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ANALYST'S FORECASTS AS EARNINGS EXPECTATIONS

Patricia C. O'Brien

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MASSACHUSETTS
INSTITUTE OF TECHNOLOGY
50 MEMORIAL DRIVE
CAMBRIDGE, MASSACHUSETTS 02139

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I examine three composite analyst forecasts of earnings per share as proxies for expected earnings. The most current forecast is at least as accurate as either the mean or median forecast, indicating that forecast dates are relevant for determining accuracy.

I compare analysts with two quarterly time-series models, a competing source of earnings expectations. Consistent with previous research, I find analysts more accurate than time-series models. However, prior knowledge of forecast errors from a quarterly autoregressive model provides better predictions of excess stock returns than prior knowledge of analysts' errors. This result is inconsistent with previous research, and is anomalous given analysts' greater accuracy.

*Sloan School of Management, M.I.T., 50 Memorial Drive, Cambridge, MA 02139

1. Introduction

Analysts' forecasts of earnings are increasingly used in accounting and finance research as expectations data, to proxy for the unobservable "market" expectation of a future earnings realization. Since a diverse set of forecasts is available at any time for a given firm's earnings, composites are used to distill the information from the diverse set into a single expectation. This paper considers the relative merits of several composite forecasts as expectations data. The primary result is that the most current forecast available is more accurate than either the mean or the median forecast. This result is consistent with the hypothesis that individual forecasters incorporate information from others' previous predictions into their own. Further, it suggests that the forecast date, which previous research has largely ignored, dominates idiosyncracies of individual forecasters as a characteristic relevant for distinguishing among forecasts.

The second contribution of this paper is a comparison of analysts with time series models, which are a competing source of earnings expectations. Consistent with previous research, I find that analysts generally are more accurate than time-series models. However, I find that prior knowledge of the forecast errors from a simple autoregressive model on the univariate series of quarterly earnings provides better predictions of

excess stock returns than prior knowledge of analysts' forecast errors. This result is inconsistent with prior research, and somewhat anomalous given analysts' greater accuracy.

A third contribution of this paper is a methodological refinement of the techniques used to evaluate forecasts. I demonstrate the existence of significant time-period-specific effects in forecast errors. If time-series and cross-section data are pooled without taking these effects into account, the statistical results may be overstated, and the results are subject to an aggregation bias.

In section 2, I describe proxies for consensus in analysts' forecasts, as well as two quarterly time-series models used in the empirical tests. In section 3 I describe the data. The statistical tests and results are discussed in section 4, and section 5 is a summary with some concluding remarks.

2. Proxies for Expected Earnings

2.1 Defining Consensus for Analysts' Forecasts

The motivations for seeking a consensus expectation when many forecasts are available are primarily practical. First, if individual forecasts contain idiosyncratic error which can be diminished or, ideally, completely diversified away, then more accurate forecasts can be obtained by combining forecasts from

different sources into a single consensus number.[1] Second, in many contexts the earnings expectation is not the central issue, but is a necessary piece of data. For example, a measure of unanticipated earnings is necessary to adjust for effects of simultaneous earnings releases in measuring non-earnings events. Reducing the measurement error in anticipated earnings, and therefore in unanticipated earnings, increases the power of tests of the non-earnings event.

Academic researchers have used a variety of methods to aggregate analysts' forecasts into a single expectation. Barefield and Comiskey (1975), and Fried and Givoly (1982) use the mean of a set of forecasts. Brown and Rozeff (1978) use a single forecast from ValueLine. Givoly and Lakonishok (1979) select the "most active" forecaster for each firm from those available in Standard and Poors' Earnings Forecaster. Elton, Gruber, and Gultekin (1981) and Brown, Foster and Noreen (1984) consider both means and medians published in the I/B/E/S Summary database. Brown, Griffin, Hagerman and Zmijewski (1985) combine a ValueLine forecast with several time-series forecasts. I compare three composites from a set of available forecasts: the mean, the median, and the most current forecast.

An implicit assumption behind the use of either the mean or the median forecast to represent the consensus is that all forecasts are current, so that cross-sectional differences in forecasts are attributable to differential use of the same global set of information. Gains from combining forecasts arise either

from the employment of more information in the aggregate than is used by any individual, or from diversification across individuals' idiosyncratic errors.

In fact, however, the analysts' forecasts available at any time have been produced at varying dates. If analysts incorporate information from others' forecasts in producing their own, then more current forecasts may be more accurate, and possibly more representative of a "market" expectation. By examining the most current forecast as a definition of consensus, I apply the extreme form of this argument, providing a comparison of the relative importance of forecast age and individual forecast error. If diversifying across individual idiosyncracies is more important than eliminating out-dated forecasts, then the single most recent forecast will not necessarily be more accurate than aggregations of many forecasts.

Using the most current forecast as a consensus expectation addresses the capital markets context in which forecasts are most likely used. The implicit assumption is that, since information is disseminated relatively rapidly in these markets, recent releases have more value than previous ones. Thus, the most current forecast has an observable characteristic which is presumed to have value. Its value, however, depends upon how the forecast is used by investors and others in decisions. The process by which earnings information is translated into prices or other outcomes is far from well-understood. I do not undertake the task of describing this process, but assume that

one exists, and that it results in more current information having higher value.

2.2 Quarterly Time-series Models of Earnings

I use quarterly time-series models of earnings as benchmarks, against which analysts' forecasts are compared. Time-series models have been used frequently in previous research to provide earnings expectations. Analysts, however, have the advantage of a much broader information set than is employed in a univariate model, including industry and firm sales and production figures, general macroeconomic information, and other analysts' forecasts, in addition to the historical series of earnings. Analysts' forecasts, therefore, seem likely to be more accurate than forecasts from univariate models.

Several studies (Brown and Rozeff (1978), Collins and Hopwood (1980), Fried and Givoly (1982)) demonstrate that analysts are more accurate than univariate models, presumably because of the broader information set they can incorporate. Fried and Givoly (1982) also find that analysts' forecast errors are more closely associated with excess stock returns than are those of univariate models. Nonetheless, univariate models remain a common means of generating earnings expectations.

An advantage of univariate time-series models is the relative ease with which earnings data can be obtained for moderate samples of firms. This advantage is tempered by the

caveat that the data requirements of the models impart a "survivorship" bias to samples. Another advantage to time-series models is the relative simplicity of the models used to generate expectations. Parsimonious models with a single, simple ARIMA structure applied to all firms have been shown to predict at least as well as univariate models with more complex, individually-specified structures, when one-step-ahead forecast errors are compared.

I use the following two quarterly time-series models, from Foster (1977):

$$E[a_{jtq}] = a_{jtq-4} + \theta_{j0} + \theta_{j1}(a_{jtq-1} - a_{jtq-5}) \quad , \qquad (1)$$

and:

$$E[a_{jtq}] = a_{jtq-4} + \theta_{j2} \quad , \qquad (2)$$

where a_{jtq} denotes quarterly reported earnings for firm j in quarter q of year t, and θ_{j0}, θ_{j1} and θ_{j2} are estimated parameters. The models are, respectively, a first order autoregressive process in the fourth differences with a drift, and a random walk in the fourth differences with a drift. I chose these particular models because of their relative simplicity, and because they have proven to be at least as good as other mechanical quarterly models. The data used and the estimation of these models are described in section 3.

3. Data

3.1 Sources

The forecast data are from the Institutional Brokers Estimate System, or I/B/E/S, a database developed by the Lynch, Jones and Ryan brokerage house. The database consists of forecasts made between early 1975 and mid-1982, by analysts at between 50 and 130 brokerage houses. Between 1000 and 2500 firms' EPS are forecast, depending on the month and year in question. The analysts and brokerage houses are identified by code numbers. Each brokerage house employs many analysts, but at most one forecast is reported from each brokerage house at any given time, for any given firm and year. The data used in this paper are the individual analysts' forecasts, and their associated forecast dates.

Lynch, Jones, and Ryan update the database on or around the 25th of each month. From the updated list of forecasts, summary statistics such as the mean, the median, the standard deviation, the number increasing, etc., are computed. The summary statistics are then sold to clients, primarily institutional investors.[2]

COMPUSTAT is the source of earnings data and most earnings announcement dates. The remaining announcement dates are from the Wall Street Journal (WSJ) and its Index. Stock return data and the trading day calendar are from the CRSP Daily Returns

file. Data on stock splits and stock dividends are from the CRSP Monthly Master file.

The initial sample comprises the set of firms in the I/B/E/S database with December yearends, and with forecasts available for each year from 1975 through 1981. This set contains 508 firms, and 3556 firm-years. Firm-years are excluded if the annual earnings are not available on COMPUSTAT, or if all four quarterly earnings announcement dates are not available from COMPUSTAT or the WSJ. This criterion reduces the sample to 457 firms, with 3440 firm-years. The estimation requirements of the quarterly models, 30 continuous quarters of data prior to 1975-IV, further reduce the sample to 190 firms, with 1284 firm-years. The final requirement, listing on CRSP, reduces the sample to 184 firms with 1260 firm-years.

