MANAGEMENT SCIENCE
Vol. 27, No. 9, September 1981
Printed in U.S.A.

EXPECTATIONS AND SHARE PRICES*

EDWIN J. ELTON,† MARTIN J. GRUBER† AND MUSTAFA GULTEKIN†

It is generally believed that security prices are determined by expectations concerning firm and economic variables. Despite this belief there is very little research examining expectational data. In this paper we examine how expectations concerning earning per share effect share price. We first show that knowledge concerning analyst's forecasts of earnings per share cannot by itself lead to excess returns. Any information contained in the consensus estimate of earnings per share is already included in share price. Investors or managers who buy high growth stocks where high growth is determined by consensus beliefs should not earn an excess return. This is not due to earnings having no effect upon share price since knowledge of actual earnings leads to excess return. Much larger excess returns are earned if one is able to determine those stocks for which analysts most underestimate return. Finally, the largest returns can be earned by knowing which stocks for which analysts will make the greatest revision in their estimates. This pattern of results suggests that share price is affected by expectations about earnings per share. Given any degree of forecasting ability managers can obtain best results by acting on the differences between their forecasts and concensus forecasts.
(FINANCE; FINANCE—INVESTMENT)

1. Introduction

A central theme of modern investment theory is that expectations about firm characteristics are incorporated into security prices. This theme can be found in most investment texts and is utilized in much of the current research in finance. Not only does this belief pervade academia it is commonly held by the financial community.

Surprisingly, in light of the strength of this belief, there is very little empirical evidence to support it. Almost all research which attempts to measure the impact of expectations utilizes not expectational data but historical extrapolations of past data that the authors hope will serve as a proxy for expectational data. This is true for most tests of valuation models as well as almost all tests in the efficient markets literature.

The purpose of this article is to examine the importance of expectations concerning one variable, earnings per share, in the determination of share price. Earnings per share is considered a key variable in determining share price and has been studied extensively in the efficient markets literature. In almost all studies, expectations of future earnings per share are formulated as an extrapolation of past earnings.[1] Justification for using historical extrapolation is sometimes found in tests of the accuracy of extrapolated data in forecasting future earnings.

While tests such as those found in [3], [4], and [5] provide some evidence of the relative accuracy of historical extrapolation versus expectational data as forecasts of the future, they do not address the question of the role of expectations in share price formation. The purpose of this paper is to directly address this question. More

*Accepted by Vijay S. Bawa, former Departmental Editor; received September 20, 1979. This paper has been with the authors 4 months for 3 revisions.

†New York University.

[1] Malkiel and Cragg [8] used expectational data on earnings growth in a valuation model. However, their sample of expectational data was very limited.

0025-1909/81/2709/0975$01.25

specifically, we will address the question of the role of actual future changes in earnings on stock returns, the role of expected changes in earnings, and finally the role of changes in expectations.

In addition to examining the importance of expectations and earnings, we briefly explore the issue of the scale of returns that can be earned by being "more accurate" than average forecasts. If market prices reflect average expectations, then superior forecasting ability should be rewarded with excess returns. We will explore both the size of these returns and the timing of their occurrence.

2. Overview: Variables Examined and Sample Design

The testing of the impact of earnings expectations has awaited the development of a broad consistent data base. Lynch, Jones and Ryan have constructed a data base which contains one and two-year consensus earnings estimates on all corporations followed by one or more analysts at most major brokerage firms.[2] Lynch, Jones, and Ryan define the consensus earnings estimate for any stock as a simple arithmetic average of the estimates prepared by all of the analysts following that stock. Given this data base, a study can be made of the role of average expectations in price formation and in particular the importance of earnings expectations in determining share price.

In order to study the role of expectations, we need some measure of the excess returns that can be earned from knowledge concerning future earnings. To examine this, we analyzed the actual growth rate in earnings. The actual growth rate was defined as actual earnings for the forecast year minus actual earnings in the previous fiscal year, divided by actual earnings in the previous fiscal year. This variable is computed only for those firms for which the denominator is positive. This does not bias the results of our tests as the denominator is known at the time this variable is formulated. However, the population of stocks to which our tests apply is restricted. Letting G_t stand for the growth rate in earnings,

$$G_t = \frac{E_t - E_{t-1}}{E_{t-1}} \quad \text{for } E_{t-1} > 0 \tag{1}$$

where E_t is reported earnings per share at time t.

