This is to certify that the

dissertation entitled

AN EMPIRICAL INVESTIGATION OF BIAS
IN ANALYSTS' EARNINGS FORECASTS

presented by

Hakan Saraoglu

has been accepted towards fulfillment
of the requirements for

Ph.D. degree in Bus. Adm.

Kirt C Butler

Major professor

Date July 24, 1996

AN EMPIRICAL INVESTIGATION OF BIAS IN ANALYSTS' EARNINGS FORECASTS

By

Hakan Saraoglu

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Finance and Insurance
Eli Broad Graduate School of Management

1996

ABSTRACT

AN EMPIRICAL INVESTIGATION OF BIAS IN ANALYSTS' EARNINGS FORECASTS

By

Hakan Saraoglu

This study investigates bias in security analysts' earnings forecasts using samples of firms in the United States. Methods to identify bias and to improve the accuracy of analyst forecasts are suggested and tested. Samples of forecasts in Japan, the U.K. and Germany are also examined for bias.

The results in the U.S. sample of 1984-91 show that (1) forecasts are on average optimistic, (2) biases in negative forecasts and in negative earnings are more obvious than those in positive forecasts and earnings, (3) positive forecasts that overestimate negative earnings are the biggest source of forecast error, (4) optimistic bias in forecasts seems to be driven by firms with negative earnings.

Based on these observations, methods to improve the accuracy of negative earnings forecasts are suggested and tested. Results show that adjustments of up to 1% of share price yield improved forecast accuracy, an increased probability of beating the consensus forecast, and little increase in the probability of underestimating actual earnings.

Multiple Discriminant Analysis and Logistic Regression are utilized to predict the sign of earnings before the announcement date using firm-specific information together with earnings forecasts. The sum of the first three quarterly earnings, the magnitude of the consensus forecast, and the percentage change in share price from the previous year are found to be good predictors of the sign of earnings. Using this methodology in a hold-out sample, optimistic positive forecasts of negative earnings are identified and adjusted. Test period results indicate that this methodology outperforms security analysts' consensus forecasts in predicting negative earnings outcomes. Mean square forecast error is greatly reduced through forecast adjustments in all but one test period.

An investigation of the accuracy of security analysts' median consensus forecasts in Japan, the U.K., and Germany for the 1987-94 the period finds that analysts' forecasts contain an optimistic bias in all three countries. A majority of negative forecasts are overoptimistic in Japan and Germany, where analysts rarely report negative forecasts for earnings that turn out to be positive. In contrast, negative earnings forecasts in the U.K. are on average pessimistic. Tests of symmetry suggest that the average forecast error is negative and its magnitude is symmetric regardless of the size of forecasts in Japan and the United Kingdom. On the other hand, the forecast errors become larger and more negative as the forecasts become smaller in Germany.

DEDICATION

To the memory of my father, Kemal Saraoglu.

ACKNOWLEDGMENTS

I wish to express my appreciation to my dissertation committee members: Dr. Kirt Butler, Dr. John Gilster, Dr. Kathy Petroni and Dr. Peter Schmidt. Dr. Gilster and Dr. Petroni have been a diligent source of insight throughout my research. Dr. Schmidt's thorough and constructive reviews of my dissertation went far beyond the call of duty.

I am grateful to Dr. Kirt Butler, my dissertation committee chairperson. With his sound advice and encouragement, Dr. Butler has been a valuable mentor and a constant source of inspiration to me throughout my doctoral program.

I would like to express my gratitude to Dr. Richard Simonds for his confidence in my capabilities and for his nominating me to a highly visible and challenging teaching position. I am also thankful to Dr. John O'Donnell, who recruited me to the doctoral program.

I am indebted to Dr. Tamer Cavusgil, who has been a constant source of support and encouragement during my years in East Lansing. Thanks are also extended to the Michigan State University Center for International Business Education and Research for generously funding my research.

Most of all, I wish to thank my mother, Aysel Saraoglu, and my wife, Poh-Lin Yeoh Saraoglu, for their unconditional support and love.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

The market value of equity is often estimated by finding the present value of its future cash flows discounted at a rate of return appropriate for its risk. Faced with the task of estimating a stock's future cash flows, investors frequently rely on security analysts' forecasts of earnings per share. Investors' reliance on earnings forecasts is evident in the association between earnings surprises and stock prices changes (Brown (1978) and Rendleman, Jones and Latane (1982)). Since investors use analysts' earnings forecasts to form their expectations of future earnings and cash flow, accuracy of the forecasts is of paramount importance.

Various research studies have evaluated the accuracy of analysts' earnings forecasts. Brown and Rozeff (1979), Brown, Hagerman, Griffin and Zmijewski (1987), Collins and Hopwood (1980) showed that analysts produce significantly better forecasts than time series models. However, research has also shown that analysts' forecasts of earnings per share tend to be optimistically biased (Dowen (1989), O'Brien (1994), Dreman and Berry (1995)). If investors in the market do not discount the forecast bias when forming their expectations, it may be possible to develop profitable trading rules based on the association of earnings surprises to stock price changes. Thus, an understanding of the nature of forecast bias gains additional importance for investors.

This study investigates bias in security analysts' earnings forecasts using samples of firms in the United States. Methods to identify bias and to improve the accuracy of analyst forecasts are suggested and tested. Samples of forecasts in Japan, the U.K. and Germany are also examined for bias.

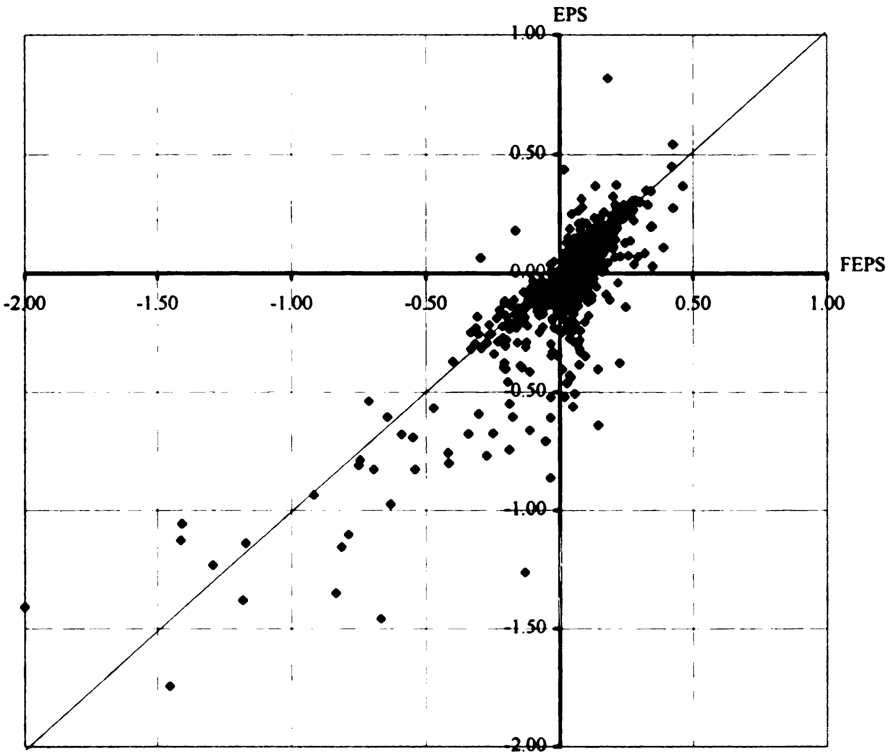
Figure 1 plots actual against expected annual earnings based on median consensus forecasts reported during November for a sample of 4250 observations over the period 1984-1991. A casual inspection of Figure 1 suggests that positive earnings outcomes tend to be clustered around a 45-degree line through the origin as one would expect of rational forecasts. The forecasts associated with negative earnings outcomes, on the other hand, appear to be over-optimistic. Indeed, rarely do negative earnings outcomes exceed the consensus forecast and fall above the 45-degree line. Based on this observation, the following research issues emerge: (1) Are analysts' consensus forecasts biased and/or inefficient in a systematic manner? (2) If they are, is the bias in the overall sample driven by forecasts of earnings that turn out to be negative? (3) Do negative earnings forecasts differ from positive earnings forecasts? (4) Can the accuracy of forecasts be improved based on observation of systematic biases such as over-optimism in forecasts of negative earnings?

To answer these questions the following related null hypotheses are formed: (1) analysts' forecasts are unbiased and efficient, (2) the rationality of forecasts is independent of the forecasts' magnitude and sign.

Chapter 1 discusses the relevant literature and highlights the research issues. Chapter 2 investigates analysts' consensus forecasts of annual earnings in the U.S. and tests null hypotheses (1) and (2). Chapter 3 suggests and tests methods to improve the accuracy of negative earnings forecasts, and evaluates the implications of forecast adjustments from the standpoint of both investors and analysts. Chapter 4 develops a methodology for predicting the sign of earnings per share before the announcement date using firm-specific information together with earnings forecasts. Significance of various measures of pre-announcement information is tested using Multiple Discriminant Analysis and Logistic Regressions. Chapter 5 uses the methodology suggested in Chapter 4 to identify and adjust optimistic forecasts of negative earnings in the sample. Out-of-sample tests are performed to assess the power of the model in predicting the negative earnings outcomes. The significance of forecast improvement is evaluated using the same out-of-sample tests. Chapter 6 investigates the accuracy of analysts' earnings forecasts in samples from Japan, the United Kingdom, and Germany. Chapter 7 summarizes the results of the study and suggests directions for future research.

Figure 1. Earnings Per Share (EPS) Vs. Forecasts of Earnings Per Share (FEPS)

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the U.S. companies in a pooled sample between 1984 and 1991.



Chapter 1

LITERATURE REVIEW

This chapter presents a discussion of the relevant literature and highlights the research issues regarding the importance of earnings numbers and forecasts of earnings per share as well as the accuracy of earnings forecasts.

The Association of Earnings and Earnings Forecasts to Stock Prices

Valuation of a share of common stock requires estimation of the share's future cash flow stream. The expectations of market participants on company fundamentals, which serve as measures of future performance, play an important role in driving the market values of stocks. Research studies show that firms' earnings per share numbers and analysts' forecasts of earnings per share are proxies for investors' expectations of firms' future prospects. In a seminal study that introduced the concept of post-earnings announcement drift (or, the literature on standardized unexpected earnings) Ball and Brown (1968) show that changes in annual earnings are associated with changes in stock prices of the same directions. Using data for nine years, 1957-65, the study shows that: (1) annual earnings capture approximately one-half of the information that becomes available during the year; and (2) approximately 85 to 90 percent of stock price movements occurs in the 12 months prior to the month in which the annual earnings number is reported. This study also shows that, after annual earnings are announced, stock prices continue to move in the same direction as the annual earnings change. The Ball and Brown study is considered as the pioneer study of the quarterly reporting literature; studies that focused on the magnitude of the earnings change rather than simply the direction; the use of cash flows numbers in lieu of earnings numbers; and the use of more sophisticated earnings forecasting models than simply earnings changes.

Empirically examining the extent to which common stock investors perceive earnings to possess informational value, Beaver (1968) supports the findings of Ball and Brown (1968) on the information content of earnings reports.

Givoly and Lakonishok (1979) evaluate the information content of analysts' earnings forecast revisions by analyzing the relationship between stock price behavior and the direction and magnitude of the revision. Their results show that revisions in earnings forecasts convey information to the stock market or reflect variables that determine stock prices.

In an empirical test of the theory that expectations about a firm's characteristics are reflected in security prices, Elton, Gruber and Gultekin (1981) examine data from a monthly file of one and two-year earnings forecasts prepared in the period 1973-75. Their finding support the theory. Their results indicate that large excess returns can be earned if the investor can determine stocks for which analysts have underestimated earnings; the larger the underestimation, the larger the return. Elton, et al. conclude that with any amount of forecasting ability, investor can earn best returns by acting on the difference between their forecasts and consensus forecasts.

Niederhoffer and Regan (1972) show that earnings changes have a significant impact on stock prices, implying that an accurate earnings forecast is of paramount importance in stock selection models. Focusing on 100 case histories, this study provides evidence that stock price changes are positively associated with forecasts of moderately increased earnings and realized earnings far in excess of analysts' expectations. The worst-performing stocks, on the other hand, are characterized by severe earnings declines in combination with unusually optimistic forecasts.

Benesh and Peterson (1986) examine the importance of unexpected and actual earnings changes on the market's determination of stock prices. In an earnings sample of 1980-1981, their results indicate that unexpected earnings changes have a major impact on share price. Firms with high return performance generally have substantial earnings increases and earnings that surpass analysts' expectations. Over time, forecasts become more optimistic for top-performing firms. Furthermore, earnings announcements may play a major role in forecast revisions, and securities that experience significant revisions tend to have substantial excess returns for the remainder of the year.

Superiority of Analysts' Forecasts to Time-Series Models

Evaluating the predictive power of security analysts' earnings forecasts, various research studies have compared forecasts produced by analysts to those generated by statistical models. Results suggest that analysts' forecasts of earnings per share are more accurate than those of time-series models.

According to Brown and Rozeff (1978), basic economic theory and the equilibrium employment of analysts imply that analysts must produce better forecasts than time series models. Their results show that Box-Jenkins models consistently produce significantly better earnings forecasts than martingale and sub-martingale models. Also, earnings forecasts of Value Line Investment Survey consistently outperform the Box-Jenkins and naive time-series models. Brown and Rozeff conclude that, if market earnings expectations are rational, the best available forecasts should be used to measure market earnings expectations. They also suggest that analysts' forecasts should be used in studies of firm valuation, cost of capital, and the relationship between unanticipated earnings and stock price changes until forecasts superior to those of analysts are discovered.

Fried and Givoly (1982) assess the quality of financial analysts' forecasts as proxies for the market expectation of earnings, compare them with other prediction models, and analyze the factors that contribute to analysts' forecasts having information content. In a forecast sample between 1969 and 1979, the results indicate that analysts' prediction errors provide a better proxy for market expectations than forecasts generated by time-series models. Fried and Givoly suggest that analysts show better performance due to their ability to utilize a much broader set of information than that used by the univariate time-series models. The study also provides evidence that the analysts efficiently exploit the extrapolative power of the earnings series itself.

Based on a multivariate analysis of variance design (MANOVA), Collins and Hopwood (1980) compare the relative accuracy of annual earnings forecasts generated from the quarterly forecasts of financial analysts and from four univariate time-series models. Results indicate that the performance comparison of univariate time-series models to the financial analyst model favor the financial analysts. Analysis of the list of outliers show that the financial analysts also generate fewer outliers than the univariate models. Collins and Hopwood conclude that the financial analysts are more capable of incorporating the effects of the economic events that are the underlying causes of the outliers.

Crichfield, Dyckman and Lakonishok (1978) show that financial analysts' predictions of earnings per share based on accounting information improve as the reporting date approaches, and that, generally, the financial analysts are better able to predict earnings per share compared to the statistical models.

Brown, Hagerman, Griffin and Zmijewski (1987) provide evidence that security analysts' are superior to univariate time-series models in predicting firms' quarterly earnings numbers. Similar to the conclusion of Fried and Givoly (1982), they attribute this superiority to: (1) better use of information that exists on the date that time-series models can be initiated (a contemporaneous advantage), and (2) use of information acquired between the date of initiation of time series model forecasts and the date when security analysts' forecasts are published (a timing advantage).

Several articles in the literature investigate the possible improvement in forecast accuracy by combining analysts' forecasts with those generated by time series models.

Consensus results of such studies indicate that a forecast synergy can be achieved when analysts forecasts are combined with forecasts from time-series models. Covering a diversified sample of 261 firms with a 1980-1982 post-sample estimation period, Guerard (1987) shows that security analysts' forecasts can be improved when combined with time-series forecasts. Results indicate that the mean square error of analysts' forecasts may be decreased by combining analyst and univariate time-series model forecasts in constrained and unconstrained OLS regression models. In a sample of four forecast horizons, Lobo (1992) investigates the effects of disagreement in financial analysts' earnings forecasts on the accuracy of analysts' forecasts, forecasts generated by time-series models, and the combined forecasts. The empirical results indicate that, while analysts do better than any of the three other time-series models studied, simple combinations of analysts' and time series forecasts are superior to forecasts from either source in every horizon.

Bias in Analysts' Earnings Forecasts

In spite of the relative accuracy of analysts' earnings forecasts compared to those generated by statistical models, numerous research studies suggest that analysts' forecasts of earnings per share tend to be optimistically biased. An understanding of the nature of bias in analysts' earnings forecasts is crucial due to the widely documented relationship between earnings surprises and stock price changes.

Affleck-Graves, Davis and Mendenhall (1990) provide an explanation for analysts' superiority as well as possible reason for bias. According to Affleck-Graves, et al. (1) analysts use more recent information, (2) analysts use information not included in the time series of past earnings, and (3) the analyst bias observed may be due to the use of judgmental heuristics.

In an analysis based on ten years of data, Dowen (1989) finds that analysts systematically overestimate firms' future earnings per share. The study shows that (1) the number of analysts following a firm is positively correlated with firm size and forecast error, and (2) firm size is positively correlated with forecast error.