Analysts occasionally produce forecasts for fully-diluted, rather than primary, EPS. Primary EPS are earnings divided by the average number of outstanding common shares, including common stock equivalents such as stock options and warrants. Fully-diluted EPS are earnings divided by the average number of outstanding common shares, computed "to show the maximum potential dilution of current EPS" (APB Opinion No. 15), and include in the denomimator securities such as contingently issuable common stock. I convert forecasts of fully-diluted EPS to primary EPS, using the ratio of fully-diluted to primary EPS for that firm and year from COMPUSTAT. I also adjust for stock splits and stock dividends that were announced between the forecast date and the annual earnings announcement date.

3.2 Measuring Forecast Errors

Forecast errors are the elementary data I use to evaluate forecasts. The forecast error $e_{ijt\tau}$ is defined as the difference between A_{jt}, actual earnings per share (EPS)[3] of firm j in year t, and $f_{ijt\tau}$, the forecast of EPS from source i, at a horizon τ prior to the realization:

$$e_{ijt\tau} = A_{jt} - f_{ijt\tau} \quad . \tag{3}$$

The source of the forecast, denoted by i, is one of the following: the mean, the median, or the most current of a set of analysts' forecasts; or one of the two benchmark quarterly models described in section 2.2. The composite analyst forecasts are constructed from a set of forecasts which includes the most recent forecast by each individual in the database, prior to a fixed horizon date.[4]

Forecasts for each firm and year are selected at five fixed horizons of less than one year in duration. They are: 240, 180, 120, 60 and 5 trading days prior to the announcement of annual earnings. The first four horizons correspond roughly to dates following each of the year's quarterly earnings announcements; the fifth is immediately prior to the annual earnings announcement. For example, a horizon of 240 trading days will usually correspond to a date after the previous year's annual announcement, but before the current year's first quarter

announcement. A horizon of 180 trading days will typically correspond to a date between the first quarter announcement and the second quarter announcement; and so on.

The motivation for selecting horizons corresponding to dates in different fiscal quarters is, first, to observe whether there is an evolution of expectations over the course of the year, and second, to ensure that the horizons differ in a well-defined, observable, and potentially relevant respect: the amount of quarterly earnings data available.[5]

Given a horizon τ, firm j, and year t, the selected forecasts are the most recent available from each brokerage house issuing a forecast for firm j in year t. I use the dates assigned to forecasts by analysts, not the dates of the I/B/E/S file in which they first appear. The lag between the analyst's date for a forecast and the date of its first appearance on I/B/E/S averages 34 trading days, and has a standard deviation of 44.5 trading days. Thus, some recently-updated forecasts are omitted from each monthly listing by I/B/E/S. Since published summary statistics are computed from these monthly lists, the summary statistics also fail to reflect some recent updates.

Using analysts' dates instead of I/B/E/S "publication" dates results in a realignment of the data, with fewer omissions of recently updated forecasts. Previous studies of analysts' forecasts have used the publication date, not the analyst's forecast date, to select forecasts. For example, Fried and Givoly (1982) and Givoly and Lakonishok (1982) select their

samples based on the publication date of the Standard & Poors' Earnings Forecaster, their source of forecast data. Fried & Givoly go on to use analysts' dates within that sample to distinguish new and old forecasts. Brown and Rozeff (1978) and Brown, Foster and Noreen (1984) use datasets for which individual analysts' forecast dates are not available. Using publication dates instead of forecast dates probably biases results against analysts, by failing to include some recent updates of forecasts.

From the set of available forecasts at horizon τ for each firm j and year t, I compute the mean and median, and find the most current. I use the mean, median and most current as proxies for the analysts' consensus.

The fundamental difference between the most current analyst forecast as a consensus definition and either the mean or the median, is that the former is constructed using the forecast date, while the latter two are not. In Table 1, I compare the distributions of forecast ages for the mean, median, and most current forecasts. The age of a forecast is defined to be the difference, measured in trading days, between the forecast date and the horizon date chosen for this study. More generally, it can be considered the lag between the forecast date and an event date of interest to the researcher. For Table 1, I define the ages of the mean and median forecasts as, respectively, the mean and the median of the ages of the forecasts in the set of available forecasts for each firm, year and horizon. The distribution described in Table 1 is over all firms and years, for each horizon.

As expected from its definition, the most current forecast has a distribution of ages much closer to zero than either the mean or median. For the four longer horizons (240, 180, 120, and 60 trading days), over fifty percent of the most current forecasts are less than five trading days old. By contrast, over fifty percent of the mean or median ages at all horizons are more than forty trading days old. While some of these older forecasts may represent circumstances where little new information has arrived, so there was no need to update, the accuracy results which follow suggest that this is not always the case.

The quarterly models (1) and (2) are estimated for each firm, for each quarter from 1975-I through 1981-IV. Parameter estimates are updated each quarter, using the previous thirty quarters' observations. Observations are adjusted for changes in the number of outstanding shares. Annual forecasts are constructed from quarterly forecasts by summing the appropriate realizations and forecasts. For example, in quarter 3, there have been two realizations of quarterly earnings for the year, and two quarters remain to be forecast. The annual forecast from a quarterly model during the third fiscal quarter of the year is the sum of actual earnings for quarters 1 and 2, and forecasts for quarters 3 and 4.

Because of a small number of untraceable influential observations which altered the regression results, I imposed an arbitrary censoring rule on the data as well: all forecast errors larger than $10.00 per share in absolute value were

deleted from the sample. Since typical values for EPS numbers are in the range of $1.00 to $5.00 per share, errors of sufficient magnitude to be deleted are rare, and suggest a data entry or transcription error.

3.3 Stock Returns

I measure the new information impounded in stock returns by the cumulated prediction errors from a market model in logarithmic form:

$$E[\ln(1 + R_{js})] = \alpha_j + \beta_j \ln(1 + R_{Ms}) \quad , \qquad (4)$$

where R_{js} is the return to security j on day s, R_{Ms} is the return on the CRSP equally-weighted market portfolio of securities on day s, and ln denotes the natural logarithm transformation.[6]

The parameters of (4) are estimated for each firm in the study using 200 trading days of data at a time, beginning in July 1974. Estimated parameters are used to predict ahead 100 trading days, and excess returns are the difference between the realization $\ln(1 + R_{js})$ and the prediction based on (4). After each iteration of estimation and prediction, the estimation period is rolled forward by 100 trading days, and new parameters are estimated.

The estimation procedure produces a stream of predicted daily excess returns, ε_{js}. The ε_{js} are cumulated over each forecast horizon, from the horizon date through the announcement date of annual EPS, to form $U_{jt\tau}$, the measure of new information

arriving over horizon τ in year t for firm j.

Excess returns, not raw stock returns, are used since excess returns represent unanticipated returns. Informationally efficient forecasts will have forecast errors comprising only unanticipated information. Forecasts which are not informationally efficient will have forecast errors consisting of both unanticipated information and information which was available at the forecast date but was not incorporated into the forecast. Forecast errors from inefficient forecasts may therefore be correlated with the anticipated component of stock returns. This correlation could cause a stronger association with raw returns to be observed for inefficient forecasts than for efficient forecasts. This argues against using the association between raw returns and forecast errors as a criterion for evaluating forecasts, and in favor of using only the unanticipated portion of returns. This discussion is continued in more detail below, where test results are reported.

4. Results

4.1 Aggregating Forecast Errors

If a forecast incorporates all the information available on the forecast date in an unbiased manner, then it can be described as an expectation in the usual statistical sense of the word. Let f^* denote such a forecast:

$$f^{*}_{jt\tau} = E[A_{jt}|\Phi_{t\tau}] \quad . \qquad (5)$$

where $\Phi_{t\tau}$ represents the information available at a horizon τ prior to the realization, and E[|] is the conditional expectation operator.

In the time between the forecast date and the realization date, new information may arrive. Even a forecast like (5), which may be ideal in the sense of employing all information available on the forecast date, will omit unanticipated information which arrives later. Forecast errors consist, in part or entirely, of new information revealed over the forecast horizon, i.e. between forecast and realization.

Two closely-related implications of unanticipated information reflected in forecast errors are important for the specification of statistical tests. First, contemporaneous forecast errors will not, in general, be cross-sectionally independent observations. Second, forecast errors within a year which are aggregated cross-sectionally may appear to be "biased" because of the common new information reflected in them.

An example of information which may be reflected in forecast errors is an unanticipated macroeconomic shock, which may affect many firms in a similar manner. This can induce correlation in forecast errors across firms, for a given year and horizon, and across horizons within a year. Moreover, if the effect of the macroeconomic shock on firms has a non-zero mean, then a cross-sectional aggregation of forecast errors, even from unbiased

forecasts, will also have a non-zero mean. This non-zero mean is not bias, but rather is time-period-specific new information.