Anticipating our results for a moment, we will find that knowledge of actual growth will allow a significant risk adjusted excess return to be earned. This indicates that growth in earnings is an important variable affecting share price, and that expectations concerning this variable are worth studying.

If expectations determine share price, then knowledge of the average value of these expectations should already be incorporated in the share price, and buying on the basis of average expectations should not lead to excess returns. Thus, the second variable we examined was the consensus forecast of the growth rate in per share

[2] Lynch, Jones and Ryan, a New York-based brokerage firm, have available in computer readable form consensus (average) earnings estimates updated monthly for the current and next fiscal year as well as forecasts of each individual analyst following each stock. They designate this as the I/B/E/S service. During the time period studied Lynch, Jones and Ryan surveyed brokerage firms. Our sample consisted of all stocks listed on the New York Stock Exchange which were followed by three or more analysts. The average number of analysts following each of these firms was slightly above seven. Furthermore, slightly less than 70 stocks were followed by ten or more analysts. The maximum number of analysts following any stock was 18.

earnings. We call this the forecasted growth rate. It is formulated as the consensus forecast of fiscal year earnings minus the actual earnings in the previous fiscal year divided by the actual earnings that occurred in the previous fiscal year. Since this measure cannot be interpreted for a negative denominator, it is computed only for those companies for which the denominator is positive. To be more explicit, let

$$FG_t = \frac{C_t - E_{t-1}}{E_{t-1}} \quad \text{for } E_{t-1} > 0, \tag{2}$$

where C_t is the consensus forecasts of the earnings per share that will occur at time t, and FG_t is the consensus forecast of the growth rate in earnings per share.

If expectations are important and are incorporated in present prices, then one should observe larger excess returns by having knowledge concerning the error in the growth estimate, than by knowing actual growth itself. Investment in a firm with high actual growth should not necessarily lead to excess returns unless investors were forecasting low growth. Thus, if expectations are important, knowledge concerning differences between actual growth and forecasted growth should lead to higher excess returns than knowledge concerning growth itself. Thus, the third variable we examine is actual growth minus forecasted growth. This differential growth can be expressed as

$$DG_t = G_t - FG_t. \tag{3}$$

Since the effect of differences between expectations and realizations is the key phenomena that we wish to study, we have measured this phenomena in two additional ways. The first is the error in the earnings forecast defined as the actual earnings in the forecast year minus the forecast earnings. If we denote this variable by M_t for misestimate in consensus forecast of earnings, then

$$M_t = E_t - C_t. \tag{4}$$

The second is the percentage forecast error, which is measured as the actual earnings in the forecast year minus the forecast earnings divided by the absolute value of the actual earnings. If we use $\%M_t$ to stand for the percentage, then

$$\%M_t = \frac{E_t - C_t}{|E_t|}. \tag{5}$$

While most of our analysis consists of an examination of one year forecasts, we decided to take a brief look at the excess returns associated with errors in two year forecasts. We duplicated the one-year measures and examined the error in earnings forecast for two years and the percentage error in earnings forecast for two years.

If consensus forecasts are more important than the actual level of future earnings in determining prices, then one should be able to do a better job of selecting stocks by knowing the change in consensus forecasts than by knowing actual earnings. To test this hypothesis, a variable measuring the percentage adjustment in forecasts over time was used. This variable is formulated as negative of the following quantity: the forecast of earnings prepared for the next (as opposed to this) fiscal year minus the forecast of earnings for the same fiscal year made one year later divided by this latter number. To better understand this variable, let ${}_{t-a}C_t$ stand for the consensus forecast for earnings at time t which are produced at time $t - a$, and ${}_{(t-a+12)}C_t$ stands for the forecast for time t which is produced 12 months later. Then the forecast revision denoted by FR_t can be represented as