According to the cognitive bias theory, the market should form overly pessimistic (optimistic) expectations of future earnings for those stocks that have experienced sharp share price declines (increases). Klein (1990) examines revisions and errors in analysts' forecasts during and after the portfolio formation period in order to distinguish between the cognitive bias theory and a rational expectations hypothesis. The evidence does not support the cognitive bias theory. Klein concludes that analysts do not underpredict earnings following large stock price declines. Rather, they remain overly optimistic about future earnings.

Various studies have focused on specific circumstances where an optimistic bias is observed. Francis and Philbrick (1993) examine analysts' earnings forecasts as products of an environment in which analysts forecast earnings and maintain management relations. Their study finds that analysts' earnings forecasts are optimistic, on average, and are more optimistic for stocks with sell or hold recommendations than for those with buy recommendations.

Dugar and Nathan (1995) present evidence that financial analysts employed by brokerage firms that provide investment banking services to a company are optimistic, relative to other analysts, in their earnings forecasts and investment recommendations.[1] The authors hypothesize that market participants rely relatively less on forecasts of the investment banker analysts in forming their expectations if information regarding the investment banking relationship of brokerage firms is publicly available.

From a different perspective, Francis and Philbrick (1992) conclude that Value Line analysts make over-optimistic forecasts although they are not on the supply side. They explain this evidence by suggesting that analysts are pressured by the managers to produce optimistic forecasts in order to continue to share management's asymmetric information. Interpreting the finding that analysts' earnings estimates are overly optimistic after stock price declines, Klein (1990) provides a similar interpretation that managers whose firms face adverse conditions pressure analysts to make overly optimistic forecasts.

Huberts and Fuller (1995) find that current forecasts of earnings are excessively optimistic for companies whose earnings have been hard to predict in the past.

Trueman (1990) suggests that analysts may be reluctant to revise their forecasts upon receipt of new information because of the negative signal such a revision provides concerning the accuracy of their prior forecasts. As a result, the accuracy of analysts' observed forecasts may understate the precision of their actual information. In a different study, Trueman (1994) provides evidence on a tendency for analysts to release

---

[1] Popular press frequently reports cases of overoptimism by sell-side analysts (see Dorfman (1991) and Sicinolfi (1992, 1995)).

information close to prior expectations than is appropriate, given their information. Trueman also argues that analysts exhibit herding behavior, whereby they release forecasts similar to those previously announced by other analysts, even when this is not justified by their information.

Chapter 2 is motivated by the research findings that (1) analysts outperform time-series models due to their ability to use a much broader set of information not included in the time series of past earnings, a human advantage, and (2) although they generate superior forecasts than the time-series models, analysts consistently overestimate earnings per share. In light of these findings, it can be argued that if analysts use their advantage selectively depending on their incentive structure and neglect certain negative information while forming their expectations, this might result in systematic optimistic biases that are reflected in their forecasts. For example, a sell-side analyst or an analyst who wants to maintain good management relations may report optimistic forecasts even though he has access to information that shows the opposite. Chapter 2 further investigates the nature of bias in analysts' consensus forecasts of earnings per share.

Recent research studies suggest that models combining analysts' forecasts with time-series models result in better forecast accuracy. These findings and results of Chapter 2 that analysts systematically over-estimate negative earnings motivate Chapter 4 where analysts forecasts are combined with firm-specific pre-announcement information to better estimate the sign of actual earnings.

Chapter 3 and 5 develop methods of forecast adjustment motivated by findings in research that (1) earnings and earnings forecasts are closely associated with stock price changes, (2) the accuracy of forecasts is of paramount importance because, if detected, systematic biases in forecasts can be utilized to devise trading rules to earn abnormal returns.

Chapter 2

DO ANALYSTS FORECAST NEGATIVE EARNINGS OUTCOMES DIFFERENTLY THAN POSITIVE EARNINGS OUTCOMES?

Forecast Bias

In his review of the academic research on security analysts' forecasts of earnings, Brown (1993) concludes that analysts' earnings forecasts are positively biased.[1] Brown leaves open the question of whether or not this forecast bias is intentional. In search of an explanation for this over-optimism, researchers have focused on those companies that: 1) use the analyst's employer to underwrite their securities (Lin and McNichols (1991)), 2) use the analyst's employer as an investment banker (Dugar and Nathan (1995)), and 3) are in financial distress (Moses (1990) and Klein (1990)). Each of these studies finds that analysts' forecasts for these firms are positively biased. An important aspect of such studies is that they pool the forecast data assuming that the forecast error is orthogonal to the forecasts. With few exceptions, research on forecast bias has treated the negative and positive forecasts within the same pool. One exception is the Francis and Philbrick (1993) study, in which the authors conclude that analysts' earnings forecasts are more optimistic for sell and for hold stocks than for buy stocks. Motivated by the anomaly manifested in Figure 1, this chapter investigates whether or not analysts forecast negative earnings

[1] Brown (1996) points out that on average, analysts' forecasts have been negatively biased in recent quarters.

differently from positive earnings. This inquiry has a potentially important contribution to the literature, since the previous findings of forecast optimism may be driven by the positive bias in forecasts of negative earnings.

This study uses Lynch, Jones and Ryan's Institutional Brokers Estimate System (I/B/E/S) data base of individual security analysts' annual earnings forecasts for the period 1984-1991. The I/B/E/S detail tape contains individual forecasts of annual primary earnings per share before extraordinary items. These earnings forecasts were matched with the corresponding earnings figures from Standard & Poor's Compustat Full-Coverage database.[1] Observations were kept if the following conditions were satisfied:

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

Forecasted and actual earnings per share for each firm were divided by beginning-of-year share price in order to scale for cross-sectional differences in the level of earnings and share price. Hereafter, "earnings" and "EPS" refer to the earnings/price ratio.

Median consensus forecasts for each sample firm and year were constructed from the November forecasts. Median consensus forecasts were chosen over mean forecasts because of O'Brien's (1988) finding that median earnings forecasts exhibit the smallest

---

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

bias of competing consensus forecast measures. The filter on share price (> $2/share) eliminated 22 observations (about one-half of one percent of the sample). A large proportion of these were firms in financial distress with depressed stock prices and large negative earnings outcomes, for which earnings/price ratios are not meaningful. Table 2.1 shows the descriptive statistics of earnings per share and forecasts of earnings per share for each sample year from 1984 to 1991, as well as for the pooled sample period of 1984-91.

Figure 1 plots actual against expected annual earnings based on median consensus forecasts reported during November for a sample of 4250 observations over the period 1984-1991. A casual inspection of Figure 1 suggests that positive earnings outcomes tend to be clustered around a 45-degree line through the origin as one would expect of rational forecasts. The forecasts associated with negative earnings outcomes, on the other hand, are clearly over-optimistic. Indeed, rarely do negative earnings outcomes exceed the consensus forecast and fall above the 45-degree line.

Table 2.2 presents the percentage of cases where forecasts overestimate actual earnings on a year-by-year basis and categorized according to the sign of actual earnings (EPS) and the sign of the consensus forecast (FEPS). While forecasts of positive earnings outcomes do not appear to be inaccurate in any systematic way, forecasts of negative earnings over-estimate actual earnings in each of the sample years in Table 2.2. The northeast quadrant of Figure 1 corresponds to the positive-earnings, positive-forecast category (EPS > 0 and FEPS > 0) in the center of Table 2.2. The forecasts in this quadrant appear to be unbiased and efficient. In contrast, over 75% of forecasts in the southwest quadrant (EPS < 0 and FEPS < 0) are over-optimistic. The ray of observations scattered along the y-axis in the southeast quadrant of Figure 1 reflects a tendency of analysts to report positive forecasts even when actual earnings are negative.

The northwest and southeast quadrants of Figure 1 are also asymmetric. In only a handful of cases do analysts make the error of reporting negative forecasts when actual earnings turn out to be positive as in the northwest quadrant. Of the 258 negative forecasts, only fourteen earnings outcomes (or about 5% of the sample) are positive. Many more analysts make the opposite error of forecasting positive earnings when actual earnings turn out to be negative. As many as 206 of the 450 forecasts associated with negative earnings outcomes are positive and about 87% of these forecasts are higher than actual earnings. Negative forecasts as a whole over-estimate actual earnings 71.71% of the time.

Forecast Bias and Firm Size

In this section I investigate whether firm size (proxied by the market value of equity) is a factor in forecast bias. The sample is divided into three size groups following the methodology of Atiase (1985). The first size group (relatively large companies) includes companies with market values ranging between $300 million-$95,697 million. Market values of the second (relatively medium size companies) and third size (relatively small companies) groups range between $50 million-$300 million and $3 million-$50 million, respectively. Figures 2.1 through 2.3 plot actual earnings against the median consensus forecasts for each size group. Tables 2.3 through 2.5, which are divided into quadrants according to the signs of EPS and FEPS, show the percentage of earnings overestimated, average bias, and average earnings per share in each quadrant for each size group.

Regardless of the firm size forecasts of negative earnings appear to be over-optimistic in these figures and tables. Analysts overestimate negative earnings 88.76% of the time for larger firms that constitute the first size group. In the second size group, the percentage of forecasts overestimating the negative earnings is 82.79%. Analysts do a relatively better job forecasting the positive earnings of firms in the first and second size groups. When the forecasts and actual earnings are both positive (northeast quadrant), forecasts are clustered around the 45-degree line and the percentage of optimistic forecasts is close to 50% (48.88% for the first size group and 53.40% for the second size group). These results suggest that the phenomenon of over-optimism in forecasting negative earnings is true for larger firms. Analysts also overestimate the negative earnings of the smallest firms in the sample that constitute the third size group. The percentage of earnings over-estimated is 86.15% in this case. The northeast quadrant of Figure 4 reveals that analysts also appear to be more optimistic when they forecast positive earnings of the small firms. For the pooled sample of 1984-91, the percentage of forecasts overestimating the actual earnings in this quadrant is 60% for small firms, which is significantly larger than for the other size groups. This finding is consistent with previous research documenting a correlation between size and forecast error (Dowen (1989)).

Is the Forecast Bias Symmetric?

To examine symmetry in negative and positive earnings forecasts the following null hypothesis is formed: "Given that there exists a forecasts error, this error is independent of the size of forecasts" To test this hypothesis, the pooled sample of 1984-91 is divided into deciles with respect to the size of the earnings forecasts.[2] Forecast error and the percentage of forecasts that overestimate actual earnings are calculated for each decile. Then, forecast error and mean square forecast error for corresponding top and bottom deciles are compared using a paired sample t-test and analysis of variance. Results of the analysis are presented in Table 2.6.

As is evident in Table 2.6, there is a clear asymmetry in forecast errors. Forecasts that are larger in magnitude have smaller error. The bottom decile has the largest forecast error (-.050159) and the forecast error is significantly different from zero. The percentage of forecasts that overestimate actual earnings is also the largest (65.73%) in the bottom decile of forecasts. A binomial test rejects the null hypothesis that the proportion of optimistic forecasts is 50%. The percentage of forecasts overestimating actual earnings monotonically decreases to 56.67% as the bottom category is widened to include the next four deciles. Mean forecast error in the bottom half of forecasts (-.019323) is smaller than in the bottom decile but still statistically significant at 5%. The negative sign of the error indicates that average forecast exceeds actual earnings. The proportion of optimistic forecasts is close to 50% in the top decile. In fact, the null hypothesis that the proportion is equal to 50% cannot be rejected. Although significantly different from zero, the mean

---

2 Size of the forecasts instead of the actual earnings is used in forming the decile groups because the actual earnings numbers are not known *ex ante*.

forecast error is smaller than that of the bottom decile. A paired sample t-test test rejects the null hypothesis (with 5% significance) that the difference between mean errors in the top and the bottom deciles are equal. In each paired sample the mean error of the bottom group of forecasts is significantly greater than that of the top group. Also, mean square errors in the bottom groups are significantly greater than mean square error in the top groups. Analysis of variance rejects the null hypothesis (with 5% significance) that the mean square errors are equal.

In summary: (1) analysts' forecast errors are asymmetric with respect to the size of the forecasts, (2) the magnitude of the forecast error increases as the magnitude of the forecast decreases, and (3) the percentage of optimistic forecasts increases as the forecasts fall below the average.

A Test of Structural Change in the Forecasts

This section investigates whether the evidence of asymmetry in forecast bias is an indication of structural change in the analysts' prediction of earnings per share. In a broad interpretation, Poirier (1976) states that structural change occurs whenever the parameters of an economic model change a "small" number of times in response to forces within or outside the model. In formulating this concept of structural change, Poirier advocates the use of spline functions as an alternative to dummy variable representations. His focus on spline functions is based on an assumption of continuity in economic models. A spline function is a piecewise function in which pieces are joined together in a smooth fashion.

Pieces of the spline are commonly chosen to be polynomials. A smoothness condition is assumed for the spline function and its derivative.

My attempt to fit a spline function to the relationship of earnings forecasts and actual earnings is motivated by the previous section's finding that forecasts become more accurate as their magnitude increases. If, in fact, analysts shy away from predicting poor performance, their forecasts are expected to reflect this as a structural change. Thus, the objective of this section is to test the existence of structural change empirically with a linear spline model.

The mathematical formulation of a linear spline is as follows:[3]

Let the set $\Delta = \{ \bar{x}_1 < \bar{x}_2 < ... < \bar{x}_{k-1} \}$ of abscissa values be referred to as a mesh and the k-1 individual points $\bar{x}_j \{j = 1, 2, ..., k - 1\}$ as interior knots or simply knots. Then the dependent variable y is a linear spline $S_\Delta(x)$ over Δ if and only if y is a continuous piecewise linear function in x consisting of k segments defined over k intervals $(-\infty, \bar{x}_1]$, $[\bar{x}_1, \bar{x}_2], ..., [\bar{x}_{k-1}, \infty)$, respectively.

In order to formulate the model, I use the following parametrization suggested by Poirier and referred to as an elementary spline function by Barrondale and Young (1966):

$$S_\Delta(x) = \beta_0 + \beta_1 w_1 + \beta_2 w_2 + ... + \beta_k w_k$$

where

$w_1 \;=\; x$

$wj \;=\; (x - \bar{x}_{j-1})_+ = \max(x - \bar{x}_{j-1}, 0)$

$\bar{x}_{j-1} \;=\;$ j - 1'th interior knot

$\beta_1 \;=\;$ slope of the spline over the first interval

---

[3] This formulation and its discussion is taken from pages 9-11 of Poirier's 1976 book entitled *"The Econometrics of Structural Change"*.

β_j = the change in slope from interval (j-1) to j, j = 2, 3, 4, ..., k

The first derivative of the above linear spline is a step function with jump discontinuities equal to β_j (j = 2, 3, 4, ..., k) at the knots. The slope in the jth segment is ($\beta_1 + \beta_2 + \ldots \beta_j$). The t-statistic corresponding to β_j (j = 2, 3, 4, ..., k) indicates the statistical significance of the change in slope over intervals (j-1) and j. If β_j is statistically nonzero, then this implies structural change occurring at $\bar{x}_{j-1}$.

In order to formulate the relationship of forecasts to actual earnings as a linear spline function, I use the following representation:

$$S_\Delta(FEPS) = \beta_0 + \beta_1 \,.\, w_1 + \beta_2 \,.\, w_2$$

where

w_1 = FEPS (forecast of earnings per share)
w_2 = max(FEPS - $\overline{FEPS}_1$, 0)
$\overline{FEPS}_1$ = the interior knot (point of structural change)
β_1 = slope of the spline over the first interval
β_2 = the change in slope from interval 1 to 2

Estimating the parameters of this spline function involves applying the method of linear multiple regression. However, the exact location of the interior knot is not known *a priori*. Thus, the above spline model is not defined unless the values of the transformed variable w_2 are known. In order to address this issue, I apply the following methodology. Starting with an initial value of -2.0 (which is the minimum value of the forecast sample) for $\overline{FEPS}_1$, the above regression is iteratively run by adding an infinitesimal incremental ε term of 0.0025 to the initial value of $\overline{FEPS}_1$ after each iteration. The value of $\overline{FEPS}_1$ that maximizes the r^2 of the regression is taken as the point of structural change. Figure

2.4 plots r^2 values of regressions against the values of $\overline{FEPS}_1$. The value of r^2 is maximized (0.7148) when the magnitude of $\overline{FEPS}_1$ is -0.8625. This point, which yields the best fit for the spline function, is a good candidate for the point of structural change.

Parameter estimates of the regression equation are as follows:

$$S_\Delta(FEPS) = \underset{(-15.26)}{-0.685223} + \underset{(9.24)}{0.415010} \,.\, w_1 + \underset{(14.84)}{0.762667} \,.\, w_2$$

where

$$w_1 = \text{FEPS (forecast of earnings per share)}$$
$$w_2 = \max(\text{FEPS} - (-0.8625), 0)$$

As the t-statistics in parentheses indicate, the coefficients of w_1 and w_2 are both significant at a 5% level. The coefficient of w_1 which represents the slope before the interior knot has a value of 0.415010. The slope then changes significantly at the interior knot by an amount 0.762667, as indicated by the coefficient of w_2. Figure 2.5 presents a graphical representation of the spline function. Although this suggests a point of structural change in the forecasts, this point lacks a clear-cut economic rationale. This may be attributed to the existence of a bimodal distribution, possibly with multiple variances.