If forecast errors are positively correlated across firms within years, then statistical comparisons based on from pooled time-series and cross-section data which assume that observations are cross-sectionally independent will overstate the statistical validity of the results. Several studies (Brown and Rozeff (1978), Elton, Gruber and Gultekin (1981), Malkiel and Cragg (1980), for example) have compared forecasts using criteria such as the number or proportion of times that one forecasting method outpredicts another. This criterion, or any other that assumes independent observations and is applied to a cross-section, could obtain the appearance of statistically significant superiority in forecasting ability from an anecdotal difference.

The tests developed in this paper adjust for time-period-specific shocks using a simple fixed effects model. This model, and the importance of the adjustment for the results, are described below.

4.2 Evaluating Forecasts - Bias

A simple model of time-period effects in forecast errors is:[7]

$$e_{jt\tau} = \mu_{t\tau} + \eta_{jt\tau} \qquad , \tag{6}$$

where $\mu_{t\tau}$ is the average forecast error for year t and horizon τ,

and $\eta_{jt\tau}$ is a random error term, representing the deviation of firm j's forecast error from the common annual mean.

There may also be firm-specific information effects which persist through time, but the unanticipated information argument does not apply.[8] If a forecast fully impounds information from previous mistakes in an unbiased manner, then systematically recurring events will not remain unanticipated year after year. Thus recurrent firm-specific forecast errors are not expected to arise on the basis of information that was unavailable at the time the forecast was made.[9]

I estimate (6) using least squares with a dummy variable for each year. The test for bias is based on the grand mean of the estimated annual averages:

$$\bar{\mu}_\tau = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{t\tau} \quad , \qquad (7)$$

where T is the number of years in the sample, and the $\mu_{t\tau}$ are the year-specific average forecast errors, estimated separately for each horizon τ. The average μ_τ defined in (7) is a linear combination of least-squares coefficients, with estimated standard error:

$$s_{\bar{\mu}_\tau} = \frac{s_\eta}{T} \cdot [\underline{\iota}'(X'X)^{-1}\underline{\iota}]^{1/2} \quad , \qquad (8)$$

where $\underline{\iota}$ is a vector of ones of length T, X is the matrix of dummy variables, and s_η is the regression residual standard error. The standard error (8) is a weighted version of the residual standard

error s_η, constructed from the $\eta_{jt\tau}$. The residuals $\eta_{jt\tau}$ are deviations from the annual averages, and so are purged of time-period-specific information which induces cross-sectional correlation in the $e_{jt\tau}$.

In Table 2, the bias results are presented. The reported numbers are the forecast bias, computed as in equation (7). The ratio of (7) to (8) is evaluated as a t-statistic, against a null hypothesis of no bias, for each analyst composite, mean, median and most current, and for the quarterly models.

Generally, forecast errors exhibit statistically significant negative bias. Of the three analyst consensus measures, the median uniformly exhibits the smallest bias, usually indistinguishable from zero.

Negative bias corresponds to overestimates of EPS. Negative bias in analysts' forecasts is consistent with some conventional wisdom, which says that analysts prefer to make optimistic predictions and "buy" recommendations, to maintain good relations with management.[10] The evidence supporting this story is weak, however, in two respects. First, the median analyst forecast appears to be unbiased. Second, and more importantly, when the analyst estimates are significantly negative, they are statistically indistinguishable from those of mechanical time-series models. The motive of maintaining good relations with management cannot be ascribed to these models. Thus, support for the contention that analysts preferentially issue optimistic forecasts is at best weak.

An alternative explanation which is also consistent with these results is that analysts issue unbiased forecasts, but this seven-year period, 1975 through 1981, is one with primarily negative unanticipated EPS. Unfortunately, the most obvious way to distinguish between the hypothesis of deliberate optimistic bias and this alternative is to collect data for a longer span of years. This is not possible using the I/B/E/S dataset.

4.3 Evaluating Forecasts - Accuracy

I use an approach similar to the bias evaluation described in the previous section for evaluating relative forecast accuracy. Accuracy is defined as absolute or squared forecast error. For the absolute error case, the model is:

$$|e_{jt\tau}| = \delta_{1j\tau} + \delta_{2t\tau} + \varepsilon_{jt\tau} \quad . \qquad (9)$$

For the squared error case, a similar model is estimated, with $(e_{jt\tau})^2$ as the left-hand-side variable. In equation (9) the $\delta_{1j\tau}$ measure average accuracy for each firm j, and the $\delta_{2t\tau}$ measure average accuracy for each year t. The $\varepsilon_{jt\tau}$ are deviations from the average accuracy in this sample for firm j and for year t. Differences in accuracy across firms could arise, for example, if there are persistent differences in the amount of information available for different firms. Differences in accuracy across years could arise if there are more, or larger, unanticipated events in some years than in others.

Equation (9) is estimated using least squares on a set of dummy variables for firms and years. Average accuracy is computed as a linear combination of the estimated effects:[11]

$$\bar{\delta}_\tau = \frac{1}{J} \sum_{j=1}^{J} \hat{\delta}_{1j\tau} + \frac{1}{T} \sum_{t=1}^{T} \hat{\delta}_{2j\tau} \quad . \qquad (10)$$

Equation (10) defines the average absolute error accuracy. Average squared error accuracy is defined similarly using the coefficients from the squared error version of (9). The estimated standard error of the average accuracy in equation (10) is:

$$s_{\bar{\delta}_\tau} = s_\xi \cdot [\underline{\omega}'(Z'Z)^{-1}\underline{\omega}]^{1/2} \quad . \qquad (11)$$

In (11), Z represents the matrix of dummy variables used to estimate equation (9) or its squared error analogue, $\underline{\omega}$ is the vector of weights that transform the estimated parameters into the average defined in (10), and s_ξ is the residual standard error from the regression equation (9).

The estimates in equations (9) through (11) are computed for the mean, median and most current analyst forecasts, and for the forecasts from the quarterly models. Pairwise differences in accuracy are compared across forecast sources using a t-statistic constructed from the average accuracies from (10) or its squared error analogue, and the standard error from (11).

Tables 3 through 5 summarize the results on forecast accuracy. The average absolute errors and average squared errors, computed as described in equation (10) for each forecast

source, appear in Table 3. Table 4 contains t-statistics testing pairwise differences in accuracy among analysts. Table 5 contains t-statistics testing pairwise differences in accuracy between analysts and the quarterly models.

Table 3 displays a pattern of increasing forecast accuracy as the earnings announcement date approaches, for all forecast sources. Both average absolute error and average squared error decline uniformly as the year progresses, for analysts and for quarterly models. For example, the average absolute error of the most current forecaster declines from $0.742 per share at a horizon of 240 days (almost a full year prior to the announcement) to $0.292 per share at a horizon on 5 days. This pattern of convergence toward the announced EPS number is consistent with forecasts incorporating some new information relevant to the prediction of EPS over the course of the year.

From Table 3 it appears that the most current analyst is no worse than the other sources, and that analysts dominate quarterly models in the longer horizons. The reader of Table 3 should avoid using the heuristic of counting the number of times that the most current forecaster is most accurate to assess these differences. The relative performance results are highly correlated, both across horizons and across definitions of accuracy. The results of a statistical test for the differences in accuracy which are suggested by a perusal of Table 3 appear in Tables 4 and 5.

In Tables 4 and 5, a positive difference means that the

first of the pair is less accurate. Table 4 contains the results of pairwise comparisons among the three analyst consensus definitions. In terms of absolute error, which is reported in Panel A, when the differences are significant they favor the mean over the median and the most current forecaster over either the mean or the median. For example, at the 60-trading-day horizon, the t-statistic on the difference between the mean and median forecasts in average absolute accuracy is -2.14, which favors the mean, and is significant at the .05 level. The t-statistic on the difference between the median and the most current forecasts for the same horizon is 4.97, which favors the most current, and is significant at the .01 level.

In contrast, in Panel B, where differences in squared error accuracy are presented, there are no measurable differences in accuracy among the three analyst consensus definitions. The signs of differences in this panel are generally the same as those in Panel A, and so the squared error evidence does not contradict the absolute error results. However, the very small t-statistics lend no additional support to the conclusions, either.

The results reported in Table 5 indicate that analyst forecasts generally dominate the time-series models at the longer horizons. For the 240, 180 and 120-trading-day horizons, wherever differences are statistically significant, the results favor analysts over the quarterly models. This evidence is consistent with the explanation that analysts use a broader information set than can be exploited by a univariate model.

At the 60-trading-day horizon, however, the quarterly time-series models dominate the mean and the median analyst forecast in all comparisons where significant differences exist. The most current forecast is never dominated to a statistically significant extent by the quarterly models, but generally is indistinguishable from them.