$$FR_t = -\frac{{}_{(t-a)}C_t - {}_{(t-a+12)}C_t}{{}_{(t-a+12)}C_t}. \tag{6}$$

3. The Sample

The raw data consisted of a monthly file of one and two-year earnings forecasts prepared in the years 1973, 1974, and 1975. We limited our sample of data in several ways. First, the sample was restricted to firms having fiscal years ending on December 31. By confining our sample to firms with fiscal years ending on the same date, forecasts prepared a certain number of months (e.g., nine) in advance of the end of the fiscal year, fall on the same calendar date. This procedure assures that the same general economic influences (e.g., the economy, the market, etc.) were available to all forecasters at the time forecasts were prepared. The date of December 31 was selected because more companies had fiscal years ending on that date than on any other.

Second, forecasts are restricted to two forecast dates, March and September. March was selected because it is the earliest date on which financial data for the previous fiscal year would be reported by most companies. September was selected as a month that is far enough from the first forecast and far enough into the fiscal year that significant evidence on companies' performance during the year should be available. Yet it is not so far into the year that earnings are known with certainty. Both dates are used for all variables involving one-year forecasts. However, so few two-year forecasts were available in March that only the September date could be used when examining two-year forecasts.

Finally, because we are interested in the impact of consensus forecasts, the sample was restricted to companies which were followed by three or more analysts. The consensus prepared from less than three forecasts could be idiosyncratic and not typical of broad feelings about the stock.

The final sample consisted of a total of 919 one-year forecasts of the fiscal years 1973, 1974, and 1975 and a total of 710 two-year forecasts of fiscal years 1974, 1975, and 1976. Because of negative earnings, some firms had to be eliminated over several measures. This caused the sample size to fall to as low as 913 and 696 for one and two-year forecasts, respectively. As discussed earlier Lynch, Jones and Ryan survey most large brokerage firms. Since we have included all stocks followed by three or more analysts, the group of stocks in our sample can be considered a universe of all stocks with important analyst interest. Since brokerage firms are interested in providing information to their customers, our sample should include most stocks of major institutional interest.

4. Methodology

The first step in our procedure was for each time period studied (March and September) and for each year to rank all stocks on each variable and to divide the stocks into deciles by each variable. For example, we formed deciles for the forecasted growth rates made in September 1973 with the first decile containing the 10% of the stocks with the highest forecasted growth rate. For each decile, we calculated the average value of the variable being studied (in this case, forecasted growth).

In order to determine whether certain types of information lead to excess returns, it is necessary to have a measure of what return is expected. If we have a measure of expected return, then excess return is the difference between actual return and expected return. In order to measure expected return, we use the market model. The market model is a relationship between the return on a security and the return on a market index.

Let

1. r_{it} be the return on portfolio i in period t.
2. r_{mt} be the return on the market in period t.
3. α_i and β_i be parameters for portfolio i.
4. e_{it} be deviations from the model.

The market model is:

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it}$$

Using the market model leads to expected returns being determined by the security's normal relationship with the market (β_i), the market return in the period (r_m) and the security's average nonmarket return (α_i). Using the market model excess return is

$$r_{it} - (\alpha_i + \beta_i r_{mt}).$$

Although the market model is frequently used in finance, there are some problems with its use that can lead to biased tests. First there is measurement error in the coefficients and if this varies systematically with the test statistic, it can lead to an appearance of a relationship when none exists. This was guarded against in several ways.

First we calculated the market model for the deciles discussed earlier. Using grouped data is one way of reducing the measurement error. The one variable where measurement error can be especially bothersome is beta. As Blume [1] has shown the error in measuring beta varies systematically with its difference from one. The use of grouped data helps. In addition, we examined the individual betas on the groups. There was no systematic pattern, nor did any group beta differ very much from one (the range was 0.93 to 1.09). Given this result, we judged that any further adjustment in beta was unnecessary. In the original CAPM tests grouping data was common. Litzenberger and Ramaswamy [7] and Ross and Roll [9] have criticized this on the grounds that the CAPM is a theory of the pricing of single assets and as such has to be shown to explain differences in asset returns. Our purpose here is not to test CAPM but rather to examine the effect of expectations on share price. Hence grouping is a reasonable procedure for dealing with measurement error.