Forecast Bias and the Sign of Forecasts

This section investigates my initial question of whether or not predictions of negative earnings are different from predictions of positive earnings. The null hypothesis is that analysts' earnings forecasts are accurate and rational, and therefore should lie on a

45-degree line drawn through the origin. In order to test this hypothesis, the following OLS regressions are run:

$$EPS_{it} = a_t + b_t \cdot FEPS_{it} + e_{it} \qquad \forall\ FEPS$$

$$EPS_{it} = a_t + b_t \cdot FEPS_{it} + e_{it} \qquad \forall\ FEPS < 0$$

$$EPS_{it} = a_t + b_t \cdot FEPS_{it} + e_{it} \qquad \forall\ FEPS > 0$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = earnings forecast per share for firm i and fiscal year t

The first regression uses all observations. The second and third regressions use observations from the negative FEPS sample and the positive FEPS sample separately in order to further examine whether predictions of negative earnings are different than those of positive earnings.

The results are summarized in Table 2.7. The regression that uses the sample of all observations yields a negative intercept that is significantly different from zero (-.018979) using a two-tailed t-test and a slope that is greater than one (1.064125). This suggests that forecasts are biased, inefficient, or both.[4]

For the pooled sample of 1984-91, the intercept term for the negative FEPS sample is significantly different from zero (-0.082138) and the slope is less than one (0.953991). The intercept term is negative in each year and is statistically significant in five of the eight annual samples. This finding of a negative intercept points to an

---

4 Appendix presents a discussion of decomposition of mean square forecast errors into bias and inefficiency components.

optimistic bias in negative forecasts. The slope term is significantly different from one in four out of eight sample years.

In the case of positive FEPS, the sample pooled over 1984 to 1991 has a slope that is less than one (.958910). The intercept term is close to, but significantly different from, zero (-.007279). This shows that positive forecasts are also optimistic, although this optimism may be driven by the positive forecasts of negative earnings in the southeast quadrant of Figure 1. An investigation of the annual samples reveals that the negative intercept term is significantly different from zero in only three of the eight years.

To summarize, for the positive earnings sample, the regression line of actual earnings versus earnings forecasts is found to have an intercept different from zero and a slope different from one. The intercept term is significantly non-zero for the negative forecasts sample. These results indicate that negative earnings forecasts are optimistically biased and that positive forecasts are biased and inefficient in the pooled sample. Regression parameters in the negative and positive FEPS samples differ from each other, as well as from the theoretical relationship between actual EPS and forecast EPS that is characterized by a 45-degree line passing through the origin.

Regressions are also run by imposing a no-intercept restriction using each year from 1984 to 1991 as well as the pooled sample of 1984-91. The regressions are:

$$EPS_{it} = b_t \,.\, FEPS_{it} + e_{it} \qquad \forall \text{ FEPS}$$

$$EPS_{it} = b_t \,.\, FEPS_{it} + e_{it} \qquad \forall \text{ FEPS} < 0$$

$$EPS_{it} = b_t \,.\, FEPS_{it} + e_{it} \qquad \forall \text{ FEPS} > 0$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t

$FEPS_{it}$ = earnings forecast per share for firm i and fiscal year t

The motive behind this inquiry is simply to compare the empirical regression line with the theoretical (or ideal) line that passes through the origin at a 45-degree angle. Results of these regressions are summarized in Table 2.8. The slope term for the negative FEPS sample is greater than one (1.088715) and statistically significant in the pooled sample of 1994-91. Regressions using the annual samples of negative FEPS result in slope terms that are greater than one in six of the eight sample years. In comparison to the theoretical line passing through the origin, this is a further indication of overoptimism in the negative earnings forecasts. On the other hand the regression slope for the positive FEPS sample is less than one (.890330) in the pooled sample as well as in each of the individual years. Results of these regressions further support my finding that predictions of negative EPS and positive EPS differ from each other.

Summary

In this chapter, analysts median consensus forecasts of earnings per share are evaluated for forecast bias in a sample drawn from 1984 through 1994. Negative forecasts of earnings per share are found to be over-optimistic. Analysts overestimate earnings 71.71% of the time when they report negative forecasts. Out of the 258 negative forecasts, only 14 correspond to a positive earnings outcome (.0036% of all the positive earnings sample). Positive forecasts of earnings per share paint a different picture. Positive forecasts overestimate actual earnings 54.19% of the time. In the case of positive forecasts of positive earnings, analysts are over-optimistic only 50.50% of the time. Only

5.16% of these positive forecasts are associated with earnings outcomes that turn out negative.

Negative earnings forecasts are more optimistic than positive forecasts, with an average bias of (-0.074176) in the pooled sample of 1984-91. Positive forecasts have an average bias of (-0.010772) in the same sample. Bias is statistically significant and reflects optimism in every year from 1984 to 1991 for both negative and positive forecast samples.

The empirical relationship of forecasts and actual earnings deviates from the theoretical relation of a 45-degree line. This deviation is most apparent in the form of large optimistic biases for the negative forecast sample. Regressions using the positive forecast sample result in parameter estimates that reflect bias and inefficiency.

The findings in this chapter suggest that the over-optimism is mostly driven by forecasts of companies with negative earnings. The percentage of earnings overestimated is 50.32% and average bias is (-0.002439) in the positive earnings sample. In the negative earnings sample, analysts are overoptimistic 86.69% of the time with an average bias of (-0.117492).

The main conclusions of the chapter are that (1) forecasts are on average optimistic, (2) bias in negative forecasts is more pronounced than bias in positive forecasts, (3) optimistic bias in forecasts seem to be driven by firms with negative earnings, and (4) positive forecasts that overestimate negative earnings are a major source of forecast error.

These observations form the motivation for the remaining chapters. In particular Chapter 3 investigates methods to improve the accuracy of negative earnings forecasts. Chapters 4 develops a methodology to predict the sign of actual earnings. Chapter 5 corrects positive earnings forecasts that are likely to be associated with negative earnings.

Figure 2.1. EPS Versus FEPS For Relatively Large Firms

The group of "relatively large firms" (first size group) includes firms with market values greater than $300 million in the pooled sample period of 1984-91.

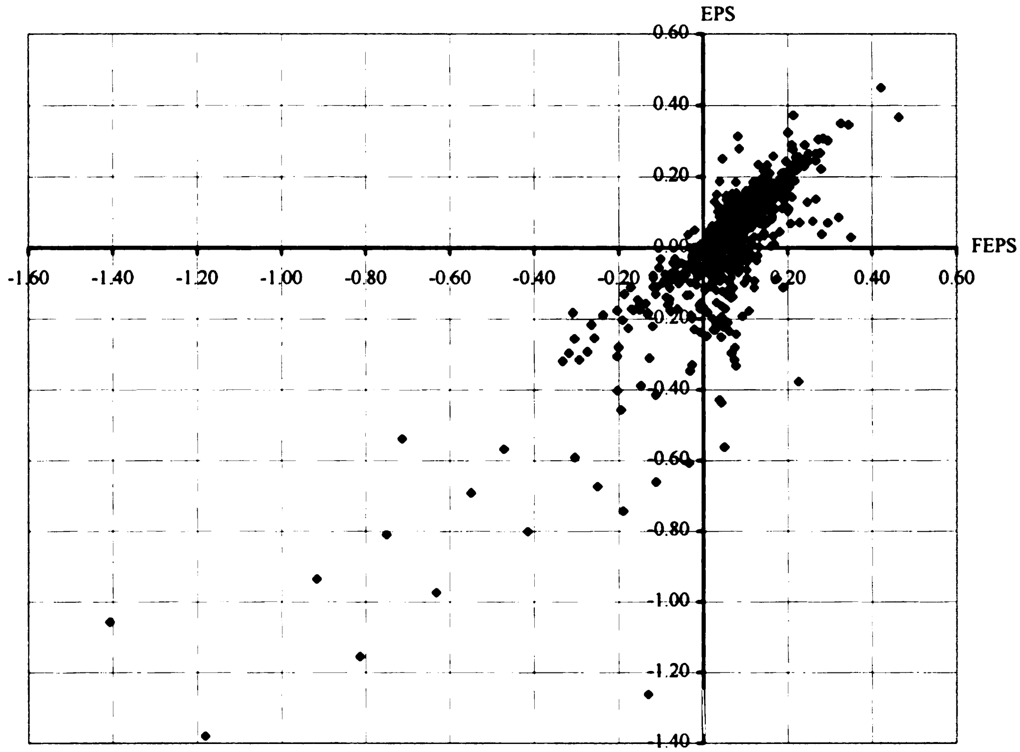


Figure 2.2. EPS Versus FEPS For Relatively Medium-Size Firms

The group of "relatively medium-size firms" (second size group) includes firms with market values greater than \$50 and less than \$300 million in the pooled sample period of 1984-91.

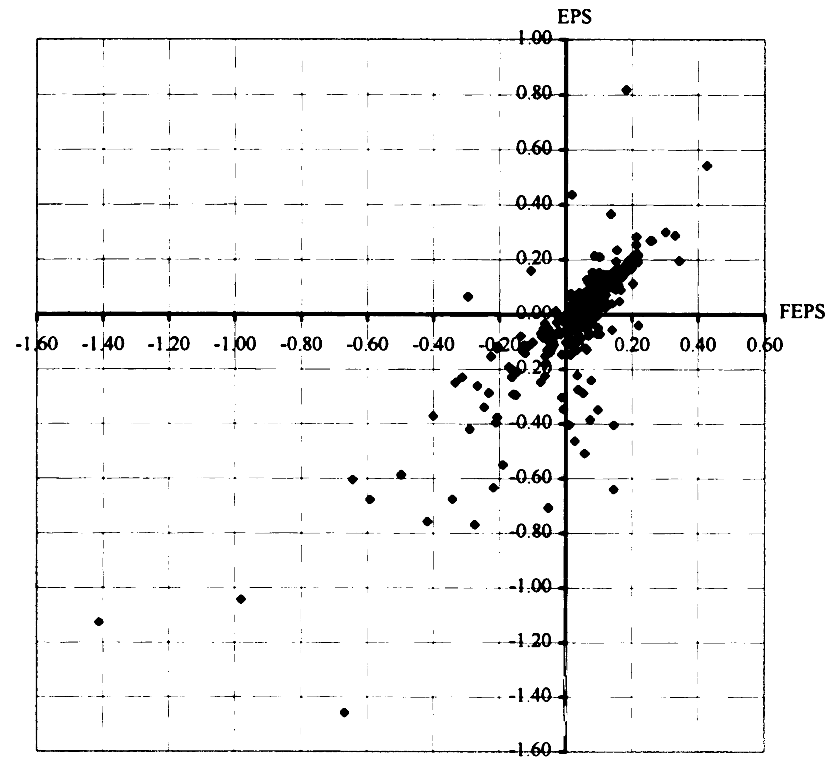


Figure 2.3. EPS Versus FEPS For Relatively Small Firms

The group of "relatively small firms" (third size group) includes firms with market values less than $50 million in the pooled sample period of 1984-91.

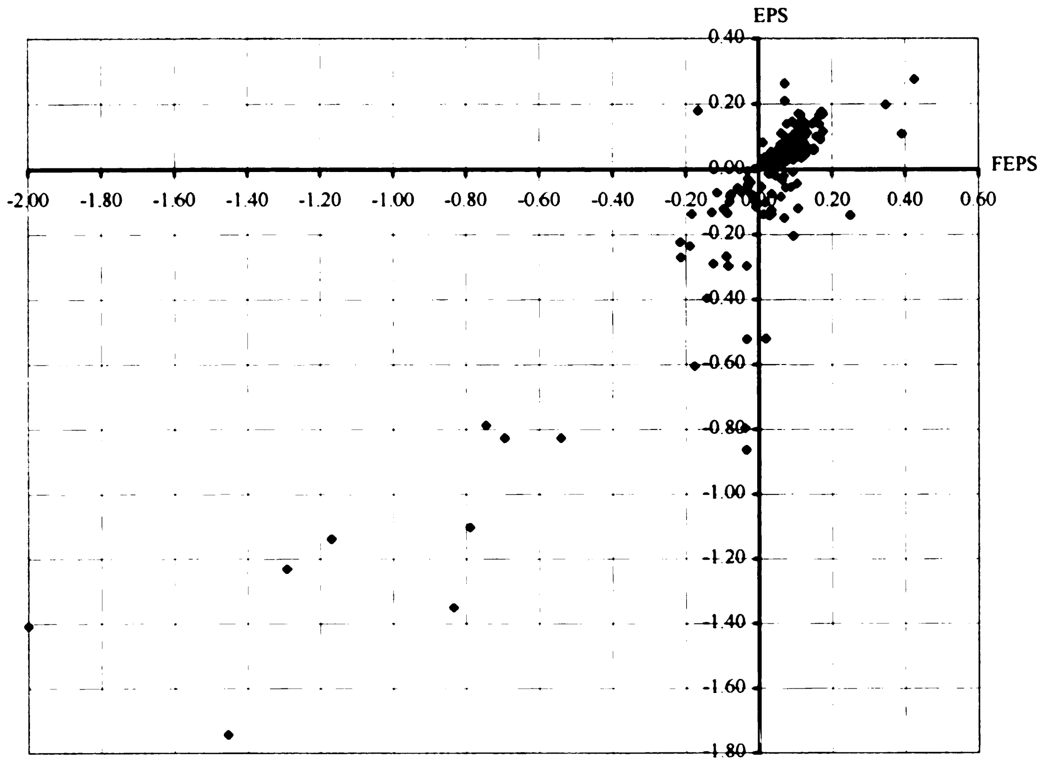


Figure 2.4. Obtaining the Point of Structural Change in Forecasts

The following regression is run iteratively. $\overline{FEPS_I}$ is assigned an initial value of -2.0, and an infinitesimal ε term of 0.0025 is added to its value at each iteration:

$$S_\Delta(FEPS) = \beta_0 + \beta_1 \,.\, w_1 + \beta_2 \,.\, w_2$$

where

w_1 = FEPS (forecast of earnings per share)
w_2 = max(FEPS - $\overline{FEPS}_I$, 0)
$\overline{FEPS_I}$ = the interior knot (point of structural change)
β_1 = slope of the spline over the first interval
β_2 = the change in slope from interval 1 to 2

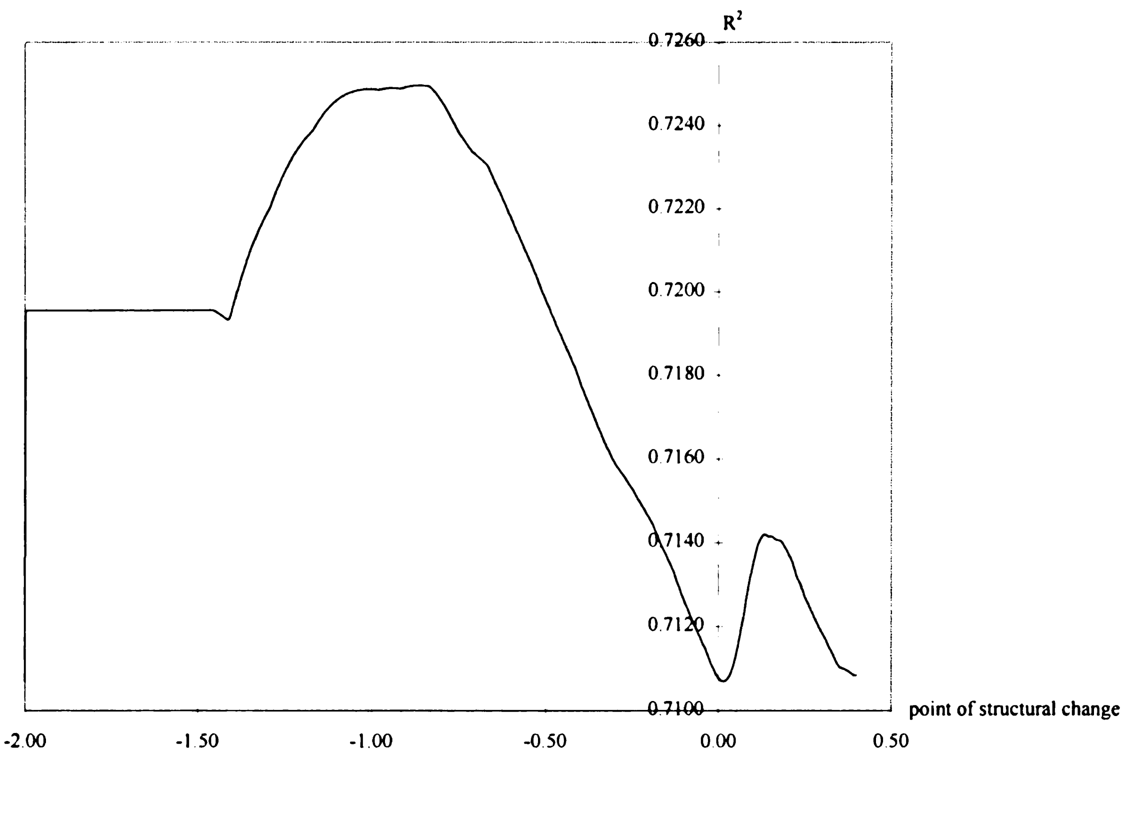


Figure 2.5. Structural Change in Forecasts Represented by a Linear Spline

Parameter estimates of the linear spline function are as follows:

$$S_{\Delta}(FEPS) = -0.685223 + 0.415010 \,.\, w_1 + 0.762667 \,.\, w_2$$

where

w_1 = FEPS (forecast of earnings per share)

w_2 = max (FEPS - (-0.8625), 0)