In summary, the accuracy results reported in Tables 3 through 5 generally support the conjectures that analysts, with their broader information set, are at least as accurate as time-series models, and that the most current analyst forecast is at least as accurate as the mean or the median. Although the statistical significance of results varies somewhat across forecasting horizons and accuracy criteria, wherever differences in accuracy between forecast sources are statistically significant, the results conform with expectations.

The results reported here probably understate the difference between the most current forecast and the mean and median definitions which appear in most other published work. My sample is selected to eliminate the "publication lag" which is characteristic of datasets which use publication dates, rather than analysts' dates, to select forecasts. Further, the results of comparisons between analysts and quarterly models may understate differences because of the sample selection process. Since the sample of firms is weighted toward stabler and longer-lived firms by the data requirements of the time-series models, the selection process may exclude firms where analysts' information advantage is largest.

4.4 Evaluating Forecasts - Market Association

The criteria developed in the previous two sections, bias and relative accuracy, are common in the literature on forecast evaluation. They do not, however, address the context in which the forecasts are used. Both researchers' and investors' use of forecast data in contexts related to securities markets suggests that association with stock returns may provide a relevant empirical comparison.

If forecast errors reflect information relevant to the firm's prospects arriving after the forecast date, then, subject to two important qualifications discussed below, this implies that forecast errors will be positively correlated with new information impounded in stock returns over the forecast horizon. The first qualification to this implied association is that the information relevant to valuing the firm's common stock is not precisely the same as the information relevant to current-year earnings. There are errors in both variables with respect to the measured association between them which represents the common information. Non-recurring events, whether they are treated as extraordinary items or not, may affect earnings in a particular year, but may be inconsequential to the long-term value of the firm. Conversely, events that influence longer-term prospects, such as changes in investment opportunities, may affect the value of the firm without altering current earnings.

The second qualification is that excess returns are constructed to exclude one source of unanticipated information. The excess return is purged of its systematic relation with market returns, which includes both anticipated and unanticipated market returns. Since informationally inefficient forecasts will be correlated with anticipated information, it is desirable to purge the stock returns of the anticipated component of the market return. Elimination of the unanticipated market return, however, may reduce the measurable association between excess returns and forecast errors. On the other hand, it is important to note that while the power of the tests for positive association is reduced, the reduction in power does not vary across forecast sources, since they are all evaluated relative to the same excess returns. In other words, the relative degree of association across sources will be unaffected.

Both qualifications noted above will have the effect of reducing the measurable association between forecast errors and excess returns. Nevertheless, previous studies facing the same inherent difficulties have found statistically significant positive associations between unexpected earnings and excess stock returns (Ball and Brown (1968), Beaver, Clarke and Wright (1979), and Fried and Givoly (1982), for example).

The regression model used to estimate the association between cumulated excess returns, represented by $U_{jt\tau}$, and forecast errors, $e_{ijt\tau}$, is:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (12)$$

In (12), $\beta_{i\tau}U_{jt\tau}$ is the portion of the forecast error from source i at horizon τ which is systematically related to excess returns. The slope coefficient $\beta_{i\tau}$ is the covariance between excess returns and forecast errors, adjusted for firm and year effects, in units of the variance of excess returns. Using excess returns as the independent variable and forecast errors as dependent has the desirable feature that $\beta_{i\tau}$ and its associated t-statistic have the same scale for all sources i. If the roles of these two variables were reversed in the regression equation, the estimated regression slope coefficient would depend explicitly on the forecast error variance from source i.

The constants $\alpha_{1ij\tau}$ and $\alpha_{2it\tau}$ measure, respectively, firm- and year-specific average forecast errors, conditional on the systematic relation with excess returns. The $\alpha_{2it\tau}$, the year effects, play an important role in equation (12), since they capture the time-period-specific information in forecast errors which is not captured by excess returns.[12] Among other things, they include the average effect of omitting the unanticipated component of the market return. If the $\alpha_{2it\tau}$ are not included in the model, then they are impounded in the regression residuals as an omitted variable. This induces cross-sectional correlation in the residuals, which if ignored leads to incorrect statistical inferences, as was discussed above for the bias computation.[13]

Equation (12) is estimated by stacking the regressions for the five forecast sources, and estimating them jointly. The forecast sources are the mean, median and most current analyst

forecast and the two quarterly models. Estimations are performed jointly for the five forecast sources, and separately for each forecast horizon.

Since the matrix of independent variables, which consists of cumulated excess returns over the forecast horizon and dummy variables indicating firms and years, is the same for each of the forecast sources, there is no efficiency gain over equation-by-equation least squares (see Zellner (1962)). The advantage of stacking the equations is for joint estimation of the firm and year effects, so that observations from each of the five forecast sources are adjusted for the same firm and year effects.

Tables 6 through 8 contain the regression results from estimation of model (12).[14] In Table 6, I report the estimated slope coefficients and their associated t-statistics, testing the statistical significance of the relation between forecast errors and excess returns over the forecasting horizon. Table 7 contains t-statistics which test for differences in the slope coefficients across forecast sources. Table 8 contains regression summary statistics, including adjusted R^2, F-statistics, and numbers of parameters, and sample sizes.

According to results reported in Table 8, equation (12) explains between 9% and 16% of the variation in forecast errors, with slight variations across horizons. The largest adjusted R^2 appears at the 5-trading-day horizon, though differences in explanatory power are not large. The model has statistically significant explanatory power, according to the regression F-

statistics, which reject the null of no explanatory power at the .001 level.

The incremental F-statistics in Table 8 confirm that the year-specific effects are important in equation (12). The F-statistic on the year-specific effects tests the null hypothesis:

$$H_0 : \alpha_{2i1\tau} = \alpha_{2i2\tau} = \ldots = \alpha_{2iT\tau} = 0$$

That is, the F-statistic tests the null hypothesis that estimation of year-specific intercepts adds no explanatory power to the model. This hypothesis is rejected at the .05 level at all horizons, and at the .001 level or better at the horizons longer than 5 days. The importance of year effects in the model increases with the length of the horizon. This is consistent with the information-based explanation for their inclusion in the model, namely that forecast errors impound time-period-specific unanticipated information. Over longer horizons, loosely speaking, the "quantity" of unanticipated information is greater. The strength of this result also confirms the assertions made earlier that a cross-section of forecast errors for a single time period is not a set of independent observations.

The F-statistics on firm-specific effects reported in Table 8 also reject the null hypothesis, which is:

$$H_0 : \alpha_{1i1\tau} = \alpha_{1i2\tau} = \ldots = \alpha_{1ij\tau} = 0$$

There are measurable firm-specific differences in average forecast error at all horizons, even after the adjustment for firm-specific information impounded in excess returns. The

strength of this result varies little across forecast horizons and across transformations of the dependent variable.

The importance of the slope coefficients in model (12), indicated by the F-statisic reported in Table 8, varies across forecast horizons and across transformations of the dependent variable. The individual slope coefficients reported in Table 6, however, are of greater relevance. Generally, the results in Table 6 show a pattern of positive association between forecast errors and excess returns. A positive association is expected if, first, there is some overlap between information relevant to firm value and information relevant to current-year earnings, and second, some of this overlapping information is unanticipated both by investors and by the predictor of EPS.

The statistical significance of the positive association varies somewhat across forecast horizons, and more importantly across forecast sources. The strongest results are for the 120-day horizon. Among the analyst consensus forecasts, the strongest results are generally for the most current forecaster, which is consistent with the most current forecaster acting as a reasonable composite of analysts' information. The strongest results, and the only ones which are consistently positive and statistically significant, however, are for the quarterly autoregressive model, equation (1). This pattern of relative performance does not vary substantially across horizons or across transformations of the dependent variable. This result is anomalous, especially in light of the quarterly model's relative

inaccuracy. It indicates that prior knowledge of the forecast error from a quarterly autoregressive model is a better predictor of excess returns than prior knowledge of the forecast error from analysts' forecasts.

The greater association of excess returns with forecast errors from a time-series model than with those from analysts is not consistent with the results of Fried and Givoly (1982). I use quarterly data in the time series models of annual earnings, while Fried and Givoly (1982) use annual data. Since models using quarterly data produce more accurate forecasts of annual earnings than models using only annual data (see Hopwood, McKeown and Newbold (1982)), presumably my tests are more demanding of analysts than those used by Fried and Givoly. However, the result remains anomalous since analysts are more accurate and can employ more information than quarterly time series models.