The second problem in the use of the market model is its difference from a capital asset pricing model. There are numerous general equilibrium models that have been derived. If one of these ultimately is shown to be correct, then better estimates of returns should be obtained by using that model rather than the market model. Brennan [2] has shown that the use of alternative models can make some difference. However, in this study the magnitude of the results, the grouping techniques, and the spread in the β_i's should mean that there is minimal chance of this source of potential bias explaining the results.[3] For example, assuming that the beta for each group was equal to one would not change any of our conclusions.

[3] We could have used differences from R_m, rather than the market model in reporting our results. However the reader might then question to what extent our conclusions were due to differences in market risk. Alternatively we could have followed Watts [10] methodology to force the Beta on each Portfolio to be exactly one. However since the differences in Beta from one were neither large nor systematically related to any criteria across our deciles we did not take this additional step.

The market model was estimated by treating each decile as an equally weighted portfolio of the stocks which composed it and estimating the market model parameters for each decile. The market index we used was the Standard and Poor's index adjusted for dividends. The parameters of the model were estimated in each case using 60 monthly observations on returns up to and including the forecast month. The data dissemination procedure followed by Lynch Jones and Ryan means that forecasts are in the hands of the subscriber by the end of the month. The estimated parameters of the market model were then used in conjunction with actual market returns to forecast normal risk adjusted returns for each of the deciles during each of the 24 months after the forecast month. The risk adjusted returns in each month were close to but not exactly equal to zero. This should not be surprising to the reader. The sum of the residuals in any one month should equal zero only if they are weighted in market proportions and include all stocks in the index. Our sample meets neither of these conditions. We adjusted our residuals to have a mean (across all deciles) of zero for ease of presentation. Our primary statistical test is a *rank* correlation test, subtracting a constant from each entry can not effect the rank. Thus our adjustment had very little effect on the numbers reported and had no effect on their statistical significance or on our conclusions.

As discussed earlier, we calculated risk adjusted excess returns for each of the deciles for each of the variables for the 24 months after the forecast month. In the case of the March data we calculated risk adjusted excess returns from April on and in the case of September from October on. This was done for each of the three years for which we had data. We combined these years and have reported the average risk adjusted return across the three years for each decile.

To aid in understanding the results, we report the sum of the risk adjusted excess returns from the month after the forecast month to the month under consideration, rather than reporting the risk adjusted excess returns in any one month.[4] Thus, for March forecasts, the entry in month 3 is the sum of the risk adjusted excess returns earned in April, May, and June. This allows the reader to more easily determine the cumulative effect of any influence.

After examining the data we determined that there were no further effects after month 15 for March data and month 9 for September data. Thus, we have not reported results beyond these dates.

In reporting results we have combined the deciles in two ways. First, we report the cumulative risk adjusted excess returns in the upper 30%, middle 40%, and lowest 30% of firms ranked on each variable. Second, we report the cumulative risk adjusted excess returns in the upper 50%. Since the risk adjusted excess returns add to zero, across all deciles the risk adjusted excess return in the upper 50% is the negative of the lowest 50%. We chose to present the data in this way since using the ungrouped deciles increases the size of the tables substantially without providing additional insights.

The reader can judge the economic significance of the results by examining the cumulative residuals in Tables 1 through 4. These excess returns are reported before

[4] Many authors accumulate residuals by calculating the product of one plus the residuals. The justification for this is that return over N periods is the product of the N one period returns. There is a difficulty with this procedure. The null hypothesis is that the residuals average zero. If this hypothesis is true, it is easy to show that the product of one plus the one period residuals minus one becomes negative and significantly so as N gets large. The sum of the residuals is zero under the null hypothesis and deviations from zero are indications of real effects.