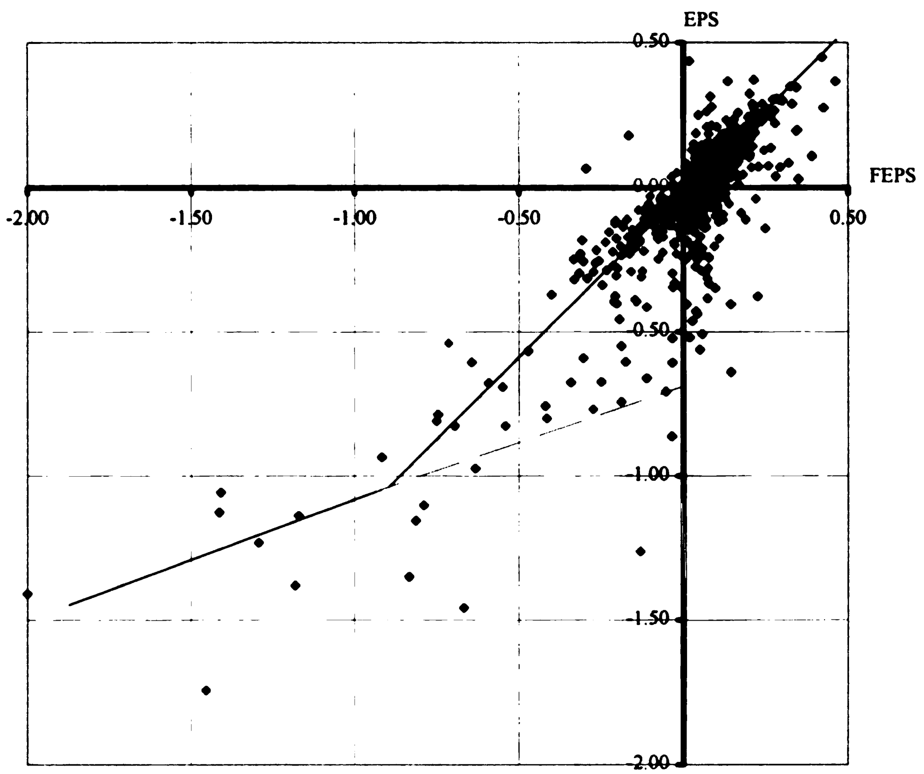


Table 2.1. Descriptive Statistics: Actual Earnings (EPS) and Analysts' Forecasts of Earnings (FEPS)

Descriptive statistics of annual earnings per share (EPS) and analysts' forecasts of annual earnings per share (FEPS)are reported for samples from each year as well as the pooled sample from 1984 to 1991. Normality of both variables are tested using the Lilliefors test statistic.

	1984	1985	1986	1987	1988	1989	1990	1991	1984-91
EPS									
number of observations	482	469	533	558	586	507	635	480	4250
mean	0.0725	0.0550	0.0361	0.0585	0.0754	0.0555	0.0476	0.0241	0.0533
standard deviation	0.1362	0.0939	0.1402	0.1339	0.1051	0.1051	0.1675	0.1179	0.1270
minimum	-1.4086	-0.7962	-1.4578	-1.1552	-1.2314	-1.2314	-1.7432	-1.1271	-1.7432
maximum	0.4495	0.3018	0.3005	0.4365	0.3671	0.3671	0.8182	0.2549	0.8182
skewness	-5.7443	-3.9495	-5.8393	-5.0821	-5.9593	-5.9593	-5.4606	-4.7099	-5.6052
kurtosis	48.8156	26.3818	47.6995	35.9135	58.6285	58.6285	44.1280	31.3470	50.0106
Lilliefors test statistic	0.2570	0.1966	0.2793	0.2706	0.2238	0.2238	0.3003	0.2570	0.2497
. p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FEPS									
number of observations	482	469	533	558	586	507	635	480	4250
mean	0.0852	0.0734	0.0546	0.0666	0.0826	0.0665	0.0693	0.0437	0.0680
standard deviation	0.1319	0.0539	0.1056	0.1091	0.0656	0.0908	0.1218	0.0906	0.1006
minimum	-2.0000	-0.2495	-1.4068	-0.9164	-0.6435	-1.2914	-1.4526	-1.4118	-2.0000
maximum	0.4633	0.2949	0.3212	0.3263	0.3437	0.3317	0.4270	0.2132	0.4633
skewness	-10.1968	-0.9330	-7.4524	-5.3222	-3.0400	-7.9492	-7.1399	-9.5371	-8.0470
kurtosis	147.1030	7.8564	83.8218	38.1171	29.6968	106.0527	71.2057	140.7255	110.3749
Lilliefors test statistic	0.2668	0.1127	0.2665	0.2537	0.1480	0.2199	0.2799	0.2630	0.2366
. p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 2.2. Predictions of Earnings Per Share

		FEPS<0				FEPS>=0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >=0	1984	2	0.00	0.007906	0.033762	443	53.27	0.100256	[a]-0.003232	445	53.03	0.099841	[a]-0.003066
	1985	0	0.00			420	53.81	0.077877	[a]-0.004030	420	53.81	0.077877	[a]-0.004030
	1986	1	0.00	0.050331	0.070199	457	47.92	0.073917	[a]-0.002453	458	47.82	0.073865	[a]-0.002294
	1987	3	0.00	0.078311	0.221718	510	47.45	0.086444	-0.001119	513	47.17	0.086396	-0.000184
	1988	1	0.00	0.010526	0.013158	540	44.63	0.091539	-0.001144	541	44.55	0.091389	-0.001117
	1989	1	0.00	0.000779	0.032409	457	51.20	0.077631	[a]-0.003195	458	51.09	0.077464	[a]-0.003117
	1990	3	0.00	0.063812	0.124655	461	55.61	0.085385	[a]-0.004017	564	55.32	0.085270	-0.003333
	1991	3	0.00	0.017386	0.033043	398	50.75	0.059805	[a]-0.003625	401	50.37	0.059487	[a]-0.003351
	All	14	0.00	0.039712	[a]0.094396	3786	50.50	0.082303	[a]-0.002797	3800	50.32	0.082146	[a]-0.002439
EPS<0	1984	21	80.95	-0.371333	-0.101611	16	100.00	-0.106710	[a]-0.164902	37	89.19	-0.256901	[a]-0.128980
	1985	20	85.00	-0.201959	[a]-0.120343	29	100.00	-0.098461	[a]-0.154834	49	93.88	-0.140705	[a]-0.140756
	1986	40	60.00	-0.261952	[a]-0.081119	35	100.00	-0.118035	[a]-0.159977	75	78.67	-0.194791	[a]-0.117919
	1987	33	84.85	-0.311831	[a]-0.080461	12	100.00	-0.115261	[a]-0.162730	45	88.89	-0.259412	[a]-0.102400
	1988	25	72.00	-0.157202	[a]-0.043477	20	100.00	-0.066905	[a]-0.128203	45	84.44	-0.117070	[a]-0.081133
	1989	30	80.00	-0.189943	[a]-0.044111	19	100.00	-0.086157	[a]-0.147544	49	87.76	-0.149700	[a]-0.084218
	1990	32	81.25	-0.423199	[a]-0.153461	39	100.00	-0.110759	[a]-0.178691	71	91.55	-0.251577	[a]-0.167320
	1991	43	72.09	-0.199233	[a]-0.062728	36	100.00	-0.103797	[a]-0.149874	79	84.81	-0.155743	[a]-0.102440
	All	244	75.82	-0.263702	[a]-0.083848	206	100.00	-0.102468	[a]-0.157342	450	86.89	-0.189893	[a]-0.117492
TOTAL	1984	23	73.91	-0.338356	-0.089840	459	54.90	0.093042	[a]-0.008867	482	55.81	0.072456	[a]-0.012731
	1985	20	85.00	-0.201959	[a]-0.120343	449	56.79	0.066487	[a]-0.013770	469	58.00	0.055040	[a]-0.018315
	1986	41	58.54	-0.254335	[a]-0.077428	492	51.63	0.060262	[a]-0.013659	533	52.16	0.036062	[a]-0.018564
	1987	36	77.78	-0.279319	[a]-0.055280	522	48.66	0.081807	[a]-0.004834	558	50.54	0.058508	[a]-0.008089
	1988	26	69.23	-0.150751	-0.041299	560	46.61	0.085880	[a]-0.005681	586	47.61	0.075381	[a]-0.007262
	1989	31	77.42	-0.183791	[a]-0.041643	476	53.15	0.071094	[a]-0.008957	507	54.64	0.055509	[a]-0.010956
	1990	35	74.28	-0.381456	[a]-0.129622	600	40.17	0.072636	[a]-0.015371	635	59.37	0.047607	[a]-0.021668
	1991	46	67.39	-0.186106	[a]-0.056482	434	54.84	0.046234	[a]-0.015757	480	56.04	0.024064	[a]-0.019660
	All	258	71.71	-0.247238	[a]-0.074176	3992	53.06	0.072768	[a]-0.010772	4250	54.19	0.053342	[a]-0.014621

[a] The null hypothesis H_0 : (Average Bias) = 0 is rejected by a t-test at 5% level significance

Table 2.3. Predictions of Earnings Per Share For Relatively Large Firms

		FEPS<0				FEPS>0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >0	1984	1	0.00	0.002479	0.023807	287	51.57	0.103734	-0.002891	288	51.39	0.103382	-0.002798
	1985		0.00			315	52.70	0.080382	[a] -0.003982	315	52.70	0.080382	[a] -0.003982
	1986	1	0.00	0.050331	0.070199	335	45.07	0.075502	-0.001797	336	44.94	0.075427	-0.001583
	1987		0.00			378	46.83	0.087465	-0.000644	378	46.83	0.087465	-0.000644
	1988	1	0.00	0.010526	0.013158	401	42.39	0.096916	-0.000181	402	42.29	0.096701	-0.000148
	1989	1	0.00	0.000779	0.032409	350	50.00	0.078911	[a] -0.002795	351	49.86	0.078688	[a] -0.002695
	1990	1	0.00	0.010526	0.014737	428	54.91	0.083504	[a] -0.003624	429	54.78	0.083334	[a] -0.003581
	1991	3	0.00	0.017386	0.033043	358	49.16	0.059563	[a] -0.003445	361	48.75	0.059212	[a] -0.003142
	All	8	0.00	0.015850	[a] 0.031680	2852	49.02	0.083097	[a] -0.002372	2860	48.88	0.082909	[a] -0.002277
EPS<0	1984	10	100.00	-0.244030	[a] -0.153250	7	100.00	-0.141923	[a] -0.203999	17	100.00	-0.201986	[a] -0.174147
	1985	9	88.89	-0.225512	[a] -0.117981	21	100.00	-0.097416	[a] -0.154762	30	96.67	-0.135845	[a] -0.143728
	1986	15	53.33	0.296569	-0.067199	18	100.00	-0.116928	[a] -0.162077	33	78.79	0.071025	[a] -0.118951
	1987	14	85.71	-0.328355	[a] -0.057993	4	100.00	-0.096693	[a] -0.136139	18	88.89	-0.276875	[a] -0.075359
	1988	11	63.64	-0.093184	-0.021588	14	100.00	-0.064285	[a] -0.126765	25	84.00	-0.077001	[a] -0.080487
	1989	12	75.00	-0.109968	-0.016230	12	100.00	-0.058786	[a] -0.122108	24	87.50	-0.084377	[a] -0.069169
	1990	20	85.00	-0.334615	[a] -0.135183	25	100.00	-0.101233	[a] -0.170039	45	93.33	-0.204958	[a] -0.154547
	1991	36	75.00	-0.157881	[a] -0.053723	30	100.00	-0.082097	[a] -0.126341	66	86.36	-0.123434	[a] -0.086731
	All	127	77.17	-0.152276	[a] -0.074678	131	100.00	-0.092594	[a] -0.148253	258	88.76	-0.121972	[a] -0.112036
TOTAL	1984	11	90.91	-0.221620	[a] -0.137154	294	52.72	0.097885	[a] -0.007679	305	54.10	0.086362	[a] -0.012349
	1985	9	88.89	-0.225512	[a] -0.117981	336	55.65	0.069270	[a] -0.013406	345	56.52	0.061580	[a] -0.016134
	1986	16	50.00	0.281179	-0.058612	353	47.88	0.065690	[a] -0.009970	369	47.97	0.075033	[a] -0.012079
	1987	14	85.71	-0.328355	[a] -0.057993	382	47.38	0.085537	-0.003063	396	48.74	0.070904	[a] -0.004040
	1988	12	58.33	-0.084542	-0.018693	415	44.34	0.091478	[a] -0.004451	427	44.73	0.086531	[a] -0.004852
	1989	13	69.23	-0.101449	-0.012489	362	51.66	0.074346	[a] -0.006750	375	52.27	0.068252	[a] -0.006949
	1990	21	80.95	-0.318180	[a] -0.128044	453	57.40	0.073309	[a] -0.012808	474	58.44	0.055964	[a] -0.017913
	1991	39	69.23	-0.144399	[a] -0.047049	388	53.09	0.048610	[a] -0.012947	427	54.57	0.030981	[a] -0.016062
	All	135	72.59	-0.142313	[a] -0.068376	2983	51.26	0.075381	[a] -0.008778	3118	52.18	0.065956	[a] -0.011359

[a] The null hypothesis H_0 : (Average Bias) = 0 is rejected by a t-test at 5% level significance

Table 2.4. Predictions of Earnings Per Share For Relatively Medium-Size Firms

		FEPS<0				FEPS>0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >0	1984	1	0.00	0.013333	0.043636	120	56.67	0.096850	-0.002421	121	56.20	0.096160	-0.002040
	1985					90	54.44	0.073448	-0.003961	90	54.44	0.073448	-0.003961
	1986					94	55.32	0.072508	-0.004071	94	55.32	0.072508	-0.004071
	1987	3	0.00	0.078311	0.221718	101	40.59	0.085947	0.003220	104	39.42	0.085727	-0.009523
	1988					112	50.00	0.075941	[a] -0.003671	112	50.00	0.075941	-0.003671
	1989					86	56.98	0.072496	-0.005475	86	56.98	0.072496	-0.005475
	1990					109	58.72	0.089984	-0.000782	109	58.72	0.089984	-0.000782
	1991					33	63.64	0.064631	-0.003594	33	63.64	0.064631	-0.003594
	All	4	0.00	0.062067	0.177198	745	53.69	0.081087	-0.002403	749	53.40	0.080985	-0.001444
EPS<0	1984	6	66.67	-0.268498	-0.032589	6	100.00	-0.082312	[a] -0.141476	12	83.33	-0.175405	[a] -0.087033
	1985	5	100.00	-0.167572	-0.085031	5	100.00	-0.127960	-0.196025	10	100.00	-0.147766	[a] -0.140528
	1986	21	66.67	-0.229740	[a] -0.103811	9	100.00	-0.095008	[a] -0.121416	30	76.67	-0.189320	[a] -0.109093
	1987	9	66.67	-0.222196	-0.032137	4	100.00	-0.152643	-0.205357	13	76.92	-0.200795	[a] -0.085435
	1988	12	75.00	-0.220155	-0.068604	1	100.00	-0.066909	-0.099636	13	76.92	-0.208367	-0.070991
	1989	5	100.00	-0.193569	[a] -0.052226	5	100.00	-0.150488	-0.207472	10	100.00	-0.172029	[a] -0.129849
	1990	9	66.67	-0.350235	-0.107899	13	100.00	-0.133224	[a] -0.199034	22	86.36	-0.222001	[a] -0.161752
	1991	7	57.14	-0.411900	-0.109039	5	100.00	-0.254246	-0.320543	12	75.00	-0.346211	[a] -0.197166
	All	74	71.62	-0.255652	[a] -0.079847	48	100.00	-0.133788	[a] -0.188965	122	82.79	-0.207706	[a] -0.122779
TOTAL	1984	7	57.14	-0.228236	-0.021700	126	58.73	0.088318	[a] -0.009043	133	58.65	0.071658	[a] -0.009709
	1985	5	100.00	-0.167572	-0.085031	95	56.84	0.062848	[a] -0.014070	100	59.00	0.051327	[a] -0.017618
	1986	21	66.67	-0.229740	[a] -0.103811	103	59.22	0.057871	[a] -0.014324	124	60.48	0.009169	[a] -0.029479
	1987	12	50.00	-0.147069	0.031327	105	42.86	0.076858	-0.004726	117	43.59	0.053891	-0.001028
	1988	12	75.00	-0.220155	-0.068604	113	50.44	0.074677	[a] -0.004520	125	52.80	0.046373	[a] -0.010672
	1989	5	100.00	-0.193569	[a] -0.052226	91	59.34	0.060244	[a] -0.016574	96	61.46	0.047025	[a] -0.018413
	1990	9	66.67	-0.350235	-0.107899	122	63.11	0.066200	[a] -0.021907	131	63.36	0.037590	[a] -0.027815
	1991	7	57.14	-0.411900	-0.109039	38	68.42	0.022674	-0.045298	45	66.67	-0.044927	[a] -0.055213
	All	78	67.95	-0.239359	[a] -0.066665	793	56.49	0.068081	[a] -0.013696	871	57.52	0.040549	[a] -0.018439

