000
10,276	LOW PRED	-0.35	(-9.51)**	-0.27	45.5	.000	.000
Panel B. Highest PRED Decile Versus Lowest PRED Decile							
2,055	HIGH PRED	0.54	(4.50)**	0.21	52.4	.014	.000
2,056	LOW PRED	-0.76	(-7.07)**	-0.65	40.9	.000	.000

[a]Observations are assigned to subsamples on the basis of PRED, the predicted seasonal random walk (SRW) forecast error. PRED ≡ $(\hat{E}_A-\hat{E}_N)/P$, where $\hat{E}_A$ ≡ the analysts' forecast of earnings per share (EPS), $\hat{E}_N$ ≡ the SRW forecast of EPS, and P ≡ the share price ten trading days before the earnings announcement.

**, significant at the 0.01 level.

Table 3

Regression Tests of the Relation Between the Abnormal Stock Returns Around Earnings Announcements (AR) and Predicted Seasonal Random Walk Forecast Errors (PRED), as a Function of Firm Size and Prediction Accuracy, 1982-1990.

$$AR = \delta_0 + \delta_1 PRED + \delta_2(ACC*PRED) + \delta_3(DEC*PRED) + error^a$$

	INTERCEPT	PRED	ACC*PRED	DEC*PRED
(1)	-0.000 (-1.35)	0.022 (9.76)**	---	-0.017 (-5.04)**
(2)	0.001 (-2.61)**	0.032 (21.12)**	0.044 (16.49)**	---
(3)	0.001 (-3.11)**	0.046 (17.40)**	0.046 (17.02)**	-0.021 (-6.56)**

N = 20,551

[a]AR is the two-day abnormal return around earnings announcements. PRED is the predicted seasonal random walk (SRW) earnings forecast error deflated by stock price. PRED = $(\hat{E}_A - \hat{E}_N)/P$, where $\hat{E}_A \equiv$ the analysts' forecast of earnings per share (EPS), $\hat{E}_N \equiv$ the SRW forecast of EPS, and P is the stock price ten trading days before the earnings announcement. PRED is converted to a coded score ranging from -0.5 (lowest decile) to 0.5 (highest decile). DEC is a coded score representing the NYSE-AMEX size decile (based on market value of equity) of which the firm is a member at the beginning of the calendar year. The codes range from 0 (smallest decile) to 1.0 (largest decile). ACC is a coded score for $|(PRED/SRWFE)-1|$, where SRWFE is the SRW forecast error, ranging from 0 (highest decile) to 1 (lowest decile).

**, significant at the 0.01 level.

Table 4

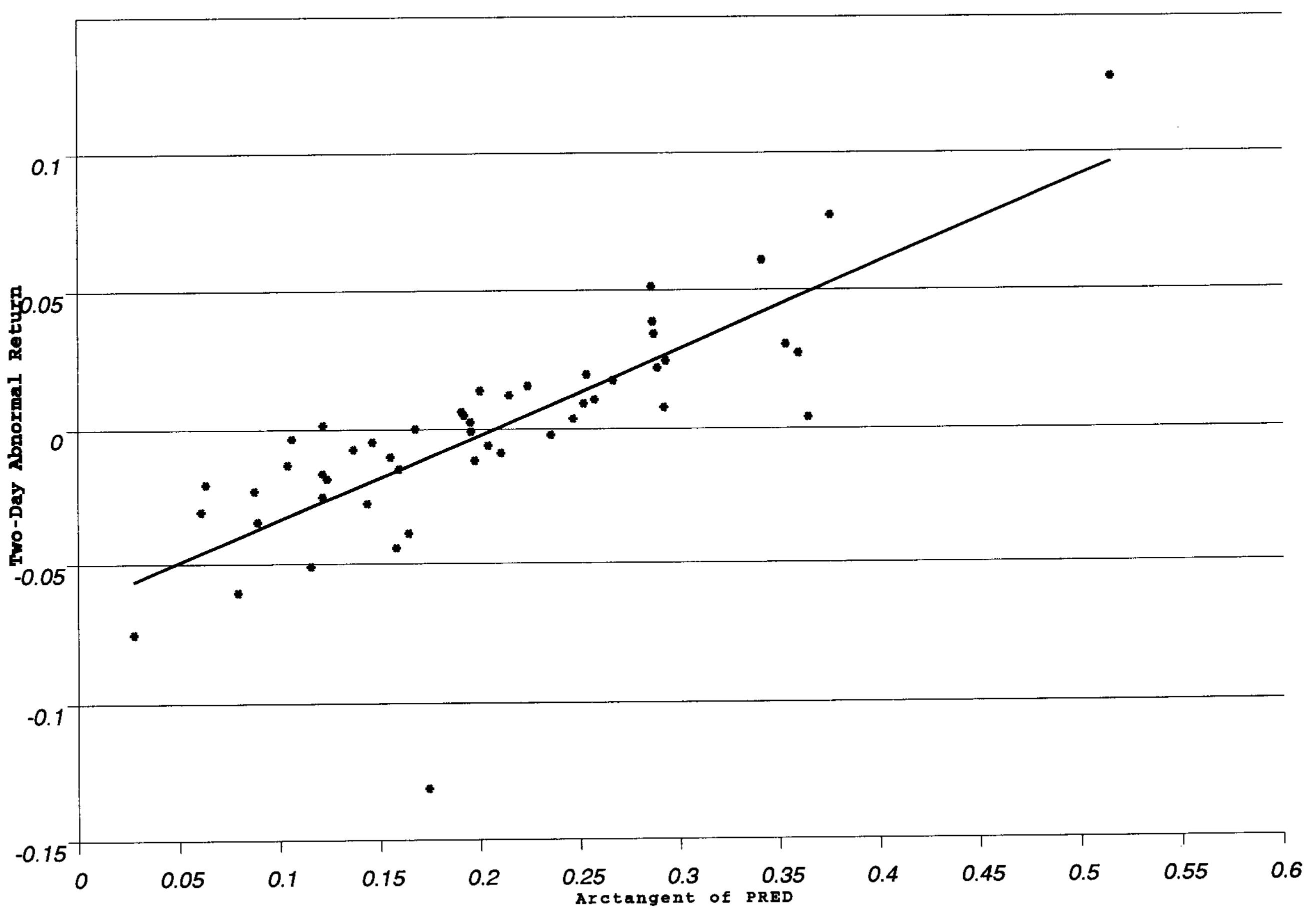
Mean Abnormal Stock Returns Around Earnings Announcements (AR) by Sign of Predicted Seasonal Random Walk Earnings Forecast Error (PRED) by Year, 1976-1990.