TABLE 1

Time Series of Cumulative Excess Returns Ranked by Error in the Forecast of the Growth Rate (Equation (3)) for March Data

Month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Upper 30%	0.0166	0.0221	0.0221	0.0321	0.0630	0.0698	0.0767	0.0782	0.0855	0.0664	0.0729	0.0775	0.0909	0.0801	0.0897
Middle 40%	− 0.0069	− 0.0037	+ 0.0037	− 0.0001	− 0.0139	− 0.0170	− 0.0038	− 0.0041	− 0.0063	− 0.0162	− 0.0107	− 0.0120	− 0.0144	− 0.0209	− 0.0126
Bottom 30%	− 0.0075	− 0.0169	− 0.0173	− 0.0320	− 0.0444	− 0.0470	− 0.0719	− 0.0726	− 0.0773	− 0.0448	− 0.0588	− 0.0731	− 0.0717	− 0.0523	− 0.0729
Rank Correlation[a]	0.71**	0.73**	0.76**	0.83*	0.83*	0.76**	0.84*	0.87*	0.89*	0.90*	0.85*	0.87*	0.93*	0.92*	0.89*

[a] Rank correlation coefficients

*Indicates significance at the 1% level.

**Indicates significance at the 5% level.

TABLE 2

Time Series of Cumulative Excess Returns for the Error in the Forecast of Growth Rate Using September Data (Equation (3))

	1	2	3	4	5	6	7	8	9
Upper 30%	0.0187	0.0272	0.0421	0.0429	0.0466	0.0506	0.0618	0.0638	0.0680
Middle 40%	0.0100	0.0092	0.0014	− 0.0035	− 0.0036	− 0.0045	− 0.0069	− 0.0065	− 0.0034
Lower 30%	− 0.0318	− 0.0394	− 0.0441	− 0.0384	− 0.0421	− 0.0445	− 0.0526	− 0.0550	− 0.0635
Rank Correlation[a]	0.77*	0.88*	0.84*	0.88*	0.99*	0.92*	0.95*	0.94*	0.85*

[a] Rank correlation coefficients are computed across deciles.
* Indicates significance at 1% level.
** Indicates significance at 5% level.

TABLE 3

Excess Returns for Months 7 and 13 March Data

Time of Analysis		Forecasted Growth Equation (2)	Actual Growth Equation (1)	Error in Growth Equation (3)	Error in Forecast (One Year) Equation (4)	Percentage Error in Forecast Equation (5)
MONTH 7	Upper 30%	− 0.0064	+ 0.0591	+ 0.0767	0.0633	+ 0.0711
	Middle 40%	0.0068	0.0006	− 0.0033	0.0092	− 0.0033
	Lower 30%	− 0.0028	− 0.0597	− 0.0719	− 0.0754	− 0.0719
	Upper 50%	− 0.0080	0.0463	0.0426	0.0462	0.0426
	Rank Correlation[a]	− 0.35	0.90*	0.84*	0.98*	0.90*
MONTH 13	Upper 30%	+ 0.0006	+ 0.0748	+ 0.0908	+ 0.0715	+ 0.0861
	Middle 40%	− 0.0093	− 0.0191	− 0.0144	+ 0.0022	− 0.0156
	Lower 30%	+ 0.0019	− 0.0493	− 0.0717	− 0.0743	− 0.0651
	Upper 50%	− 0.0139	0.0411	0.0577	0.0571	0.0554
	Rank Correlation[a]	− 0.30	0.88*	0.93*	0.96*	0.85*

[a] Rank Correlation coefficients are computed across deciles.
* Indicates significance at the 1% level.
** Indicates significance at the 5% level.

TABLE 4

Excess Returns for Month 7 from September Data

	Forecasted Growth Equation (1)	Actual Growth Equation (2)	Error in Growth Equation (3)	Error in Forecast (One Year) Equation (4)	Error in Forecast (One Year) Equation (5)	Error in Forecast (Two Years) Equation (4)	Error in Forecast (Two Years) Equation (5)	Forecast Revision Equation (6)
Upper 30%	0.0135	0.0399	0.0618	0.0567	0.0652	0.0773	0.0792	0.0889
Middle 40%	− 0.0079	− 0.0161	− 0.0069	− 0.0053	− 0.0084	− 0.0023	− 0.0062	− 0.0141
Lower 30%	− 0.0029	− 0.0186	− 0.0526	− 0.0497	− 0.0541	− 0.0741	− 0.0711	− 0.0701
Upper 50%	0.0073	0.0245	0.0405	0.0402	0.0409	0.0496	0.0498	0.0512
Rank Correlation[a]	0.37	0.53	0.95*	0.95*	0.89*	0.96*	0.98*	0.83*

[a] Rank correlation coefficients are computed across deciles.