[a] The null hypothesis H_0 : (Average Bias) = 0 is rejected by a t-test at 5% level significance

Table 2.5. Predictions of Earnings Per Share For Relatively Small Firms

		FEPS<0				FEPS>0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >0	1984					36	55.56	0.083882	-0.008650	36	55.56	0.083882	-0.008650
	1985					14	71.43	0.055547	-0.005569	14	71.43	0.055547	-0.005569
	1986					26	61.54	0.064247	-0.005264	26	61.54	0.064247	-0.005264
	1987					30	76.67	0.078119	[a] -0.019170	30	76.67	0.078119	[a] -0.019170
	1988					26	53.85	0.079329	-0.003638	26	53.85	0.079329	-0.003638
	1989					21	47.62	0.077326	-0.000532	21	47.62	0.077326	-0.000532
	1990	2	0.00	0.090455	0.179614	24	54.17	0.098040	-0.025727	26	50.00	0.097457	-0.009932
	1991					6	83.33	0.057290	-0.015496	6	83.33	0.057290	-0.015496
	All	2	0.00	0.090455	0.179614	183	60.66	0.077566	[a] -0.010478	185	60.00	0.077705	[a] -0.008423
EPS<0	1984	5	60.00	-0.749342	-0.081161	3	100.00	-0.073340	[a] -0.120525	8	75.00	-0.495841	-0.095923
	1985	6	66.67	-0.195258	-0.153314	3	100.00	-0.086686	-0.056608	9	77.78	-0.159085	-0.121079
	1986	4	50.00	-0.301255	-0.014184	5	100.00	-0.194255	[a] -0.277780	9	77.78	-0.241811	[a] -0.160626
	1987	10	100.00	-0.369367	[a] -0.155409	4	100.00	-0.096448	[a] -0.146693	14	100.00	-0.291390	[a] -0.152919
	1988	2	100.00	-0.131579	-0.013099	4	100.00	-0.067507	-0.147136	6	100.00	-0.088864	-0.102457
	1989	13	76.92	-0.262372	-0.066726	2	100.00	-0.089558	[a] -0.150338	15	80.00	-0.239330	-0.077874
	1990	3	100.00	-1.232653	[a] -0.411998	1	100.00	-0.056842	-0.130526	4	100.00	-0.938700	[a] -0.341630
	1991												
	All	43	79.07	-0.399746	[a] -0.117817	22	100.00	-0.106506	[a] -0.160310	65	86.15	-0.300495	[a] -0.132199
TOTAL	1984	5	60.00	-0.749342	-0.081161	39	58.97	0.071788	-0.017256	44	59.09	-0.021522	-0.024518
	1985	6	66.67	-0.195258	-0.153314	17	76.47	0.030447	-0.014576	23	73.91	-0.028440	-0.050768
	1986	4	50.00	-0.301255	-0.014184	31	67.74	0.022553	[a] -0.049218	35	65.71	-0.014454	[a] -0.045214
	1987	10	100.00	-0.369367	[a] -0.155409	34	79.41	0.057582	[a] -0.034173	44	84.09	-0.039452	[a] -0.061726
	1988	2	100.00	-0.131579	-0.013099	30	60.00	0.059751	-0.022771	32	62.50	0.047793	-0.022167
	1989	13	76.92	-0.262372	-0.066726	23	52.17	0.062814	-0.013559	36	61.11	-0.054614	-0.032758
	1990	5	60.00	-0.703410	-0.175353	25	56.00	0.091845	[a] -0.029919	30	56.67	-0.040698	-0.054158
	1991					6	83.33	0.057290	-0.015496	6	83.33	0.057290	-0.015496
	All	45	75.56	-0.104598	[a] -0.104598	205	64.88	0.057812	[a] -0.026558	250	66.80	-0.020627	[a] -0.040605

[a] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance

Table 2.6. Matched Pair Test of Symmetry in Forecast Errors

The pooled sample of 1984-91 is divided into deciles with respect to the size of the earnings forecasts. Forecast error and the percentage of forecasts that overestimate actual earnings are calculated for each decile. Then, forecast error and mean square forecast error for corresponding top and bottom deciles are compared using a paired sample t-test and analysis of variance. Numbers in parentheses denote to the p-value of a binomial test in the "% over", the value of the t-statistic in the "Mean error" and "Me_b - ME_t", and the value of the F-statistic in the MSE_b/MSE_t columns.

		Bottom group			Top group			Bottom vs Top group	
Bottom vs top forecasts	N	% over	Mean error (ME)	MSE	% over	Mean error (ME)	MSE	ME_b - ME_t	MSE_b/MSE_t
10%	426	65.73[a] (0.0000)	-.050159[b] (-7.07)	.023927	51.41 (0.5941)	-.020003 (-4.80)	.007770	-.030156 (-3.55)[c]	3.079359 (10.25)[d]
20%	852	60.56[a] (0.0000)	-.035751[b] (-8.95)	.014872	51.52 (0.3917)	-.013393 (-5.97)	.004463	-.022358 (-4.84)[c]	3.332288 (15.63)[d]
30%	1278	58.61[a] (0.0000)	-.026796[b] (-9.61)	.010651	51.41 (0.4859)	-.010778 (-6.91)	.003221	-.016018 (-4.97)[c]	3.306737 (17.30)[d]
40%	1704	56.92[a] (0.0000)	-.022325[b] (-10.21)	.008634	51.82 (0.1395)	-.010377 (-8.15)	.002866	-.011948 (-4.79)[c]	3.012561 (17.59)[d]
50%	2123	56.67[a] (0.0000)	-.019323[b] (-10.81)	.007160	51.72 (0.1181)	-.009932 (-9.00)	.002684	-.009391 (-4.43)[c]	2.667660 (16.08)[d]

[a] The null hypothesis H_0 : (% over) = 50% is rejected by a binomial test with 5% significance
[b] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance
[c] The null hypothesis H_0 : (ME_b - ME_t) = 0 is rejected by a t-test at 5% level significance
[d] The null hypothesis H_0 : $MSE_{top} = MSE_{bot}$ is rejected by a an analysis of variance at 5% level significance

Table 2.7. OLS Regressions of EPS Against FEPS (Categorized by the Sign of FEPS)

$$EPS_{it} = a_t + b_t \,.\, FEPS_{it} + e_{it}$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = earnings forecast per share for firm i and fiscal year t

Sample period is 1984-1991. Coefficients of OLS regression are estimated separately using flags for negative FEPS and positive FEPS as well as without flags (all observations). This procedure is repeated for samples from each year, and for the pooled sample from 1984 to 1991. Parameters for the intercept (a_t) and slope (b_t) terms are estimated, and their values are reported with their t-values underneath. The intercept term is tested against zero, and the slope term is tested against one with a one-sample t-test. For each regression r^2 are reported as well.

	FEPS<0			FEPS>0			ALL OBSERVATIONS		
YEAR	a	b	r^2	a	b	r^2	a	b	r^2
1984	-.172213 (-3.461)	.668540 (-3.384)	.6892	[c]-.000970 (-.205)	[d].922505 (-1.860)	.5176	-0.002911 (-0.764)	0.884719 (-4.747)	.7344
1985	-.084259 (-1.337)	1.442128 (.754)	.2518	[c]-.013476 (-2.541)	[d].996328 (-.062)	.3912	-0.038302 (-7.661)	1.272474 (4.960)	.5347
1986	-.099960 (-2.182)	.872635 (-.883)	.4843	[c]-.012459 (-2.207)	[d].987537 (-.184)	.3052	-0.020803 (-4.898)	1.040978 (1.146)	.6151
1987	-.022190 (-.761)	1.147696 (1.741)	.8434	[c]-.000062 (-.015)	[d].944923 (-1.243)	.4664	-0.016522 (-6.249)	1.126624 (6.116)	.8419
1988	-.038288 (-1.390)	1.027504 (.171)	.6301	[c]-.002036 (-.568)	[d].962124 (-1.072)	.5710	-0.012482 (-4.437)	1.063162 (2.368)	.7313
1989	-.044379 (-2.045)	.980747 (-.253)	.8518	[c]-.002057 (-.489)	.913802 (-1.850)	.4481	-0.012602 (-4.683)	1.024777 (1.035)	.7840
1990	-.081319 (-2.193)	1.191806 (2.237)	.8541	[c]-.005674 (-.942)	[d].889818 (-1.817)	.2647	-0.036201 (-9.942)	1.209787 (8.069)	.7738
1991	-.083319 (-3.098)	.791355 (-1.923)	.5473	[c]-.015730 (-2.153)	[d].998418 (-.015)	.1692	-0.018429 (-4.636)	0.971859 (-.712)	.5584
1984-91	-.082138 (-6.233)	.953991 (-1.134)	.6835	[c]-.007279 (-4.071)	.958910 (-2.166)	.3909	-0.018979 (-15.011)	1.064125 (6.156)	.7107

[c] The intercept term in the positive forecast sample is significantly different than the intercept term in the negative forecast sample at 5% level
[d] The slope term in the positive forecast sample is significantly different than the slope term in the negative forecast sample at 5% level

Table 2.8. OLS Regressions of EPS Against FEPS With a Zero-Intercept Restriction (Categorized by Sign of FEPS)

$$EPS_{it} = b_t \cdot FEPS_{it} + e_{it}$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = earnings forecast per share for firm i and fiscal year t

Sample period is 1984-1991. Slope coefficients of OLS regression are estimated separately using flags for negative EPS and positive EPS as well as without flags (all observations). This procedure is repeated for samples from each year, and for the pooled sample from 1984 to 1991. Parameter estimates for slope (b_t) terms are reported with their t-values underneath. The intercept term is tested against zero, and the slope term is tested against one with a one-sample t-test. For each regression r^2 are reported as well.

	FEPS<0		FEPS>0		ALL OBSERVATIONS	
YEAR	b	r^2	b	r^2	b	r^2
1984	.834443 (-1.583)	.7431	[d].914857 (-4.616)	.8431	0.874647 (-6.149)	.7929
1985	2.036562 (2.662)	.5900	[d].863416 (-5.059)	.6954	0.933285 (-1.936)	.6104
1986	1.047904 (.382)	.6363	[d].853924 (-4.820)	.6203	0.960519 (-1.218)	.6227
1987	1.189722 (2.966)	.9081	[d].944341 (-2.878)	.8207	1.059163 (3.240)	.8580
1988	1.170195 (1.351)	.7754	[d].943990 (-3.706)	.8749	0.970476 (-1.754)	.8503
1989	1.058053 (.838)	.8860	[d].893597 (-4.946)	.7841	0.958513 (-2.106)	.8239
1990	1.301374 (4.100)	.9021	[d].839148 (-5.733)	.5989	1.081926 (3.375)	.7580
1991	.965714 (-.339)	.6692	[d].789488 (-4.727)	.4217	0.892159 (-2.967)	.5570
1984-91	1.088715 (2.412)	.7732	[d].890330 (-12.554)	.7228	0.976576 (-2.645)	.7411

[d] The slope term in the positive forecast sample is significantly different than the slope term in the negative forecast sample at 5% level

Chapter 3

IMPROVING THE ACCURACY OF NEGATIVE EARNINGS FORECASTS

Given a consensus forecast is negative in Table 2.2 the forecast is overoptimistic 71.71% of the time. This raises the possibility that the accuracy of *negative* forecasts can be improved by adjusting for forecast bias. This chapter investigates gain in forecast performance arising from adjusting forecasts of negative earnings for analyst overoptimism. Forecast adjustments of varying magnitudes are evaluated using the following three measures of forecast performance: (1) the change in forecast accuracy relative to the consensus as measured by mean square forecast error, (2) the probability of being closer to actual earnings than the consensus forecast, and (3) the probability that adjusted forecasts overshoot the mark and underestimate actual earnings. Forecast performance is evaluated along each of these dimensions so that both producers and consumers of earnings forecasts can make an informed decision regarding their own optimal adjustment of consensus earnings forecasts.

Results indicate that relative forecast accuracy as well as the probability of beating the consensus forecast can be improved by adjusting negative forecasts downward by a small amount without an inordinate increase in the probability of underestimating earnings. Because the costs and benefits of overadjusting or underadjustment differ depending on one's perspective, the choice of how far to diverge from the consensus forecast is best left to the individual.

The Earnings Forecast Adjustment

Overoptimism in negative earnings forecasts (FEPS < 0) manifests itself in Table 2.2 as a negative bias (where BIAS = EPS - FEPS) ranging from 4.35% to 15.35% of share price for annual samples and averaging 7.42% of share price over the pooled sample. Both consumers and producers of earnings forecasts should be able to obtain better forecasts by lowering the negative consensus forecasts even further. I perform the following adjustment:

$$AFEPS_{it} = FEPS_{it} - ADJ_{it}$$

where

$AFEPS_{it}$ = adjusted forecast for firm i and fiscal year t,

$FEPS_{it}$ = unadjusted earnings forecast for firm i and fiscal year t,

ADJ_{it} = adjustment factor ($ADJ_{it} > 0$) as a percentage of share price for firm i and fiscal year t.

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

Measures of Analyst Forecast Performance

In this section, forecast adjustments of varying magnitudes are evaluated using the following three measures of forecast performance: (1) the change in forecast accuracy relative to the consensus as measured by mean square forecast error, (2) the probability of being closer to actual earnings than the consensus forecast, and (3) the probability that adjusted forecasts overshoot the mark and underestimate actual earnings.

Relative Forecast Accuracy

Consumers of earnings forecasts such as individual investors and fund managers use forecasts of current and future earnings as inputs into valuation models designed to identify mispriced securities. Consequently, consumers of earnings forecasts are concerned with the magnitude of actual earnings and would like their earnings forecasts to be unbiased and efficient. Unbiased and efficient forecasts are neither systematically too high nor too low and are distributed as tightly as possible around actual earnings. A good measure of forecast performance for consumers of earnings forecasts is the mean squared forecast error.

In order to measure the accuracy of adjusted earnings forecasts relative to unadjusted consensus forecasts, mean squared forecast errors before and after adjustment are computed according to:

$$MSE = \left(\frac{1}{n}\right)\left[\sum_{i=1}^{n}\left(EPS_{it} - FEPS_{it}\right)^2\right] \qquad t=1984,....,1991$$

and

$$AMSE = \left(\frac{1}{n}\right)\left[\sum_{i=1}^{n}\left(EPS_{it} - AFEPS_{it}\right)^2\right] \qquad t=1984,....,1991$$

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

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

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

Figure 3.1 plots the observed improvement in MSE against the magnitude of the forecast adjustment over each of the years 1984-91 and over the pooled 1984-91 sample (the dark line in the figure). A bias adjustment of about 6% of share price results in the best forecast accuracy in the negative forecast sample pooled across all sample years. This corresponds to an earnings forecast adjustment of $6 on a $100 share of stock. Not surprisingly this is fairly close to the mean bias of 7.4% of share price in the negative forecast sample of Table 2.2. With this adjustment, the squared errors of the adjusted forecasts are 85.7% of unadjusted forecast squared errors. Adjusted forecast accuracy begins to deteriorate in the overall sample beyond an adjustment of about 6% of share price. By the time forecasts have been reduced by 12% of share price, adjusted and unadjusted forecasts have nearly equal forecast accuracy in the pooled sample. At this level, adjusted forecasts are about as far below actual earnings as unadjusted forecasts are above earnings.

Within each sample year, relative forecast accuracy improves monotonically for adjustments of up to 4% of share price. Beyond this point, the magnitude of the optimal adjustment exhibits a good deal of year-to-year variation. Those years with the largest ex post bias in the negative forecast sample of Table 2.2 (1985 and 1990) benefit the most from large forecast adjustments in Figure 3.1. Improvement in forecast accuracy during those years with the smallest bias (1988 and 1989) is correspondingly smaller. The magnitude of the forecast bias in the negative forecast samples is about 4.1% of share price in 1988 and 1989 and adjustments of more than this amount begin to lose their effectiveness. Nevertheless, relative forecast accuracy is improved over unadjusted forecasts for adjustments of up to 8% of share price in these two years. The forecast accuracy of adjusted forecasts is superior to that of unadjusted forecasts for adjustments of up to 11% of share price in the remaining six years.

Beating the Consensus

Forecast accuracy as measured in the previous section is most prized by consumers of earnings forecasts such as individuals and fund managers using earnings forecasts in valuation models. In contrast to consumers of earnings forecasts, the forecasts of earnings forecast *producers* are primarily judged not on forecast accuracy but on whether their forecasts are closer to actual earnings than those of other analysts. A successful security analyst is one whose forecasts are consistently closer to actual earnings than competing forecasts. Given the observed overoptimism in the negative forecast samples, analysts should be able to consistently beat consensus forecasts simply by adjusting consensus forecasts downward by an arbitrarily small amount. More aggressive analysts can attempt larger adjustments in an effort to further improve their forecast accuracy relative to the consensus.