This anomaly is further investigated in Table 7, by testing for the statistical significance of differences in the slope coefficients. A further advantage of stacking equations across forecast sources to estimate them is that statistical testing is simplified, since a set of linear constraints on the estimated slope coefficients $\beta_{i\tau}$ generates direct tests of differences in slope across forecast sources. For example, if $\underline{\beta}_{\tau}$ is the vector of five slope coefficients, one for each forecast source, and if $\underline{c}_{12}'$ is the vector (1,-1,0,0,0), then $\underline{c}_{12}'\underline{\beta}_{\tau}$ estimates the difference in slopes between the first and second sources, with estimated standard error:

$$s_{\underline{c}'\underline{\beta}} = s_v \cdot [\underline{c}'(X'X)^{-1}_{\beta}\underline{c}]^{1/2} \quad (13)$$

In (13), s_v is the residual standard error from the joint estimation of equation (12). $(X'X)^{-1}_{\beta}$ is the lower-right submatrix of five rows and five columns from the $(X'X)^{-1}$ matrix of equation (12). This submatrix determines the variance-covariance relations among the five slope coefficients.

Linear constraints of the form of $\underline{c}_{12}$ are used to evaluate differences in the slope coefficients that appear in Table 6, i.e. differences across forecast sources in the association between excess returns and forecast errors. Table 7 contains the results of these statistical tests. Results are shown for tests of pairwise differences between the quarterly autoregressive model and all other forecast sources, and for differences between the most current analyst and the mean and median analyst forecasts. The statistical tests confirm the anomalous result that errors from a mechanical quarterly model often are significantly more closely related to excess returns than errors from analysts. In addition, the tests indicate that while the most current forecast typically shows the strongest result among analyst consensus forecasts, the difference is not statistically significant, in general.

5. Summary and Conclusions

Analysts' predictions of EPS are a potential source of

"market expectations" information. I have examined properties of different composites, or consensus forecasts. Results reported here indicate that the most current forecast from a set of analysts' forecasts is a reasonable aggregation of the information in the set.

Five alternate sources of forecasts are examined: the mean, median, and most current from a set of analysts' forecasts, an autoregressive model in fourth differences of the univariate series of quarterly EPS, and a fourth-differenced random walk using quarterly EPS. The two quarterly time-series models are included primarily as benchmarks.

The most current forecast is at least as accurate as either the mean or median forecast, and generally dominates them in absolute error terms. This result indicates that the date of the forecast is relevant for determining its accuracy, and dominates "diversification" obtained by aggregating forecasts from different sources. Since most published aggregations of forecasts and most previous research treat all forecasts as if they are equally current, they ignore this relevant piece of information. In this sample the forecast error from the most current forecast is more closely associated with excess returns over the forecast horizon than the error from the mean or the median forecast, but the difference in association is not, in general, statistically significant.

Analysts generally are significantly more accurate than time-series models. Errors from the quarterly autoregressive

model, however, appear to be more closely related with excess returns over the forecasting horizon than those of analysts, however. Because of this anomalous result, it is unclear that analysts provide a better model of the "market expectation" than mechanical models.

It should be noted, though, that the sample of firms was reduced sharply by the data requirements of the time-series models. This sample, with its selection bias toward longer-lived firms with continuous data available, does not clearly isolate cases where analysts might be expected to have the most advantage over mechanical models, and perhaps eliminated many of these cases. These firms, where there is a substantial amount of non-earnings information expected to have an impact on earnings, may be a fruitful area for future investigation.

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FOOTNOTES

[1]An example of the intuitive agument that diversification across forecast sources improves accuracy can be found in Beaver (1981), which discusses forecasts of sports scores.

[2]Brown, Foster and Noreen (1984) analyze a related, but different, dataset, taken from the set of summary statistics which I/B/E/S produces for clients.

[3]"Earnings" and "earnings per share" (or "EPS") are sometimes used interchangeably in this paper. The data consist of forecasts of EPS, and I wish to abstract from the effects of changes in capitalization on the prediction of earnings. When a stock split or stock dividend is announced between a forecast date and a realization, I adjust the forecast by the actual change in capitalization.

[4]The results reported in this paper use the raw (unscaled) forecast errors as defined in equation (3). Other forecast error metrics, or scales, may be appropriate, for example to control for heteroscedasticity. The substantive conclusions of the paper are not altered, however, when other scales are used to measure forecast errors. In Appendix A, results are reported for two alternative scales: standardized forecast errors, and percent forecast errors. Standardized forecast errors are forecast errors divided by the average, over the previous five years, of absolute changes in EPS. Percent forecast errors are forecast errors, divided by the absolute value of the prior year's EPS. Other scales which I have investigated, and for which the qualitative results of this paper are replicated, are: a version of the standardized forecast error where the denominator is the standard deviation of EPS changes, and versions of the the percent forecast error where the sample is censored to exclude negative denominators, or denominators less than $0.20.

[5]Firms announce earnings with remarkable consistency year after year, so choosing fixed lengths of time prior to the announcement date is a fairly accurate means of finding dates that differ by one quarter's earnings. Of the 6218 horizons included in this paper, 13 dates did not fall between the quarterly announcements as intended. The results are not affected by deletion of these observations.

[6]Results did not differ from those reported here when the value-weighted market portfolio of securities was used as a proxy for the market.

[7]The subscript i, which indexes the source of the forecast, is suppressed in the following discussion for readability.

[8]The estimation was also done with firm-specific effects in the

model. The bias results do not differ qualitatively from those reported here.

[9]This discussion does not argue against the existence of firm-specific effects which persist through time. It argues against an explanation for such effects based on unanticipated information.

[10]For example, see Dirks and Gross, The Great Wall Street Scandal, especially pp. 252-257. Also see "Bank Analysts Try to Balance their Ratings", WSJ, May 29, 1984. p. 33; and "Picking a Loser", WSJ, September 28, 1983, p. 1.

[11]The estimated effects are not the same as the estimated coefficients, because model (9) has two sets of effects, firms and years. A simple example will illustrate this. If there were two years and three firms in the sample, then model (9) could be estimated with no intercept, using two year dummy variables (DY1 and DY2) and two firm dummy variables (DF1 and DF2):

$$|e_{jt\tau}| = d_{11\tau}DF1 + d_{12\tau}DF2 + d_{21\tau}DY1 + d_{22\tau}DY2 + \xi_{jt\tau}.$$

The "year 1 effect" is the average $|e_{jt\tau}|$ for t=1. This effect is not estimated by $d_{21\tau}$. Rather, $d_{21\tau}$ is the average $|e_{jt\tau}|$ for year 1 for the omitted (third) firm. The "year 1 effect" is estimated in this formulation by:

$$\delta_{21\tau} = d_{21\tau} + (1/3)\, d_{11\tau} + (1/3)\, d_{12\tau} \quad .$$

The "firm 1 effect" is estimated by:

$$\delta_{11\tau} = d_{11\tau} + (1/2)\, d_{21\tau} + (1/2)\, d_{22\tau} \quad .$$

The "firm 3 effect" is estimated by:

$$\delta_{13\tau} = (1/2)\, d_{21\tau} + (1/2)\, d_{22\tau} \quad .$$

Since any non-redundant spanning set of dummy variables can be used, the particular linear combinations of coefficients to estimate the firm and year effects depend on the model used.

[12]Dropping the $\alpha_{1ij\tau}$, the firm-specific effects, does not alter the estimates of the slope coefficients $\beta_{i\tau}$ or their statistical significance by a substantial amount. Omitting the $\alpha_{2it\tau}$, however, alters both the estimates and their statistical significance.

[13]An alternative way to model this problem is to include the year or firm effects as "random effects", contributing off-diagonal elements to the covariance matrix of the $v_{ijt\tau}$. Mundlak (1978) shows that the estimate of the slope coefficient $\beta_{i\tau}$ obtained from a model like (12), is identical to the GLS estimate which would be obtained if the firm- and year-specific effects, $\alpha_{1ij\tau}$ and $\alpha_{2it\tau}$, were modeled as random effects and included in the covariance matrix.

[14]An alternate method of measuring the association between forecast errors and excess returns, similar to that of Ball and Brown (1968), is to construct portfolios based on foreknowledge of the sign of EPS forecast error. That is, a long position is taken in each of the securities for which the forecast error is positive, and a short position is taken in those with negative errors. This procedure, applied to these data, produces results qualitatively identical to those reported here.

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Table 1

Selected Characteristics of the Distribution of Forecast Ages, for the Mean, Median and Most Current Analyst Forecasts, for Five Forecast Horizons

Source	Horizon	Fractiles .1	.25	.5	.75	.9	Sample Moments mean	stdev	skew	N
mean	240	34	46	60	74	89	61.5	24.7	0.8	1198
	180	33	43	58	73	91	59.9	23.9	0.8	1235
	120	34	47	62	82	102	65.9	28.1	1.0	1254
	60	38	51	67	88	110	71.7	31.8	1.6	1258
	5	40	52	67	87	109	72.3	31.2	2.5	1260
median	240	7	20	51	83	127	59.4	47.9	1.1	1198
	180	5	16	41	78	131	56.6	54.5	1.5	1234
	120	7	19	47	80	135	61.1	58.0	1.8	1254
	60	7	19	49	88	155	66.6	67.7	2.0	1258
	5	15	26	43	71	131	61.7	60.8	2.6	1260
current	240	1	2	4	14	43	14.4	24.7	3.3	1198
	180	1	1	3	9	24	9.0	16.9	4.8	1233
	120	1	2	4	11	25	10.0	18.8	6.3	1254
	60	1	1	4	10	26	10.6	22.5	6.8	1259
	5	1	5	11	20	34	15.8	22.0	8.9	1259

Notes:

The forecast sources are:
- mean - the mean of available analysts' forecasts.
- median - the median of available analysts' forecasts.
- current - the most recent forecast from an analyst.