* Indicates significance at the 1% level.

** Indicates significance at the 10% level.

TABLE 5

Mean Values for Each Variable

	Equat. (1) Forecasted Growth	Equat. (2) Actual Growth	Equat. (3) Error in Growth	Equat. (4) Forecast Error (1 yr)	Equat. (5) Percentage Forecast Error (1 yr)	Equat. (4) Percentage Forecast Error (2 yrs)	Equat. (5) Percentage Forecast Error (2 yrs)	Equat. (6) Forecast Revision
March Data								
Upper 30%	56.61%	107.45%	63.62%	1.08%	26.24%			
Middle 40%	6.9	8.27	1.35	0.01	− 0.32			
Lower 30%	− 9.16	− 34.95	− 38.88	1.05	− 159.24			
Sept. Data								
Upper 30%	81%	98.83%	26.36%	0.53%	14.72%	0.13%	26.74%	43.76%
Middle 40%	9.34	8.32	− 0.17	− 0.07	− 0.23	− 0.09	− 3.75	1.19
Lower 30%	− 15.75	− 32.95	− 27.02	− 0.67	− 94.01	− 1.64	− 155.29	− 27.34

transaction costs. While estimates of round trip transaction costs differ, a reasonable estimate is in the range of two to four percent. Thus, cumulative residuals in excess of 4% can be accepted as of economic significance.

It is also logical to examine whether the relationship between any of the variables under study and excess return is statistically significant. This was examined by computing Spearman rank order correlation coefficient between the decile and the rank order of the cumulative excess return for each decile. A statistically significant rank order correlation coefficient would indicate that there was a significant relationship between the variable under study and cumulative excess returns. Furthermore, by using a nonparametric test this statement is free of any distributional assumptions (across deciles) about the pattern of excess returns and/or the variables under study. Note that when we compute, the statistical significance of the cumulated residuals in successive periods these tests are not independent.

Table 5 presents the average values for each variable studied in this paper.

5. Results

The first question to analyze is: Can an investor earn excess returns by selecting stocks on the basis of the consensus growth rate forecasted by security analysts (Equation (2))? The answer is no. There is no discernable pattern in the cumulative excess returns. In some months the stocks for which high growth was forecasted had positive risk adjusted cumulative excess returns; in other months they had negative ones. As a further check we performed a rank order correlation test on the deciles in each month. The rank order correlation between forecasted growth and risk adjusted cumulative excess return was never significantly different from zero at the 1% level and only significantly different from zero from the 5% level in two months. In the months it was significant it was negative, which is opposite to what one would expect if growth estimates contained information which was not incorporated in stock prices. The lack of a pattern was even more evident in the September data. In no month was the cumulative excess return significantly different from zero at even the 5% level and the average cumulative excess return varied frequently from positive to negative. The results for each individual month is not reported in the paper but the results for selected months can be seen by examining Tables 3 and 4.

This lack of risk adjusted excess returns occurs even though the analysts were projecting some very large growth rates. In September the analysts were projecting that the average growth rate for the top decile would be over 100% and the growth rate in the second decile would be 33%. In contrast the earnings of stocks in the last decile were expected to decline by 34%.

A number of financial institutions purchase growth stocks as an investment strategy. In the three years we examined, pursuing such a strategy based on consensus estimates would not have led to superior returns, growth forecasts were already incorporated in the security prices. This is what one would expect if expectations are incorporated into security price.

On the other hand, our results show that growth is an important determinant of security returns. Investors with perfect forecasting ability could make risk adjusted excess returns. The results for individual months are not reported. However, the results for selected months, can be seen by examining Tables 3 and 4. From month 4 on, the rank order of excess returns for the deciles is significant at the 1% level. The excess return builds up to 7.23% for the upper 30% of all stocks by month 9. It then declines and builds up again to over 7%. A similar but less distinct pattern can be seen by examining the lowest 30%.