The measure of relative forecast accuracy in the following equation is based on a squared error criterion. Forecast accuracy can alternatively be measured as the probability that adjusted forecasts lie closer to actual earnings than the consensus. This frequency can be used to estimate the probability of an analyst beating the consensus forecast:

$$P[\text{beating the consensus}] = P[\,|\,EPS_{it} - FEPS_{it}\,| > |\,EPS_{it} - AFEPS_{it}\,|\,].$$

For the negative forecast sample, arbitrarily small downward adjustments will beat the consensus forecast by the amount shown in the "% over" column under "TOTALS" in Table 2.2. For example, since 71.71% of the total sample of negative forecast observations overestimate actual earnings, small downward adjustments to the consensus forecasts will be closer to actual earnings 71.71% of the time across the entire sample. Relative forecast accuracy will improve as progressively larger downward adjustments are made, but the probability of beating the consensus forecast will be less than the initial level of 71.71%. As succesively larger adjustments are made, relative forecast accuracy will begin to deteriorate and the probability of beating the consensus will fall below 50%.

Figure 3.2 plots the probability of beating the consensus forecast for progressively larger downward adjustments for the yearly samples and for the pooled sample. For arbitrarily small downward adjustments $ADJ_i > 0$, these probabilities emerge from the y-axis in Figure 3.2 according to the "% over" probabilities in Table 2.2. The overall sample as well as each of the yearly samples begin at probabilities well over 50%, so it is a good bet that small downward adjustments will beat the consensus. As the size of the downward adjustment is increased, the probability of beating the consensus falls. In the pooled sample, downward adjustments of up to 4.75% of stock price continue to yield a greater than 50% probability of beating the consensus. Downward adjustments of up to 2.2% of stock price yield a greater than 50% probability of beating the consensus in each of the yearly samples. Adjusted forecasts of up to 10% of share price continued to beat the consensus over 50% of the time in half of the sample years. The years in which forecast bias is smallest tend also to be the years in which the probability of beating the consensus falls most rapidly, although the relation between these two variables is not as pronounced as the relation between forecast bias and changes in relative forecast accuracy in Figure 3.1.

Probability of Underestimating Earnings

Klein (1990) suggests that managers are most likely to exert pressure on security analysts when their firm is in financial distress. It is at these times when managers are most sensitive to negative publicity and a negative earnings forecast is most likely to sour an analyst's relation with management. If good relations with management are more important than an unbiased forecast, then a 'politically correct' forecast will be more generous than is warranted by the facts.

An analyst adjusting negative consensus forecasts downward will want an estimate of the probability of being exposed to this kind of scrutiny by management. One measure of the analysts' exposure to negative criticism from management is the probability that a forecast adjustment of a given size results in earnings underestimates. Analysts can use the probability $P[EPS_i > AFEPS_i]$ as an estimate of their exposure to this risk. Conversely, the probability of overestimating earnings is given by:

$$P\ [\text{overestimating earnings}] = P[EPS_{it} < AFEPS_{it}\ ]$$

where P [overestimating earnings] = 1 - P[underestimating earnings]. As an example, unadjusted forecasts over-estimate actual earnings 71.7% of the time in the pooled sample (see Table 2.2), so the risk of underestimating earnings is 28.3%. Progressively larger adjustments for overoptimism increase the probability of underestimating earnings. At a probability of 0.5, adjusted forecasts are as likely to be too high as too low.

Figure 3.3 plots changes in the probability of overestimating earnings for incremental adjustments of zero to 15% of share price. In the pooled sample, the probability of overestimating earnings falls to 50% for downward forecast adjustments of about 2.2% of share price. The yearly samples fall to a 50% probability for adjustments of between 1.2% (1986 and 1991) and 5.5% (1984 and 1990) of share price. Beyond 5.5% of share price, the probability of underestimating earnings exceeds that of overestimating earnings in each yearly sample.

Summary

Summarizing the results in Figures 3.1 through 3.3, I find that adjustments of up to 1% of share price result in improved forecast accuracy, a high probability of beating the consensus forecast, and little increase in the probability of underestimating actual earnings. Forecast adjustments of between 1% and 2% of share price consistently beat consensus forecasts and continue to improve forecast accuracy, although there is an increasing risk of underestimating earnings. Relative forecast accuracy continues to improve for adjustments of up to 5% of share price. While the probability of beating the consensus is still on average greater than half for adjustments of up to 5% of share price, the extent to which forecasts can be adjusted and still beat the consensus more than half the time exhibits a good deal of year-to-year variation. The maximum adjustment before the probability of beating the consensus falls below one-half in the yearly samples ranged from 2% to 11% of share price. Beyond an adjustment of 2% of share price there is substantial risk of underestimating earnings. Forecast adjustments of up to 11% of share price are still likely to be superior to unadjusted forecasts on relative forecast accuracy, although by this point one has probably overshot the mark; the probability of beating the consensus and the probability of underestimating earnings are both unacceptably high.

Each analyst must make an individual decision on how much to adjust negative earnings forecasts according to the incentives and penalties they face in their individual circumstance. Small downward adjustments can improve forecast accuracy as well as the probability of beating the consensus forecast. Larger adjustments continue to improve forecast accuracy at the expense of an increasing probability of underestimating earnings and a lower probability of beating the consensus forecast.

If forecast accuracy is paramount, then adjustments of about 5% of share price are likely to prove optimal. If beating the consensus forecast is prized, then adjustments of up to 2% of share price will capture gains in forecast accuracy while providing the analyst with bragging rights over consensus forecasts. To the extent that a security analyst is penalized for underestimating earnings, attempting to adjust for the full extent of the bias will expose the analyst to undue criticism. Adjustments of up to 1% of share price are likely to keep the analyst's probability of underestimating earnings below 50%, although the management of individual companies might still find room to complain. Adjustments of 1% do not take full advantage of the potential gain in forecast accuracy, but do provide a high probability of beating the consensus forecast.

If all analysts adjust their forecasts by the average forecast bias reported in Table 2.2, then forecasts will on average underestimate actual earnings by the amount of the current forecast overestimate. Since the institutional incentive (and penalty) structure faced by security analysts is unlikely to change overnight, a possible prediction is that analysts will be slow to adopt the recommendations in this chapter. There will still be room for improvement in forecast performance so long as analysts make only incremental rather than complete adjustments to their negative earnings forecasts.

Figure 3.1. Relative Forecast Accuracy

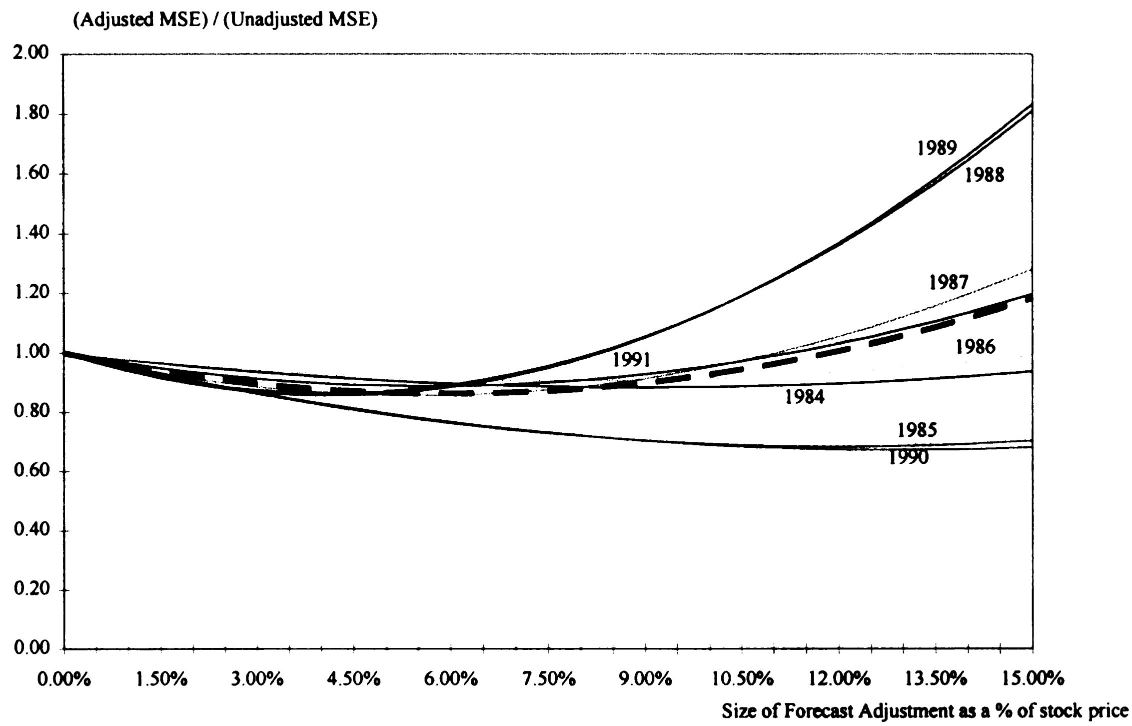


Figure 3.2. Probability of Beating the Consensus

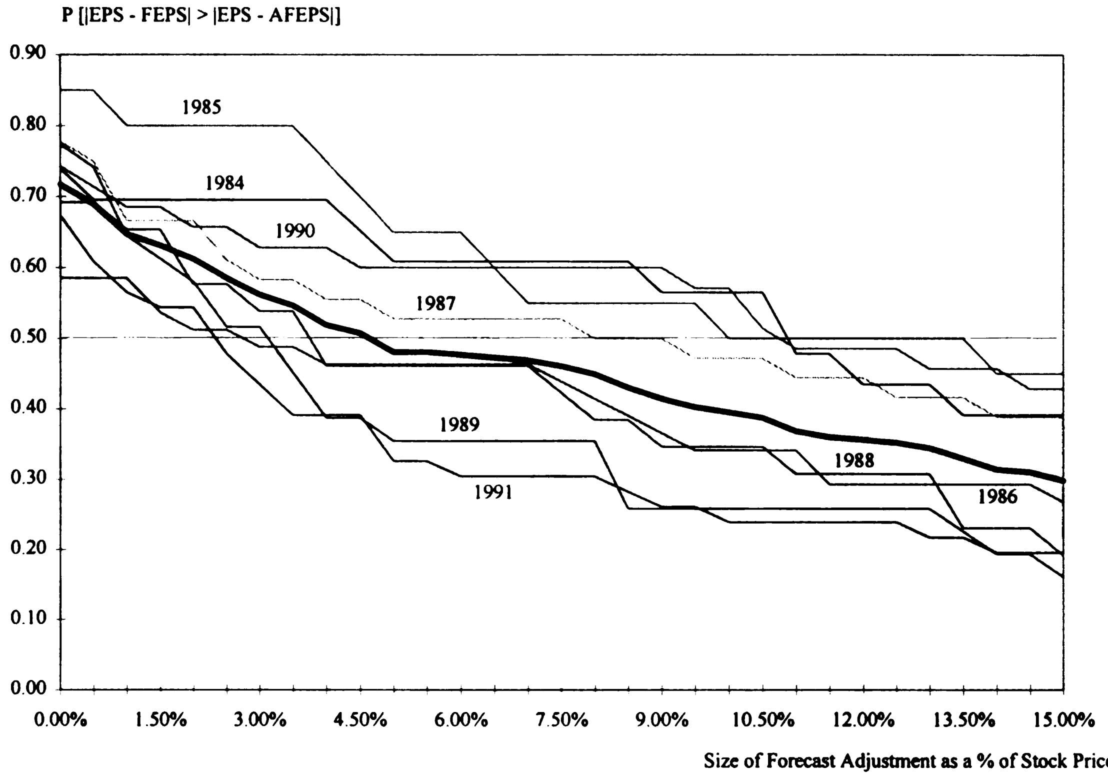
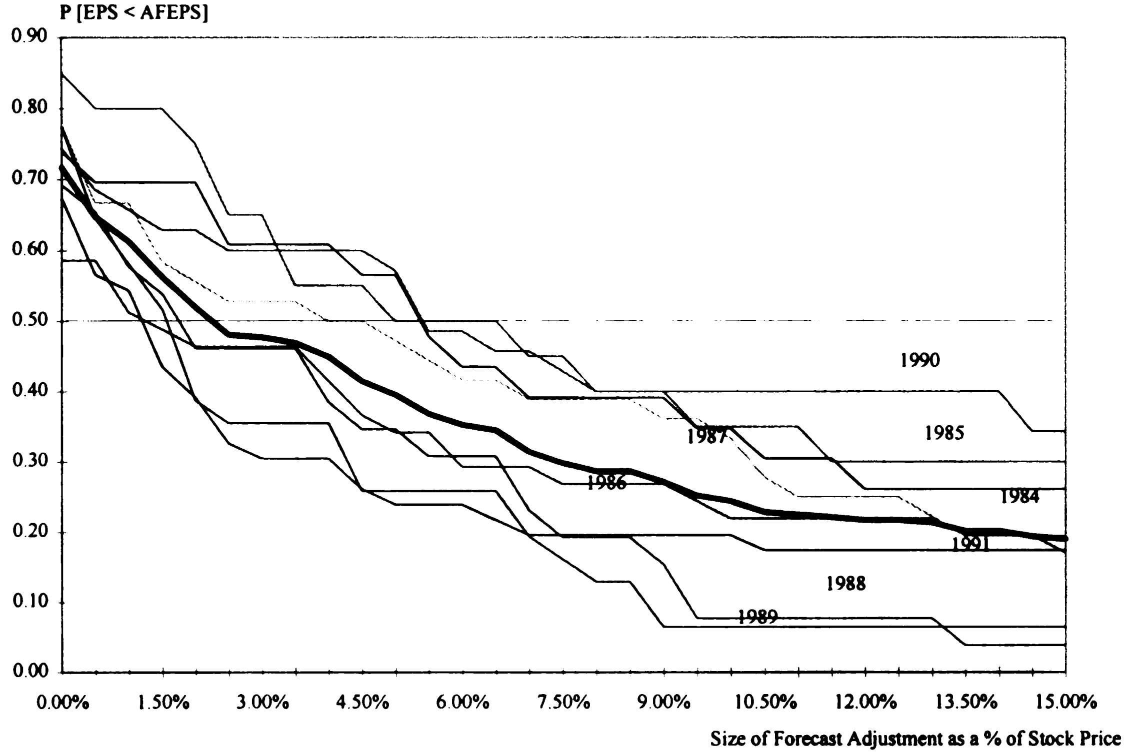


Figure 3.3. Probability of Overestimating Earnings



Chapter 4

PREDICTING THE SIGN OF EARNINGS

The methodology in the previous chapter serves as a tool to correct the overoptimism in *negative* forecasts of earnings. Most of the earnings outcomes corresponding to these negative forecasts indeed turn out to be negative. On the other hand, *positive* forecasts that correspond to *negative* earnings outcomes result in an even bigger overestimation problem. Knowing that the sign of a forecast is negative implies a .7171 probability of overestimating earnings. In contrast, a positive forecast may correspond to a positive earnings outcome where it is quite accurate (50.50% chance of overestimation in Table 2.2), or to a negative earnings outcome where it is grossly overoptimistic. This raises the possibility that the accuracy of positive earnings forecasts can be improved if the sign of actual earnings can be predicted using predisclosure information.

This section uses Multiple Discriminant Analysis (MDA) and Logistic Regressions (LR) based on a predisclosure estimation period to identify those company-specific variables that help predict the sign of actual earnings for the sample of positive forecasts. Multiple discriminant analysis, using a linear set of input variables also called discriminating variables, provides an index (discriminant score) that allows classification of an observation into one of several *a priori* groupings (Weston and Copeland (1986)).

Logistic regression is a conditional probability model that uses the coefficients of the independent variables to predict the probability of occurrence of a dichotomous (or polytomous) dependent variable (Zavgren (1983)).

Predicting the Sign of Earnings Using Multiple Discriminant Analysis (MDA)

Despite a debate on its applicability in finance and accounting, (see Eisenbeis (1977), Joy and Tollefson (1975, 1978), Altman and Eisenbeis (1978)), discriminant analysis has been a valuable tool in areas that require predictive model building (Altman (1968), Altman, Haldeman and Narayanan (1977)).

Discriminant analysis is a statistical technique that allows the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously. In order to be able to use the discriminant analysis on a particular sample, certain assumptions must be satisfied: (1) there must be two or more groups, (2) there must be at least two cases per group, (3) there can be any number of discriminating variables, provided that it is less than the total number of cases minus two, (4) discriminating variables are measured at the interval level, (5) discriminating variables must be linearly independent, (6) the covariance matrices for each group must be approximately equal (unless special formulas are used), and (7) each group has been drawn from a population with a multivariate normal distribution on the discriminating variables (Klecka [1980]). The most important of these assumptions are numbers (6) and (7), and debate on the applicability of discriminant analysis to finance research focuses on the argument that samples of finance and accounting numbers are most likely to violate these assumptions. However, Klecka [1980] states that: "For the researcher whose main interest is in a mathematical model which can predict well or serve as a reasonable description of the real world, the best guide is the percentage of correct classifications. If this percentage is high, the violation of assumptions was not very harmful. Efforts to improve the data or use alternative formulas can give only marginal improvements. When the percentage of correct classifications is low, however, we cannot tell whether this is due to violating the assumptions or using weak discriminating variables."