The age of a forecast is the number of trading days between the analyst's forecast date and the horizon date chosen in this study. Specifically, for the sources in this table, age is defined:
- mean - the mean of the ages of available analyst forecasts.
- median - the median of the ages of available analyst forecasts.
- current - the age of the most recent analyst's forecast.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table 2

Forecast Bias, for Five Forecast Sources, at Five Forecast Horizons

Source	Forecast Horizon, in Trading Days				
	240	180	120	60	5
q.a.r.	-0.15 (-3.82)	-0.11 (-3.15)	-0.14 (-5.18)	-0.08 (-4.11)	
q.r.w.	-0.09 (-2.17)	-0.05 (-1.49)	-0.11 (-4.24)	-0.06 (-3.25)	
mean	-0.08 (-2.09)	-0.12 (-3.57)	-0.12 (-4.70)	-0.09 (-4.96)	-0.05 (-2.74)
median	-0.03 (-0.72)	-0.05 (-1.52)	-0.06 (-2.25)	-0.02 (-1.19)	0.02 (1.00)
current	-0.08 (-1.91)	-0.10 (-2.93)	-0.09 (-3.27)	-0.04 (-2.34)	-0.02 (-1.42)

Notes:

The computation of forecast bias and its associated t-statistic (in parentheses) are described in equations (6) through (8) in the text.

The forecast sources are:
- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

The degrees of freedom for all reported t-statistics are over 1,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points of the N(0,1) distribution are 1.96 and 2.58, respectively.

Table 3

Forecast Accuracy: Average Absolute or Squared Forecast Error for Five Forecast Sources, and Five Forecast Horizons

	Source:	Forecast Horizon, in Trading Days 240	180	120	60	5
	q.a.r.	0.975	0.780	0.592	0.350	
Average	q.r.w.	0.963	0.781	0.620	0.363	
Absolute	mean	0.747	0.645	0.516	0.395	0.291
Forecast	median	0.788	0.677	0.546	0.435	0.321
Error	current	0.742	0.610	0.468	0.342	0.292
	q.a.r.	2.771	1.877	1.203	0.460	
Average	q.r.w.	2.626	1.897	1.255	0.447	
Squared	mean	1.531	1.239	0.818	0.478	0.351
Forecast	median	1.595	1.246	0.790	0.546	0.409
Error	current	1.638	1.178	0.669	0.389	0.361

Notes:

The computation of average absolute error is described in equations (9) and (10) in the text. The computation of average squared error is analogous to the computation of average absolute error.

The forecast sources are:
- q.a.r. - a quarterly autoregressive model in fourth differences: equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table 4

Pairwise Differences in Forecast Accuracy
Among the Mean, Median and Most Current Analyst Forecasts,
for Five Forecast Horizons

Panel A: t-Statistics on Differences in Average Absolute Error

	Forecast Horizon, in Trading Days				
	240	180	120	60	5
mean - median	-1.06	-0.98	-1.11	-2.14	-1.62
mean - current	0.11	1.07	1.82	2.83	-0.02
median - current	1.18	2.05	2.93	4.97	1.60

Panel B: t-Statistics on Differences in Average Squared Error

	Forecast Horizon, in Trading Days				
	240	180	120	60	5
mean - median	-0.26	-0.04	0.20	-0.83	-0.59
mean - current	-0.44	0.30	1.06	1.09	-0.10
median - current	-0.18	0.34	0.86	1.91	0.50

Notes:

The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table 3 for the average absolute and squared errors. The computations are described in equations (9) through (11) in the text.

The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

The forecast sources are:
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table 5

Pairwise Differences in Forecast Accuracy Between Analysts and Quarterly Time-Series Models, for Five Forecast Horizons

Panel A: t-Statistics on Differences in Average Absolute Error

Quarter:	1	2	3	4
Horizon:	240	180	120	60
q.a.r. - mean	5.85	4.15	2.85	-2.36
q.a.r. - median	4.79	3.17	1.74	-4.51
q.a.r. - current	5.96	5.22	4.67	0.46
q.r.w. - mean	5.56	4.20	3.92	-1.70
q.r.w. - median	4.50	3.21	2.81	-3.84
q.r.w. - current	5.67	5.27	5.74	1.13

Panel B: t-Statistics on Differences in Average Squared Error

Quarter:	1	2	3	4
Horizon:	240	180	120	60
q.a.r. - mean	5.08	3.16	2.73	-0.22
q.a.r. - median	4.81	3.13	2.93	-1.04
q.a.r. - current	4.64	3.47	3.79	0.87
q.r.w. - mean	4.49	3.26	3.09	-0.38
q.r.w. - median	4.22	3.23	3.29	-1.21
q.r.w. - current	4.05	3.56	4.15	0.70

Notes:

The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table 3 for the average absolute and squared errors. The computations are described in equations (9) through (11) in the text.

The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a quarterly random walk model in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

Table 6

Slope Coefficients from the Regression of EPS Forecast Error on Excess Return, for Five Forecast Horizons:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (12)$$

	Forecast Horizon, in Trading Days				
	240	180	120	60	5
Source:					
q.a.r.	0.98	0.96	0.99	0.48	
	(5.38)	(5.72)	(6.46)	(3.26)	
q.r.w.	0.29	0.24	0.63	0.18	
	(1.61)	(1.44)	(4.15)	(1.25)	
mean	0.14	0.01	0.34	0.14	0.66
	(0.78)	(0.04)	(2.20)	(0.96)	(1.68)
median	0.07	0.07	0.41	0.20	0.77
	(0.40)	(0.40)	(2.68)	(1.38)	(1.97)
current	0.32	0.29	0.53	0.37	0.25
	(1.75)	(1.75)	(3.49)	(2.49)	(0.64)

Notes:

The forecast sources are:

- q.a.r. – a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. – a random walk model with drift in fourth differences; equation (2) in the text.
- mean – the mean of the available analysts' forecasts.
- median – the median of the available analysts' forecasts.
- current – the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

The variables in regression equation (12) are the forecast error from forecast source i for firm j in year t at horizon τ, $e_{ijt\tau}$, and the cumulated excess returns for firm j in year t over horizon τ, $U_{jt\tau}$. Equation (12) is estimated jointly for the five forecast sources and separately for each of the forecast horizons. The parameters $\alpha_{1ij\tau}$ are firm-specific effects, and the parameters $\alpha_{2it\tau}$ are year-specific effects.

A slope coefficient $\beta_{i\tau}$ is estimated for each forecast source i and horizon τ. The statistical significance of the correlation between forecast errors and excess returns is measured by the t-statistic on the slope coefficient, which is reported in parentheses. These t-statistics have degrees of freedom greater than 1,000. For a one-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.65 and 2.33, respectively.

Table 7

Pairwise Differences in Slope Coefficients from the Regression of EPS Forecast Error on Excess Return, for Five Forecast Horizons:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (12)$$

Panel A: t-Statistics on Differences between Quarterly Autoregressive Model [eqn. (1)] and Other Forecast Sources

Quarter:	1	2	3	4	
Horizon:	240	180	120	60	5
q.a.r. - q.r.w.	2.69	3.08	1.68	1.47	
q.a.r. - mean	3.28	4.08	3.09	1.68	
q.a.r. - median	3.55	3.82	2.74	1.37	
q.a.r. - current	2.59	2.85	2.16	0.56	

Panel B: t-Statistics on Differences between the Most Current and the Mean or Median Analyst Forecasts

Horizon:	240	180	120	60	5
mean - current	-0.69	-1.23	-0.94	-1.12	0.76
median - current	-0.96	-0.97	-0.59	-0.82	0.97

Notes:

The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

The variables in regression equation (12) are the forecast error from forecast source i for firm j in year t at horizon τ, $e_{ijt\tau}$, and the cumulated excess returns for firm j in year t over horizon τ, $U_{jt\tau}$. Equation (12) is estimated jointly for the five forecast sources and separately for each of the forecast horizons. The parameters $\alpha_{1ij\tau}$ are firm-specific effects, and the parameters $\alpha_{2it\tau}$ are year-specific effects.

A slope coefficient $\beta_{i\tau}$ is estimated for each forecast source i and horizon τ. The slope coefficients are reported in Table 6. The t-statistics reported in this table test differences in slope across forecast sources, against a null hypothesis of no difference. These t-statistics have degrees of freedom greater than 2,000. For a one-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.65 and 2.33, respectively.