The risk adjusted excess returns from possessing perfect forecasting ability in September are much lower than they were from possessing perfect forecasting ability in March. Furthermore in most months the rank order of the deciles is insignificant at the 1% level (although it's still sometimes significant at the 5% level). This is what one would expect. By September investors have a much better idea of actual growth than they do in March.

If prices reflect consensus forecasts, then knowing the error in the consensus estimate of growth should lead to larger profits than just knowing actual growth. How large is the mis-estimate of actual growth by the analysts? In March, the average error for the 30% of the companies for which earnings growth was most underestimated was 63.6%, while the average error for the 30% of the companies for which growth was most overestimated was 38.9%. The corresponding numbers for September forecasts are 26.4% and 20.3%. It is apparent that while there are still large size errors in the September forecasts, the size of the error has decreased markedly between March and September. Analysts can improve the accuracy of their forecasts as interim earnings reports or as other information comes out and more information is available on company performance.

Tables 1 and 2 show the time series of cumulative risk adjusted excess return for the errors in the March and September estimates (Equation (3)). The rank order of the deciles is significant from the first month for both the September and March estimates.

The risk adjusted excess returns build up very quickly in both cases. For the March forecasts, the risk adjusted excess returns are close to 7% by month 6 (September), the major increase occurring in month 5. Once again, the risk adjusted excess returns have a temporary peak in month 9 and then increase to a global peak in month 13. This rapid build-up is consistent with information about true earnings growth being disseminated over time and the market correctly incorporating the information.

Even in September investors with a better estimate of growth than the consensus had an opportunity for excess profits. Notice that while knowledge of the forecast error as of September allows an excess profit to be earned, perfect forecast ability did not allow an excess profit to be earned. This suggests that on average forecasts are accurate enough in September that excess profits can be earned only by isolating those cases where forecasted growth is very much different than actual.

The time pattern for all variables is very similar with March forecasts producing excess returns which level out after month 13 and September forecasts producing excess returns which level out after month 7. Consequently, we shall only report results for these months. The cumulated excess returns in these months are reported in Table 3 and Table 4. In addition, in Table 3 we show the risk adjusted cumulative excess returns 7 months after the March forecasts for comparison with the effect 7 months after the September forecast.

Note that among the variables discussed so far for both March and September forecasts, the risk adjusted excess return was highest for the error in the growth rate, next highest for actual growth and close to zero for the forecasted growth. What an investor desirous of making excess profits should be most concerned with is finding securities where his forecasts are not only good in the sense of being right but where they are both accurate and different from the consensus.

The same conclusion can be reached by examining errors in the earnings estimates. Tables 3 and 4 present the analysis of excess returns for the error in forecast earnings and the percentage error in earnings forecasts for one year forecasts as of March and September and two-year forecasts as of September. In each case the excess returns appear to be sufficient to cover transaction costs and the rank order correlation coefficient is significant at the 1% level.

Furthermore, the amount of excess returns that can be earned vary with the magnitude of the forecast error. The two-year estimates made in September and the one-year estimates made in March were considerably less accurate than the one-year forecast made in September. They also produced higher risk adjusted excess returns. However, even in September there is a considerable forecast error in year-end earnings. In September, the percentage forecast error was 26% for the top decile, 11.6% in the next decile, and 6.3% in the next. These errors, while lower, were still significant enough to lead to an excess risk adjusted return.