The following equation is fit to the positive forecast sample for each year in the period 1985-1991. For each year, positive forecasts are reclassified in-sample as negative if the dependent variable D_t is less than the MDA cut-off score. The performance of the analysts is then compared to the performance of the MDA in predicting the sign of earnings. This methodology is extended to an out-of-sample test period (that is predicting the sign of earnings in the following year with current year's parameters) in Chapter 5:

$$D_t = a + b.EPS_{t-1} + c.FEPS_t + e.OVEREST_{t-1} + f.FOLLCHG_t + g.SUM3QEPS_t$$
$$+ h.MV_t + i.PRICECHG_t \qquad \forall\ FEPS_t > 0 \qquad t = 1985,....,1991$$

where

D_t	=	the value of the discriminant function
EPS_{t-1}	=	previous year's earnings per share
$FEPS_t$	=	current year's median earnings forecast
$OVEREST_{t-1}$	=	the magnitude of previous year's EPS overestimation[1]
$FOLLCHG_t$	=	percentage change in number of analysts following the firm
$SUM3QEPS_t$	=	sum of first three quarters' earnings per share

[1] OVEREST is calculated by subtracting EPS from FEPS in order to assign positive values to cases where forecasts are greater than the actual earnings. Note that elsewhere in this study forecast errors are calculated by subtracting FEPS from EPS reflecting optimism with a negative sign in the error.

MV_t = natural logarithm of the market value of the firm
$PRICECHG_t$ = percentage price change

Each of these variables is discussed in the paragraph that follow.[2]

In line with the findings of a study by Ali, Klein and Rosenfeld (1992), previous year's earnings per share (EPS_{t-1}) is included in the analysis with the hypothesis that earnings in one year can be used to predict the sign of earnings in the following year if company performance persists over time. Ali, et al. examine whether analysts properly recognize the time-series properties of annual earnings when setting their annual earnings per share. The study documents an optimistic forecast bias that is most pronounced in firms that previously reported negative earnings.

Analysts' positive forecasts are fairly accurate in the northeast quadrant of Figure 2.2. However, the southeast quadrant contains an apparent ray of observations that extend close to the y-axis. These observations represent overoptimistic negative forecasts of positive earnings. This indicates that analysts are issuing slightly positive or zero forecasts for negative earnings outcomes, perhaps because of pressure by management. If this is the case, the magnitude of the current year's forecasts ($FEPS_t$) may be useful in predicting the sign of actual earnings.

The magnitude of the previous year's forecasts optimism ($OVEREST_{t-1}$), which is the difference between the previous year's forecast minus the previous year's actual

---

2 In addition to these variables, the timing of annual earnings announcements (Chambers and Penman (1984), Damodaran (1987)), earnings predictability (Pincus (1983), Lipe (1990)), institutional ownership (Potter (1992)), exchange listing (Grant (1980)), systematic risk and earnings growth (Collins and Kothari (1989)), and factors relating to life cycle stage (Anthony and Ramesh (1992)) could also be included in the analysis due to insights provided by the cited research work.

earnings, may be a good predictor if analysts are consistently overestimating the earnings of particular companies. This is in line with the management pressure (Francis and Philbrick (1992)) and investment banking relationship (Lin and McNichols (1991), Dugar and Nathan (1995)) arguments that are cited in the literature as cases where optimistic biases are most prominent. Furthermore, Ali, et al. document significantly positive serial correlations in 8-month and one-month forecast errors, a result that is consistent with the hypothesis that analysts consistently underestimate the permanence of the last year's forecast error.

$FOLLCHG_t$ is calculated as the percentage change from the previous year in the number of analysts following the company. The null hypothesis regarding the inclusion of $FOLLCHG_t$ is that the sign of earnings is independent of the number of analysts following a firm. Several studies use the number of analysts' following a firm as a measure of the amount of prior information available about a firm (Lobo and Mahmoud (1989), Bhardwaj and Brooks (1992)). Brennan and Hughes (1991) show that the number of analysts following a firm is inversely related to its share price in a sample covering the period of 1976-1987. Bhushan (1989) analyzes relationship of a firm's analyst following to such firm characteristics as ownership structure, firm size, return variability, number of lines of business, and the correlation between market return and firm return. Bhushan suggests that these factors have a significant impact on the aggregate demand for, or supply of, analysts' services for the firm. In line with these studies, if analyst following of a company is related to firm characteristics such as performance, then analysts may choose to neglect a poorly performing company rather than forecasting negative earnings.

The change in the number of analysts following a company ($FOLLCHG_t$) may be useful in predicting the sign of earnings per share.[3]

Atiase (1980, 1985) and Freeman (1987) use firm size as a proxy for the amount of predisclosure information. Atiase (1987) suggests that the greater the predisclosure information the less the surprise element in earnings announcements. My analysis in Chapter 2 documents that the forecasts of smaller firms are optimistic, both in the case of positive and negative forecasts. In line with this finding, market value (MV_t defined as the natural log of the market value of equity at the beginning of the year) is included in the analysis to test whether it can predict the sign of earnings.

When analysts report their November forecasts they already possess information regarding earnings performance in the first three quarters. Previous research has shown that analysts follow an adaptive behavior to new information releases. Nevertheless, if analyst optimism towards negative earnings is intentional, then one would expect them to disregard the information revealed in quarterly earnings. In this case, the sum of the first three quarters' earnings ($SUM3QEPS_t$) may predict negative earnings.

The percentage change in the stock price from the previous year ($PRICECHG_t$) may itself contain information regarding the sign of annual earnings. Abarbanell (1991) suggests a positive relationship between earnings forecasts and prior price changes whether or not price changes are combined with analysts' private signals as they formulate their earnings forecasts. This suggests that, if information in price changes is

---

[3] Number of analysts following the company during the year was not a significant factor in predicting the sign of EPS in Multiple Discriminant Analysis. To measure a possible performance-related neglect or drop-out effect, the percentage change in the number of analysts following a firm is included in the analysis.

omitted from analysts' forecasts, these price changes will help predict the sign of forecast errors. This result is contrary to the hypothesis that analysts' forecasts fully incorporate prior price changes. Abarbanell offers two possible explanations for this result: (1) analysts are inefficient in collecting and interpreting publicly observable signals, and (2) private information is more easily inferred by investors if it is not combined with other signals whose information content is open to individual interpretation.[4]

Table 4.1 provides summary statistics on each of these variables. An overview of the correlation matrix of these variables, which is presented in Table 4.2, reveals that the *magnitude* of current year's earnings is positively correlated with the magnitude of forecasts and is negatively correlated with the magnitude of the previous year's forecast overoptimism. An interesting finding is that the previous year's overoptimism is also strongly negatively correlated with the magnitude of the previous year's earnings per share. This may be another indication that forecast bias is driven by negative earnings. There is a small positive correlation between the magnitude of the current year's earnings and the market value of the firm. Current year's earnings are also positively correlated with the magnitude of the previous year's earnings, as they should be in this cross-sectional sample.

The results of a Multiple Discriminant Analysis using the forced entry method are presented in Table 4.3, including the coefficient values and p-values for univariate F-ratio

---

[4] Klein (1990) provides evidence that is not supportive of the cognitive bias theory where the market should form overly pessimistic (optimistic) forecasts of future earnings for stocks that have experienced sharp price declines (increases). Klein finds that analysts do not underpredict earnings following large price declines. Rather, they remain overly optimistic about future earnings.

statistics.[5] Under the forced entry method, all independent variables that satisfy tolerance criteria are entered simultaneously. For each one-year estimation period from 1985 to 1991, $SUM3QEPS_t$ has a significantly strong explanatory power at a .05 confidence level. With the exception of 1989 and 1990, $FEPS_t$ is also significant in predicting the sign of earnings per share. The coefficient estimates of these two variables are stable and consistent from year to year except for 1986, where they have the opposite signs compared to other years.

An intuitive explanation of the sign of these coefficients requires an explanation of the MDA's classification principle. The probability that a case with a discriminant score D belongs to a group $SIGNEPS_i$ (sign of earnings per share) is estimated in MDA using the following principle:

$$P(SIGNEPS_i|D) = \frac{P(D|SIGNEPS_i).P(SIGNEPS_i)}{\sum P(D|SIGNEPS_i).P(SIGNEPS_i)}$$

$P(SIGNEPS_i)$, which is called the *prior probability*, is an estimate of the likelihood that an observation belongs to a particular sign group when no information is available. $P(D|SIGNEPS_i)$ is the conditional probability of D given the group. It is calculated by assuming that an observation belongs to a particular group, and the probability of the observed score given that particular group membership is estimated. $P(D|SIGNEPS_i)$, which is called the *posterior probability*, is a representation of how likely membership in

---

5 Another measure of significance for the discriminatory power of a variable is Wilks' lambda. Wilks' lambda is a multivariate measure of group differences over the discriminating variables. Values of lambda that are near zero denote high discrimination. As lambda increases toward its maximum value of 1.0, it is reporting progressively less discrimination (Klecka (1980)).

a certain group is, given the available information. An observation is classified into a sign group for which the posterior probability with the given discriminant score is the largest.

Discriminant scores at negative and positive earnings group centroids (presented on the bottom of Table 4.3) show that the negative earnings group consists of smaller (and on average negative) discriminant scores with the exception of the 1986 sample. In this case, a negative coefficient for $FEPS_t$ implies that inclusion of this variable is helping to classify those observations with positive forecasts and negative earnings into the negative earnings group. The opposite effect of classifying observations with positive forecasts and positive earnings into the negative earnings group is counter-balanced by the inclusion of $SUM3QEPS_t$ where a negative value for this variable would imply a large negative D score and hence a negative earnings classification.[6] Also, $PRICECHG_t$ has strong predictive power in four of the seven sample periods. $OVEREST_{t-1}$ and EPS_{t-1} have statistically significant coefficients only in the 1986 and 1990 samples. $FOLLCHG_t$ and MV_t have statistically significant predictive power only in one yearly sample.

Table 4.4 shows that the MDA function does a better job than the analysts in predicting negative earnings outcomes. In the positive forecast sample, analysts have a 0.00% success rate in predicting negative earnings by construction. In the pooled sample positive forecasts of negative earnings are correctly reclassified 57.01% of the time. This improvement is achieved at the expense of classifying some positive actual earnings into the negative earnings group. The overall correct classification rate is not significantly

---

[6] Note the strong positive correlation of SUM3QEPS with EPS. One should be careful when interpreting the coefficient of a single variable in isolation from the others. Since the variables are correlated, the coefficient value for a certain variable depends on the other variables in the analysis.

improved through a Multiple Discriminant Analysis. However, because the largest forecast errors are in the sample of positive forecasts of negative earnings, this reclassification may provide improved forecast accuracy. That is, even MDA misclassifies the sign of earnings, it correctly identifies the overestimated earnings.[7]

In order to ensure the viability of variable selection in the analysis, the MDA function is also estimated using a stepwise selection method that involves forward selection and backward elimination.[8] The variable selection criterion is based on the p-value of the F statistic, where the entry value is set to .05 and the removal value is set to .10. Table 4.5 shows the coefficient values and p-values of their F statistics for the variables that remain in the analysis. Summary statistics in Table 4.6 for the stepwise selection method are qualitatively similar to those in Table 4.4 for the forced entry selection method.

Improvements on these results might be achieved by (1) including other variables that proxy predisclosure information, or (2) extending the estimation period and estimating the discriminant function by pooling data into two (or more) years.

---

[7] The next chapter shows that positive earnings outcomes that are misclassified as negative in Table 4.4 are in fact much more likely to be overestimated by security analysts.

[8] Different variable selection criteria such as minimization of Wilks' Lambda, Rao's V or the Lawley-Hotelling trace, and the sum of unexplained variance can be employed to determine the most important variables in discriminant analysis.

Predicting the Sign of Earnings Using Logistic Regression (LR)

Focusing mainly on bankruptcy prediction, several authors (Press and Wilson (1978), Zavgren (1983, 1985), Ohlson (1980)) have debated the choice between multiple discriminant analysis and logistic regression for predictive model building in accounting and finance. The consensus of these studies is that logistic regression is less restrictive in terms of its statistical assumptions and provides better results than multiple discriminant analysis in cases where MDA's assumptions are violated. Moreover, the rationale for the choice of a cut-off point is an ongoing issue in multiple discriminant analysis (Altman (1968), Edmister (1972), Zavgren (1983)).

Logistic regression involves obtaining the probability of an event occurring conditional on a linear combination of independent variables. The functional form the logistic regression is of a logistic cumulative density function. The parameters of the logistic regression are estimated from the data using the maximum likelihood method. Thus, the estimated parameters are such that they make the observed outcomes most likely.

In the case of predicting the sign of earnings per share, the logistic regression model can be written as:

$$P\{EPS < 0|X\} = \frac{1}{1+e^{-z}} \quad \text{and}$$
$$P\{EPS \geq 0|X\} = 1 - Prob\{EPS < 0|X\}$$

where

X = a vector of explanatory variables, $X = [x_1,........x_n]$
z = the linear combination, $z = b_0 + b'X$
b = the vector of coefficients, $b = [b_1,........,b_n]$

Using the same variables as in MDA, the coefficients of the function z have been estimated for each year of the sample data from 1985 to 1991:

$$z = b_0 + b_1 .EPS_{t-1} + b_2 .FEPS_t + b_3 .OVEREST_{t-1} + b_4 .FOLLCHG_t + b_5 .SUM3QEPS_t$$
$$+ b_6 .MV_t + {}_7 .PRICECHG_t \qquad \forall\ FEPS_t > 0 \qquad t = 1985,....,1991$$

Values of the coefficients and the p-value of their Wald statistic as well as model chi-square and its significance value are presented in Table 4.7.[9] With the exception of the 1987 sample, the coefficient of $SUM3QEPS_t$ is statistically significant at a 5% level. $FEPS_t$ has no explanatory power in any of the sample periods. $PRICECHG_t$, which is a good discriminatory variable in MDA, has a statistically significant coefficient value except for the 1987 and 1988 samples. $FOLLCHG_t$ and EPS_{t-1} have discriminatory power in two of the eight sample periods, $OVEREST_{t-1}$ is significant only in the 1988 sample. The coefficient of MV_t is insignificant in each sample. The variables are entered into the regression equations using the forced entry method.

Classification results are presented in Table 4.8. Logistic regression has a better overall success rate in correct classification compared to both the analysts and MDA. The percentage of correct classification by LR is better than the correct classification rate of the analysts in each estimation period from 1985 to 1991. In the pooled sample, LR

[9] The Wald statistic, which has a chi-square distribution, is used in order to test the hypothesis that a coefficient is zero. The Wald statistic is calculated by squaring the ratio of the coefficient to its standard error (when a variable has a single degree of freedom). Large Wald statistic values result in rejecting the null hypothesis that a coefficient has a value of zero.

achieves a success rate of 96.12% in correctly predicting negative earnings given a positive forecast. Although this is not as good as MDA's success rate, MDA makes more reclassification errors than LR. Correct classification of positive earnings is very close to 100% in each of the sample periods. For example, in the pooled sample, LR correctly classifies 39.25% of the negative earnings while misclassifying only 14 of 1930 positive earnings outcomes. 1986 and 1991 samples give similar results; about a 50% success rate in correctly predicting negative earnings with a very small reclassification error for positive earnings.

Summary

In this chapter, firm specific variables that can help predict the sign of an earnings outcome are tested in estimation samples of positive forecasts between 1985 and 1991. Using MDA and LR, observations are classified into negative and positive earnings groups. Classification rates of both methods are evaluated against a benchmark of correct classification by security analysts. Both MDA and LR outperform security analysts in the prediction of negative earnings outcomes. In terms of the overall correct classification LR tops the list while analysts and MDA come second and third, respectively. However, MDA performs better than both LR and the analysts in correctly predicting the negative earnings outcomes.

The best variables for predicting negative earnings in MDA are $SUM3QEPS_t$, $FEPS_t$, and $PRICECHG_t$, respectively. Although LR gives results that agree with MDA for the inclusion of $SUM3QEPS_t$ and $PRICECHG_t$, the same cannot be said for $FEPS_t$ which is insignificant in each sample period.

Previous research studies conclude that analysts outperform time-series models because they are able to utilize a broader set of information in forming their earnings forecasts. The results in this chapter show that analysts' predictions of the sign of earnings can be improved by them with the sum of the first three quarters' earnings per share and the percentage change in stock price from the previous year. This is an indication that analysts exclude or fail to include some relevant information when forming their forecasts. The findings are more in line with studies that show analysts forecasts can be improved when they are combined with other information such as time-series characteristics of earnings (Guerard (1987), Lobo (1992)).

The next chapter involves (1) obtaining MDA parameters in an estimation period, (2) using these parameter estimates in a hold-out test period to predict the sign of earnings, and (3) adjusting those forecasts that correspond to the negative earnings group using an adjustment factor obtained in the estimation period. MDA is chosen as the methodology for the next chapter because of its better success rate in predicting negative earnings. Also, the LR results have been only recently added to this chapter. A comparison of the MDA and LR methods in the context of Chapter 5 has not been possible in the time frame of this study.