Table 8

Regression Summary Statistics for the Regression of EPS Forecast Error on Excess Return, for Five Forecast Horizons:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (12)$$

	Forecast Horizon, in Trading Days				
	240	180	120	60	5
adjusted R^2	.116	.095	.107	.114	.156
full model F(k-1,N-k)	5.02	4.27	4.79	5.09	4.60
year-effect F(k1,N-k)	54.13	36.79	25.17	19.25	2.94
firm-effect F(k2,N-k)	3.34	3.08	3.87	4.82	4.65
excess returns F(k3,N-k)	6.89	7.33	14.37	3.57	2.18
d.f. for F-statistics:					
sample size (N)	5986	6171	6267	6293	3779
# of parameters (k)	199	199	199	199	195
# of years (k1+1)	7	7	7	7	7
# of firms (k2+1)	184	184	184	184	184
# of slopes (k3)	5	5	5	5	3

Notes:

The variables in regression equation (12) are the forecast error from forecast source i for firm j in year t at horizon τ, $e_{ijt\tau}$, and the cumulated excess returns for firm j in year t over horizon τ, $U_{jt\tau}$. Equation (12) is estimated jointly for the five forecast sources and separately for each of the forecast horizons. The parameters $\alpha_{1ij\tau}$ are firm-specific effects, and the parameters $\alpha_{2it\tau}$ are year-specific effects.

The full model F-statistic tests the null hypothesis that the regression model (12) has explanatory power. The year, firm, and excess return F-statistics test the incremental explanatory power of including groups of parameters in the model. Selected critical points for the F distribution are:

	α = .05		α = .001	
	Denominator d.f.		Denominator d.f.	
Numerator d.f.	120	∞	120	∞
3	2.68	2.60	5.78	5.42
5	2.29	2.21	4.42	4.10
6	2.18	2.10	4.04	3.74
120	1.35	1.22	1.77	1.45

Appendix

In this appendix I present results for two alternate forecast error scales: forecast errors scaled by the average absolute deviation of the past five years' changes in EPS, which I call standardized forecast errors:

$$se_{ijt\tau} = \frac{e_{ijt\tau}}{\frac{1}{5}\sum_{s=t-5}^{t-1} \left|\Delta A_{js}\right|} , \qquad (A1)$$

and forecast errors as a percent of the absolute value of the prior year's EPS, or percent forecast errors:

$$pe_{ijt\tau} = \frac{e_{ijt\tau}}{\left|A_{jt-1}\right|} . \qquad (A2)$$

There are two reasons for considering several scales for forecast errors in this study. The first is comparability with previous work. Variants of (A2) have been used frequently in previous research to create a unitless measure (e.g., Cragg and Malkiel (1968), Brown and Rozeff (1978), Beaver, Clarke and Wright (1979), Malkiel and Cragg (1981), and Elton, Gruber and Gultekin (1981)). Equation (A2) is appropriate if forecasts of EPS growth, not EPS, are relevant for decisions.

The second reason for considering alternate scales is that EPS forecast errors may be heteroscedastic. That is, there may be differences in predictability of EPS across firms, perhaps related to firm size, earnings variability, or available

information. Equation (A1) scales forecast errors by the average variation in previous years' EPS, as a benchmark for predictability. The average variation is measured here by the average absolute value of past changes. This measure is less sensitive to outliers than the standard deviation, and describes the variablility of a random walk with trend when loss is proportional to absolute error. Alternatively, if predictability is proportional to the level of EPS, then equation (A2) controls for cross-sectional variation in predictability.

Table A2

Forecast Bias, for Five Forecast Sources, at Five Forecast Horizons

(t-statistics are in parentheses)

	Source:	Horizon 240	180	120	60	5
Panel A: Standardized forecast error [eqn. A1]	q.a.r.	-0.24 (-3.69)	-0.12 (-2.41)	-0.20 (-4.70)	-0.11 (-3.59)	
	q.r.w.	-0.14 (-2.24)	-0.03 (-0.66)	-0.15 (-3.57)	-0.08 (-2.56)	
	mean	-0.17 (-2.58)	-0.20 (-4.05)	-0.18 (-4.20)	-0.14 (-4.35)	-0.07 (-2.08)
	median	-0.09 (-1.38)	-0.09 (-1.89)	-0.08 (-1.83)	-0.03 (-0.94)	0.03 (1.00)
	current	-0.18 (-2.84)	-0.17 (-3.48)	-0.13 (-3.01)	-0.08 (-2.60)	-0.04 (-1.36)
Panel B: Percent forecast error [eqn. A2]	q.a.r.	0.05 (1.90)	0.05 (2.14)	.00 (-0.31)	-0.01 (-0.69)	
	q.r.w.	0.06 (2.24)	0.07 (3.25)	0.03 (1.78)	0.01 (1.54)	
	mean	-0.01 (-0.52)	-0.02 (-0.80)	-0.02 (-1.61)	-0.02 (-2.72)	-0.02 (-2.55)
	median	.00 (0.07)	.00 (0.05)	-0.01 (-0.37)	-0.01 (-0.70)	.00 (0.21)
	current	-0.01 (-0.34)	-0.01 (-0.47)	-0.01 (-0.94)	-0.01 (-1.31)	-0.01 (-1.11)

Notes:

The computation of forecast bias and its associated t-statistic are described in equations (6) through (8) in the text.

The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

The degrees of freedom for all reported t-statistics are over 1,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points of the N(0,1) distribution are 1.96 and 2.58, respectively.

Table A3

Forecast Accuracy:
Average Absolute or Squared Forecast Error
for Five Forecast Sources, and Five Forecast Horizons

Panel A: Average Absolute Error

	Source:	Horizon 240	180	120	60	5
	q.a.r.	1.478	1.112	0.867	0.505	
Standardized	q.r.w.	1.494	1.121	0.919	0.523	
forecast error	mean	1.147	0.990	0.777	0.616	0.467
[eqn. A1]	median	1.208	1.035	0.833	0.677	0.516
	current	1.181	0.958	0.733	0.555	0.492
	q.a.r.	0.337	0.273	0.191	0.115	
Percent	q.r.w.	0.335	0.273	0.212	0.124	
forecast error	mean	0.244	0.212	0.164	0.121	0.090
[eqn. A2]	median	0.255	0.219	0.173	0.132	0.096
	current	0.242	0.202	0.154	0.104	0.088

Panel B: Average Squared Error

	Source:	Horizon 240	180	120	60	5
	q.a.r.	6.702	3.042	2.719	0.788	
Standardized	q.r.w.	6.482	2.950	2.724	0.793	
forecast error	mean	3.450	2.810	2.066	1.458	1.083
[eqn. A1]	median	3.615	2.857	2.035	1.529	1.146
	current	4.766	3.245	1.896	1.466	1.257
	q.a.r.	1.694	0.914	0.247	0.103	
Percent	q.r.w.	1.479	1.107	0.481	0.144	
forecast error	mean	0.456	0.314	0.163	0.066	0.052
[eqn. A2]	median	0.455	0.326	0.146	0.073	0.052
	current	0.468	0.316	0.206	0.045	0.037

Notes:

The computation of average absolute error is described in equations (9) and (10) in the text. The computation of average squared error is analogous to the computation of average absolute error.

The forecast sources are:
- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table A4

Pairwise Differences in Forecast Accuracy
Among the Mean, Median and Most Current Analyst Forecasts,
for Five Forecast Horizons

Panel A: t-Statistics on Differences in Average Absolute Error

ependent ariable:		Horizon 240	180	120	60	5
td'zed	mean - median	-0.83	-0.85	-1.12	-1.70	-1.29
rror	mean - current	-0.47	0.60	0.89	1.68	-0.65
eqn. A1]	median - current	0.36	1.44	2.01	3.38	0.64
ercent	mean - median	-0.33	-0.28	-0.50	-1.12	-0.82
rror	mean - current	0.07	0.35	0.58	1.77	0.29
eqn. A2]	median - current	0.40	0.64	1.08	2.89	1.12

Panel B: t-Statistics on Differences in Average Squared Error

ependent ariable:	Horizon:	240	180	120	60	5
td'zed	mean - median	-0.15	-0.07	0.05	-0.15	-0.12
rror	mean - current	-1.22	-0.64	0.26	-0.02	-0.33
eqn. A1]	median - current	-1.06	-0.57	0.21	0.13	-0.21
ercent	mean - median	.00	-0.02	0.09	-0.16	0.02
rror	mean - current	-0.01	.00	-0.25	0.46	0.76
eqn. A2]	median - current	-0.01	0.02	-0.34	0.61	0.74

Notes:

The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table A3 for the average absolute and squared errors. The computations are described in equations (9) through (11) in the text.