We have now examined evidence that consensus forecasts are incorporated into price. Further, we have seen that the ability to forecast with more accuracy than the consensus forecast can lead to an excess risk adjusted return. If consensus forecasts play a major role in price determination, then the ability to forecast consensus forecasts themselves should lead to a superior return. Since we have estimates of the earnings for each company made 15 months in advance (the two-year forecast as of September) and estimates of the same earnings made 12 months later (one-year forecast made in September of the following year), we can measure the impact of being able to forecast the change in the estimate (Equation (6)). As shown in Table 4, the

TABLE 6
*Error in Growth**
(Forecast-actual)

Percentage of Firms eliminated	Excess return if completely accurate	Excess return if 50% error	Excess return if 90% error
0%	0	0	0
10%	1.56	0.78	0.16
20%	2.88	1.44	0.29
30%	3.07	1.53	0.31
40%	4.32	2.16	0.43
50%	5.77	2.88	0.58
60%	7.35	3.67	0.74
70%	9.08	4.54	0.91
80%	9.90	4.95	0.99
90%	10.42	5.21	1.04

*Forecasts of one year growth rates prepared in March. Cumulative returns calculated as of April of the following year.

returns from being able to estimate forecast revision are substantial. In fact, the return from forecasting future forecasts themselves is higher than the return from being able to forecast actual earnings. This is consistent with our other evidence that it is consensus forecasts which determine security prices.

All of the results presented in this section could be used to analyze the amount of accuracy necessary to earn excess returns. Assume the analysts can identify firms that are in various deciles with respect to the error in estimated earnings. For example, suppose he could identify the 10% of the firms with the largest forecast error. Column 2 of Table 6 shows the cumulative excess return he would earn. Columns 3 and 4 assumes that he identifies the members of a decile with error. Column 3 assumes that 50% of the time he identifies a firm as a member of a decile he is randomly selecting from among all firms and 50% of the time he is accurate. Column 4 assumes that 90% of the time he is randomly selecting from all firms.

For example, if an analyst is attempting to select from among the 30% of the firms for which the consensus forecast most underestimate true earnings, and he is right 50% of the time, he will earn an excess risk adjusted return of 4.54%.

As can be seen from an examination of the table, a little bit of information leads to substantial cumulative excess returns. These kinds of excess returns provide some justification for the effort undertaken by many organizations to forecast earnings.

6. Conclusions

In this study we present evidence in support of the hypothesis that expectations are incorporated into security prices. In addition, we have analyzed the timing and size of returns from forecasts which are more accurate than the consensus. Since prices reflect consensus forecasts, the payoff from being accurate in forecasting is increased markedly as the consensus forecast becomes inaccurate. Finally, we have demonstrated that the payoff from being able to forecast the consensus estimate is higher than the payoff from being able to forecast earnings. The market reacts to expectational data. But despite this, or rather because of it Lord Keynes [6] appears to have been right when he likened professional investing to participating in a newspaper contest on a beauty contest, where "... each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of other competitors, all of whom are looking at the contest from the same point of view."

References

1. Blume, Marshall, "Betas and their Regression Tendencies," *J. Finance* (June, 1975).
2. Brennan, M., "The Sensitivity of the Efficient Market Hypothesis to Alternative Specifications of the Market Model," *J. Finance*, Vol. 34 (1979), pp. 53–69.
3. Brown, B. and Rozeff, M., "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings." *J. Finance*, Vol. 33 (1978), pp. 1–16.
4. Cragg, L. and Malkiel, B., "The Consensus and Accuracy of Some Predictions of the Growth of Corporate Earnings," *J. Finance*, Vol. 23 (1968), pp. 67–84.
5. Elton, B. J. and Gruber, M. J., "Earnings Estimate and the Accuracy of Expectations Data," *Management Sci.*, Vol. 18 (1972), pp. 409–424.
6. Keynes, M., *The General Theory of Employment, Interest, and Money*, Harcourt, Brace and World, New York, 1964, p. 156.
7. Litzenberger, Robert and Ramaswamy, K., "The Effects of Personal Taxes and Dividends on Capital Asset Prices: Theory and Empirical Evidence," *J. Financial Econom.* (June 1979).
8. Malkiel, B. and Cragg, J., "Expectations and the Structure of Share Prices," *Amer. Econom. Rev.*, Vol. 60 (1970), pp. 601–617.
9. Roll, Richard and Ross, Steve, "An Empirical Investigation of Arbitrage Pricing Theory," *J. Finance* (December, 1980), pp. 1073–1105.
10. Watts, R. L., "Systematic 'Abnormal' Returns After Quarterly Savings Announcements," *J. Financial Econom.* (1978), pp. 127–150.