YEAR	PRED[a] GROUP	N	MEAN[b] AR %	AR DIFFERENCE (T-STATISTIC)	% POS AR
1976	> 0	352	0.70	0.40	55.2
	< 0	199	0.30	(1.18)	49.7
1977	> 0	438	0.19	0.55	53.8
	< 0	154	-0.36	(2.24)*	45.2
1978	> 0	528	0.27	0.42	54.3
	< 0	195	-0.15	(1.40)	49.5
1979	> 0	659	0.44	0.99	54.4
	< 0	281	-0.45	(3.95)**	42.7
1980	> 0	557	-0.00	0.53	48.3
	< 0	382	-0.53	(2.11)*	39.3
1981	> 0	590	0.16	0.35	54.1
	< 0	408	-0.19	(1.44)	44.6
1982	> 0	514	0.43	1.15	52.5
	< 0	530	-0.72	(4.56)**	40.9
1983	> 0	949	0.39	0.65	53.2
	< 0	705	-0.26	(3.49)**	43.5
1984	> 0	1,459	0.07	0.49	53.7
	< 0	479	-0.42	(2.36)*	45.1
1985	> 0	1,978	0.06	0.67	50.0
	< 0	1,124	-0.61	(4.01)**	40.7
1986	> 0	2,132	0.20	0.55	53.2
	< 0	1,039	-0.35	(3.69)**	44.3
1987	> 0	2,109	0.36	0.78	51.7
	< 0	844	-0.42	(4.40)**	42.7
1988	> 0	1,421	0.04	0.51	50.7
	< 0	430	-0.47	(2.59)**	42.3
1989	> 0	1,532	0.14	0.62	49.5
	< 0	709	-0.48	(3.41)**	47.4
1990	> 0	1,470	0.32	0.81	54.6
	< 0	767	-0.49	(4.00)**	47.3

[a]PRED is the predicted seasonal random walk (SRW) forecast error. PRED = $(\hat{E}_A-\hat{E}_N)/P$, where $\hat{E}_A \equiv$ analysts' forecast of earnings per share (EPS), $\hat{E}_N \equiv$ SRW forecast of EPS, and P is the stock price ten days before the earnings announcement.

[b]AR is the two-day abnormal stock return around the earnings announcement.

**, significant at the 0.01 level; *, significant at the 0.05 level.



Two-Day Abnormal Return
0.1
0.05
0
-0.05
-0.1
-0.15
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
0.55
0.6
Arctangent of PRED

Figure 1

Figure 1. Regression plot of mean two-day cumulative abnormal returns around earnings announcements (AR) on the mean arctangent of 205.83 PRED for fifty portfolios formed on the basis of AR. PRED is given by $(\hat{E}_a-\hat{E}_N)/P$, where $\hat{E}_A$ is the analysts' forecast of earnings, $\hat{E}_N$ is the seasonal random walk forecast of earnings (i.e., actual earnings for the same quarter of the previous year), and P is the stock price ten days before the abnormal return cumulation period. The coefficient of 205.83 was determined using the Gauss-Newton iterative method.