The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

The forecast sources are:
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table A5

Pairwise Differences in Forecast Accuracy Between Analysts and Quarterly Time-Series Models, for Five Forecast Horizons

Panel A: t-Statistics on Differences in Average Absolute Error

Dependent Variable:	Quarter: / Horizon:	1 / 240	2 / 180	3 / 120	4 / 60
Std'zed error [eqn. A1]	q.a.r. - mean	4.54	2.28	1.82	-3.06
	q.a.r. - median	3.71	1.43	0.70	-4.76
	q.a.r. - current	4.07	2.88	2.71	-1.38
	q.r.w. - mean	4.75	2.45	2.86	-2.57
	q.r.w. - median	3.92	1.61	1.74	-4.27
	q.r.w. - current	4.29	3.05	3.75	-0.89
Percent error [eqn. A2]	q.a.r. - mean	2.74	2.34	1.55	-0.67
	q.a.r. - median	2.41	2.06	1.05	-1.79
	q.a.r. - current	2.81	2.69	2.13	1.11
	q.r.w. - mean	2.68	2.33	2.80	0.32
	q.r.w. - median	2.35	2.04	2.29	-0.80
	q.r.w. - current	2.75	2.68	3.37	2.10

Panel B: t-Statistics on Differences in Average Squared Error

Dependent Variable:	Quarter: / Horizon:	1 / 240	2 / 180	3 / 120	4 / 60
Std'zed error [eqn. A1]	q.a.r. - mean	3.00	0.34	0.99	-1.38
	q.a.r. - median	2.85	0.27	1.04	-1.53
	q.a.r. - current	1.79	-0.30	1.25	-1.40
	q.r.w. - mean	2.80	0.21	1.00	-1.37
	q.r.w. - median	2.65	0.14	1.05	-1.52
	q.r.w. - current	1.59	-0.43	1.26	-1.39
Percent error [eqn. A2]	q.a.r. - mean	1.30	1.11	0.48	0.81
	q.a.r. - median	1.30	1.09	0.57	0.65
	q.a.r. - current	1.29	1.10	0.23	1.26
	q.r.w. - mean	1.08	1.46	1.81	1.71
	q.r.w. - median	1.08	1.44	1.90	1.55
	q.r.w. - current	1.06	1.46	1.56	2.17

Notes:

The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table 3 for the average absolute and squared errors. The computations are described in equations (9) through (11) in the text.

The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences: equation (1) in the text.
- q.r.w. - a quarterly random walk model in fourth differences: equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

Table A6

Slope Coefficients from the Regression of EPS Forecast Error on Excess Return, for Five Forecast Horizons:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (12)$$

Panel A: Standardized forecast error [eqn. A1] as dependent variable

	Horizon				
	240	180	120	60	5
Source:					
q.a.r.	0.95	1.15	1.25	0.55	
	(3.18)	(4.68)	(5.00)	(2.25)	
q.r.w.	0.48	0.33	0.78	0.17	
	(1.61)	(1.33)	(3.11)	(0.68)	
mean	0.55	0.07	0.45	0.10	0.49
	(1.85)	(0.29)	(1.80)	(0.40)	(0.67)
median	0.49	0.14	0.53	0.21	0.88
	(1.65)	(0.55)	(2.14)	(0.84)	(1.21)
current	0.73	0.18	0.76	0.43	-0.88
	(2.44)	(0.72)	(3.04)	(1.75)	(-1.21)

Panel B: Percent forecast error [eqn. A2] as dependent variable

	Horizon				
	240	180	120	60	5
Source:					
q.a.r.	0.34	0.38	0.35	0.15	
	(2.74)	(3.58)	(4.26)	(2.36)	
q.r.w.	0.18	0.15	0.27	-0.01	
	(1.47)	(1.42)	(3.23)	(-0.15)	
mean	0.12	0.05	0.15	0.02	-0.00
	(0.95)	(0.49)	(1.84)	(0.25)	(-0.01)
median	0.11	0.06	0.16	0.03	0.10
	(0.88)	(0.53)	(1.92)	(0.47)	(0.72)
current	0.16	0.10	0.22	0.11	0.02
	(1.34)	(0.96)	(2.65)	(1.83)	(0.14)

Notes:

The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

A slope coefficient $\beta_{i\tau}$ is estimated for each forecast source i and horizon τ. The statistical significance of the correlation between forecast errors and excess returns is measured by the t-statistic on the slope coefficient, which is reported in parentheses. These t-statistics have degrees of freedom greater than 1,000. For a one-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.65 and 2.33, respectively.

Table A7

Pairwise Differences in Slope Coefficients from the Regression of EPS Forecast Error on Excess Return, for Five Forecast Horizons:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \quad (12)$$

Panel A: t-Statistics on Differences between Quarterly Autoregressive Model [eqn. (1)] and Other Forecast Sources

Dependent Variable:	Quarter: / Horizon:	1 / 240	2 / 180	3 / 120	4 / 60	5
	q.a.r. - q.r.w.	1.12	2.41	1.37	1.15	
Std'zed	q.a.r. - mean	0.95	3.15	2.32	1.35	
error	q.a.r. - median	1.09	2.97	2.08	1.03	
[eqn. A1]	q.a.r. - current	0.53	2.85	1.43	0.36	
Percent	q.a.r. - q.r.w.	0.91	1.55	0.74	1.84	
error	q.a.r. - mean	1.28	2.22	1.75	1.54	
[eqn. A2]	q.a.r. - median	1.33	2.19	1.70	1.38	
	q.a.r. - current	1.00	1.88	1.17	0.39	

Panel B: t-Statistics on Differences between the Most Current and the Mean or Median Analyst Forecasts

Dependent Variable:	Horizon:	240	180	120	60	5
Std'zed	mean - current	-0.42	-0.30	-0.90	-0.99	1.37
error	median - current	-0.56	-0.12	-0.65	-0.67	1.77
Percent	mean - current	-0.28	-0.34	-0.58	-1.15	-0.11
error	median - current	-0.33	-0.31	-0.52	-0.99	0.42

Notes:

The forecast sources are:
- q.a.r. - a quarterly autoregressive model in fourth differences; equation (1) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

The forecast horizons are measured in trading days prior to the annual earnings announcement.

A slope coefficient $\beta_{i\tau}$ is estimated for each forecast source i and horizon τ. The slope coefficients are reported in Table 6. The t-statistics reported in this table test differences in slope across forecast sources, against a null hypothesis of no difference. These

t-statistics have degrees of freedom greater than 2,000. For a one-sided test, the .05 and .01 critical points from the $N(0,1)$ distribution are 1.65 and 2.33, respectively.

t-statistics have degrees of freedom greater than 2,000. For a one-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.65 and 2.33, respectively.

Table A8

Regression Summary Statistics for the Regression of EPS Forecast Error on Excess Return, for Five Forecast Horizons:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (12)$$

Dependent Variable:		Horizon 240	180	120	60	5
Std'zed error [eqn. A1]	R^2	.139	.138	.129	.144	.154
	F(k-1,N-k)	5.80	5.93	5.61	6.25	4.51
	k	195	195	195	195	191
	N	5783	5966	6057	6083	3653
Percent error [eqn. A2]	R^2	.104	.099	.097	.088	.138
	F(k-1,N-k)	4.49	4.37	4.35	4.02	4.08
	k	199	199	199	199	195
	N	5928	6111	6202	6228	3740

Notes:

Selected critical points for the F distribution are:

	$\alpha = .001$
F(120,120)	1.77
F(120, ∞)	1.45

Table A9

Summary of Regression Results:
Incremental F-statistics for Groups of Parameters,
in the Regression of EPS Forecast Error on Excess Return

Dependent Variable:			Horizon 240	180	120	60	5
Std'zed error [eqn. A1]	year	F(k1,N-k)	48.82	47.56	25.77	19.04	3.47
		k1	6	6	6	6	6
	firm	F(k2,N-k)	4.36	4.54	4.86	6.10	4.61
		k2	179	179	179	179	179
	excess return	F(k3,N-k)	4.71	4.74	8.89	1.64	1.19
		k3	5	5	5	5	3
		N-k	5588	5771	5862	5888	3462
Percent error [eqn. A2]	year	F(k1,N-k)	18.94	15.9	18.21	15.47	2.71
		k1	6	6	6	6	6
	firm	F(k2,N-k)	4.08	3.98	3.83	3.74	4.19
		k2	183	183	183	183	183
	excess return	F(k3,N-k)	2.51	3.07	7.28	1.72	0.18
		k3	5	5	5	5	3
		N-k	5729	5912	6003	6029	3545

Notes:

The full model F-statistic tests the null hypothesis that the regression model (12) has explanatory power. The year, firm, and excess return F-statistics test the incremental explanatory power of including groups of parameters in the model. Selected critical points for the F distribution are:

	$\alpha = .05$ Denominator d.f.		$\alpha = .001$ Denominator d.f.	
Numerator d.f.	120	∞	120	∞
3	2.68	2.60	5.78	5.42
5	2.29	2.21	4.42	4.10
6	2.18	2.10	4.04	3.74
120	1.35	1.22	1.77	1.45