Table 4.1. Mean and Standard Deviation of Variables in Analysis

	1985	1986	1987	1988	1989	1990	1991
$FEPS_t$							
Mean	.08010	.07457	.08691	.09657	.08284	.08768	.06116
St. deviation	.04129	.03536	.04143	.04210	.04234	.04462	.02624
$SUM3QEPS_t$							
Mean	.05617	.05656	.06825	.07058	.06474	.06678	.04105
St. deviation	.05597	.04191	.04131	.03914	.04287	.04931	.03300
$OVEREST_{t-1}$							
Mean	.00838	.01434	.01221	.00124	.00713	.00711	.01651
St. deviation	.03884	.05522	.05965	.03781	.04132	.03895	.06310
$PRICECHG_t$							
Mean	.24022	.03346	-.07831	.11676	.16467	-.15940	.30720
St. deviation	.33959	.29446	.36166	.34960	.30010	.24633	.44135
$FOLLCHG_t$							
Mean	.05744	.10190	.12013	.16202	-.04435	.39880	.05825
St. deviation	.56458	.53970	.53990	.57627	.47017	.68558	.60826
MV_t							
Mean	7.20369	7.51522	7.55159	7.53875	7.72408	7.61319	7.87024
St. deviation	1.37030	1.35381	1.18527	1.22821	1.36364	1.39196	1.33195
EPS_{t-1}							
Mean	.08772	.06669	.04932	.07648	.08581	.07129	.06717
St. deviation	.09957	.07952	.10261	.08870	.06256	.05922	.09892

Table 4.2. Correlation Matrix of Variables in Analysis

	EPS_t	$FEPS_t$	$SUM3QEPS_t$	$OVEREST_{t-1}$	$PRICECHG_t$	$FOLLCHG_t$	MV_t	EPS_{t-1}
EPS_t	1.0000	.6252 (.000)	.7165 (.000)	-.0797 (.000)	.0466 (.006)	.0053 (.796)	.0588 (.000)	.1777 (.000)
$FEPS_t$	.6252 (.000)	1.0000	.7399 (.000)	-.0358 (.084)	-.1068 (.895)	.0237 (.253)	.0033 (.835)	.3121 (.000)
$SUM3QEPS_t$	.7165 (.000)	.7399 (.000)	1.0000	-.0390 (.079)	-.1097 (.000)	.0223 (.313)	.0178 (.309)	.2387 (.000)
$OVEREST_{t-1}$	-.0797 (.000)	-.0358 (.084)	-.0390 (.079)	1.0000	.0417 (.045)	-.0320 (.122)	-.0570 (.006)	-.5035 (.000)
$PRICECHG_t$	.0466 (.006)	-.1068 (.000)	-.1097 (.000)	.0417 (.045)	1.0000	-.0628 (.003)	.0663 (.000)	-.0771 (.000)
$FOLLCHG_t$	.0053 (.796)	.0237 (.253)	.0223 (.313)	-.0320 (.122)	-.0628 (.003)	1.0000	.0517 (.012)	.0052 (.800)
MV_t	.0588 (.000)	.0033 (.835)	.0178 (.309)	-.0570 (.006)	.0663 (.000)	.0517 (.012)	1.0000	.1130 (.000)
EPS_{t-1}	.1777 (.000)	.3121 (.000)	.2387 (.000)	-.5035 (.000)	-.0771 (.000)	.0052 (.800)	.1130 (.000)	1.0000

Table 4.3. Multiple Discriminant Analysis (Forced Entry Method)

$D_t = a + b.\ FEPS_t + c.\ SUM3QEPS_t + e.\ OVEREST_{t-1} + f.\ PRICECHG_t + g.\ FOLLCHG_t + h.\ MV_t + i.\ EPS_{t-1} \quad \forall\ FEPS_t > 0 \quad t = 1985,....,1991$

Coefficients for the unstandardized canonical discriminant function are estimated using samples for each year separately from 1985 to 1991. Coefficient estimates for each variable are reported with p-values of their univariate F-ratio statistic underneath. D_SCORES at group centroids denote to the values of the discriminant function evaluated at the group means.

	1985	1986	1987	1988	1989	1990	1991
Constant term	-1.6272	1.2252	-.8162	-.0786	-1.3503	-1.9403	-1.1452
Coefficient of $FEPS_t$	-7.5252	1.1517	-22.8266	-31.4299	-13.6930	-16.7247	-15.1914
	(.0063)	(.0004)	(.0180)	(.0162)	(.1551)	(.1843)	(.0106)
Coefficient of $SUM3QEPS_t$	22.1559	-29.4374	40.5365	50.6643	32.1738	28.2039	39.7965
	(.0000)	(.0000)	(.0000)	(.0000)	(.0001)	(.0000)	(.0000)
Coefficient of $OVEREST_{t-1}$	-6.8102	15.6840	.7037	-4.8725	2.0736	-12.4362	-7.6328
	(.1146)	(.0142)	(.4783)	(.0881)	(.5915)	(.0012)	(.4802)
Coefficient of $PRICECHG_t$	1.0290	-1.9943	1.1358	.6731	2.4783	1.5524	.5052
	(.0816)	(.0016)	(.2322)	(.7738)	(.0012)	(.0174)	(.0173)
Coefficient of $FOLLCHG_t$	.2368	.2862	-.0818	.3620	.1909	.1308	.1540
	(.2253)	(.1761)	(.9012)	(.0447)	(.8462)	(.1273)	(.6354)
Coefficient of MV_t	.1378	-.0624	-.0091	-.0755	.0164	.2252	.1064
	(.2313)	(.2696)	(.4637)	(.6941)	(.2367)	(.0022)	(.2299)
Coefficient of EPS_{t-1}	-2.4078	9.5282	1.1082	-.3168	-1.6207	1.2968	-6.4706
	(.2992)	(.0029)	(.5435)	(.6474)	(.7726)	(.0037)	(.0720)
D-score at (-) group centroid	-1.7668	2.6400	-3.8840	-3.1028	-2.2828	-2.1506	-2.1858
D-score at (+) group centroid	.1466	-.1740	.0412	.1254	.0758	.1564	.1865
Number of observations	274	275	286	309	280	295	318

Table 4.4. Multiple Discriminant Analysis Classification Summary (Forced Entry Method)

Number of cases correctly classified by analysts and MDA is reported. The significance of gain (loss) in classification accuracy as a result of MDA is evaluated with a binomial test. The p-values of the binomial test are shown in parentheses in the last row.

	ESTIMATION PERIOD							
	1985	1986	1987	1988	1989	1990	1991	1985-91
Correct Classification by Analysts	253/274 (92.34%)	258/275 (93.82%)	283/286 (98.95%)	297/309 (96.12%)	271/280 (96.78%)	275/295 (93.22%)	293/318 (92.14%)	1930/2037 (94.75%)
Correct Classification by MDA	250/274 (91.24%)	262/275 (95.27%)	281/286 (98.25%)	295/309 (95.47%)	258/280 (92.14%)	267/295 (90.51%)	297/318 (93.40%)	1910/2037 (93.76%)
. of negative earnings	11/21 (52.40%)	13/17 (76.50%)	2/3 (66.70%)	6/12 (50.00%)	6/9 (66.70%)	11/20 (55.00%)	12/25 (48.00%)	61/107 (57.01%)
. of positive earnings	239/253 (94.50%)	249/258 (96.50%)	279/283 (98.60%)	289/297 (97.30%)	252/271 (93.00%)	256/275 (93.10%)	285/293 (97.30%)	1849/1930 (95.80%)
Gain (Loss) in Classification Accuracy	-3/274 (.2931)	4/275 (.1874)	-2/286 (.2214)	-2/309 (.3351)	-13/280 (.0000)	-8/295 (.0427)	4/318 (.2257)	-20/2037 (.0334)

Table 4.5. Multiple Discriminant Analysis (Stepwise Selection Method)

$D_t = a + b.\ FEPS_t + c.\ SUM3QEPS_t + e.\ OVEREST_{t-1} + f.\ PRICECHG_t + g.\ FOLLCHG_t + h.\ MV_t + i.\ EPS_{t-1} \quad \forall\ FEPS_t > 0 \quad t = 1985,....,1991$

Coefficients for the unstandardized canonical discriminant function are estimated using samples for each year separately from 1985 to 1991. Coefficient estimates for each variable are reported with p-values of their univariate F-ratio statistic underneath. D_SCORES at group centroids denote to the values of the discriminant function evaluated at the group means.

	1985	1986	1987	1988	1989	1990	1991
Constant term	-.6327	.8168	-.7373	-.5715	-1.2272	-1.9999	.2146
Coefficient of $FEPS_t$	-11.7457 (.0000)		-22.5005 (.0000)	-33.5342 (.0000)	-15.2370 (.0000)	-15.7694 (.0000)	14.4200 (.0000)
Coefficient of $SUM3QEPS_t$	23.7374 (.0000)	-29.5481 (.0000)	40.6411 (.0000)	52.6307 (.0000)	32.0764 (.0001)	28.3071 (.0000)	-40.7939 (.0000)
Coefficient of $OVEREST_{t-1}$		16.6312 (.0000)				-13.7066 (.0000)	-7.7949 (.0000)
Coefficient of $PRICECHG_t$	.9998 (.0000)	-1.9820 (.0000)	1.0326 (.0000)	.8156 (.0000)	2.5079 (.0000)	1.5529 (.0000)	
Coefficient of $FOLLCHG_t$							
Coefficient of MV_t						.2413 (.0000)	6.6875 (.0000)
Coefficient of EPS_{t-1}		10.2306 (.0000)					
D-score at (-) group centroid	-1.6683	2.5992	-3.8589	-2.9723	-2.2479	-2.1402	2.1110
D-score at (+) group centroid	.1385	-.1713	.0409	.1201	.0747	.1556	-.1801

Table 4.6. Multiple Discriminant Analysis Classification Summary (Stepwise Selection Method)

Number of cases correctly classified by analysts and MDA is reported. The significance of gain (loss) in classification accuracy as a result of MDA is evaluated with a binomial test. The p-values of the binomial test are shown in parentheses in the last row.

	ESTIMATION PERIOD							
	1985	1986	1987	1988	1989	1990	1991	1985-91
Correct Classification by Analysts	333/357 (93.28%)	258/275 (93.82%)	392/400 (98.00%)	406/423 (95.98%)	365/380 (96.05%)	275/295 (93.22%)	293/318 (92.14%)	2322/2448 (94.85%)
Correct Classification by MDA	331/357 (92.72%)	260/275 (94.55%)	390/400 (97.50%)	400/423 (94.56%)	339/380 (89.21%)	269/295 (91.19%)	299/318 (94.03%)	2288/2448 (93.46%)
. of negative earnings	9/24 (37.50%)	12/17 (70.60%)	4/8 (50.00%)	7/17 (41.20%)	9/15 (60.00%)	11/20 (55.00%)	12/25 (48.00%)	64/126 (50.79%)
. of positive earnings	322/333 (96.70%)	248/258 (96.10%)	386/392 (98.50%)	393/406 (96.80%)	330/365 (90.40%)	258/275 (93.80%)	287/293 (98.00%)	2224/2322 (95.78%)
Gain (Loss) in Classification Accuracy	-2/357 (.3985)	2/275 (.3492)	-2/400 (.2961)	-6/423 (.1030)	-26/380 (.0000)	-6/295 (.1042)	6/318 (.1212)	-34/2448 (.0017)

Table 4.7. Logistic Regression (Forced Entry Method)

$z = b_0 + b_1 .EPS_{t-1} + b_2 .FEPS_t + b_3 .OVEREST_{t-1} + b_4 .FOLLCHG_t + b_5 .SUM3QEPS_t + b_6 .MV_t + b_7 .PRICECHG_t \quad \forall\ FEPS_t > 0 \quad t = 1985, \ldots, 1991$

Coefficients of the logistic regression function are estimated using samples of positive forecasts for each year separately from 1985 to 1991. Coefficient estimates for each variable are reported with p-values of their Wald statistic underneath. Model chi-square and its p-value are also shown at the bottom of the table.

	1985	1986	1987	1988	1989	1990	1991
Constant term	.7894 (.5911)	1.6536 (.4185)	5.0412 (.5367)	7.0540 (.0132)	1.3731 (.5152)	-.2550 (.8835)	1.3187 (.5333)
Coefficient of $FEPS_t$	-6.8540 (.6334)	9.0680 (.6746)	-1.3543 (.9800)	9.8454 (.6795)	-12.3761 (.5469)	-13.1342 (.3481)	35.4689 (.0586)
Coefficient of $SUM3QEPS_t$	40.8766 (.0011)	63.4276 (.0045)	98.7186 (.1192)	62.4324 (.0005)	37.7250 (.0719)	40.8820 (.0001)	63.4884 (.0000)
Coefficient of $OVEREST_{t-1}$	-7.9829 (.4337)	-19.2662 (.0678)	12.6893 (.4411)	-46.0396 (.0045)	31.1263 (.1308)	-13.6940 (.1639)	-17.4332 (.2146)
Coefficient of $PRICECHG_t$	3.0823 (.0108)	5.1919 (.0017)	.0049 (.9987)	.0501 (.9731)	4.9590 (.0049)	2.7795 (.0142)	2.3716 (.0252)
Coefficient of $FOLLCHG_t$	.5202 (.4205)	-.9782 (.0459)	-2.1985 (.3687)	2.0190 (.0767)	.3208 (.7675)	.2628 (.6504)	.9219 (.2581)
Coefficient of MV_t	.1127 (.5760)	-.0225 (.9321)	-.2743 (.7758)	-.6231 (.0805)	.0782 (.7755)	.3322 (.1416)	.0388 (.8809)
Coefficient of EPS_{t-1}	-9.0462 (.2259)	-12.0521 (.1206)	5.2381 (.4787)	-27.8209 (.0213)	5.0479 (.6509)	3.9998 (.6527)	-34.5562 (.0000)
Model Chi square	44.068 (.0000)	66.929 (.0000)	21.205 (.0035)	56.541 (.0000)	27.614 (.0003)	55.728 (.0000)	89.550 (.0000)

Table 4.8. Logistic Regression Classification Summary (Forced Entry Method)

Number of cases correctly classified by analysts and LR is reported. The significance of gain (loss) in classification accuracy as a result of LR is evaluated with a binomial test. The p-values of the binomial test are shown in parentheses in the last row.

	1985	1986	1987	1988	1989	1990	1991	1985-91
Correct Classification by Analysts	253/274 (92.34%)	258/275 (93.82%)	283/286 (98.95%)	297/309 (96.12%)	271/280 (96.78%)	275/295 (93.22%)	293/318 (92.14%)	1930/2037 (94.75%)
Correct Classification by LR	257/274 (93.80%)	264/275 (96.00%)	284/286 (99.30%)	301/309 (97.41%)	272/280 (97.14%)	280/295 (94.92%)	300/318 (94.34%)	1958/2037 (96.12%)
. of negative earnings	6/21 (28.57%)	8/17 (47.06%)	1/3 (33.33%)	6/12 (50.00%)	2/9 (22.22%)	7/20 (35.00%)	12/25 (48.00%)	42/107 (39.25%)
. of positive earnings	251/253 (99.21%)	256/258 (99.22%)	283/283 (100.00%)	295/297 (99.33%)	270/271 (99.63%)	273/275 (99.27%)	288/293 (98.29%)	1916/1930 (99.27%)
Gain (Loss) in Classification Accuracy	4/274 (.2074)	6/275 (.0826)	1/286 (.3571)	4/309 (.1484)	1/280 (.4379)	5/295 (.1458)	7/318 (.0843)	28/2037 (.0042)

Chapter 5

IMPROVING THE ACCURACY OF POSITIVE EARNINGS FORECASTS

In this chapter, the parameters of the MDA discriminant function are estimated using an estimation period sample. Discriminant scores from the analysis are saved and regressed against the forecast errors. Then, estimated discriminant function parameters are applied to a test period sample to predict the sign of actual earnings. Positive earnings forecasts that are predicted to be associated with negative earnings according to MDA are adjusted in the test period using the regression parameters of the forecast errors against the discriminant scores. In line with the findings of Chapter 4, the sum of the first three quarterly earnings announcements and the November consensus forecast are used as discriminatory variables in the MDA to predict the sign of actual earnings outcomes.

Estimation Period

When analysts produce their November forecasts of annual earnings per share, they have the advantage of knowing the earnings numbers for the first three quarters. However, the large proportion of over-optimistic forecasts of negative earnings announcements suggests that they disregard this information when forming their forecasts of earnings outcomes that turn out to be negative. If the overoptimism is intentional, analysts will continue reporting optimistic forecasts regardless of the bad news revealed in the first three quarters. This results in overoptimistic *positive* forecasts of *negative* earnings. Because analysts are quite accurate when reporting positive forecasts of earnings that turn out to be positive, an attempt to correct positive forecasts must first predict the sign of actual earnings outcomes. As the results in Chapter 4 suggest, combining this predisclosure information with the analyst forecasts may yield an improved forecast of the sign of earnings, especially for negative earnings outcomes.

$$SIGNEPS_{it} = f\,(SUM3QEPS_{it}, FEPS_{it})$$

where

$SIGNEPS_{it}$ = sign of the annual earnings per share for firm i in period t
$FEPS_{it}$ = median forecast of earnings per share for firm i in period t
$SUM3QEPS_{it}$ = sum of the first three quarters' earnings per share for firm i in period t

The following unstandardized canonical discriminant function is used to compute discriminant scores (D_SCORE),

$$D\_SCORE_{it} = a_t + b_t \,.\, SUM3QEPS_{it} + c_t \,.\, FEPS_{it} \qquad \forall\ FEPS_{it} > 0 \qquad t = 1984, \ldots, 1990$$

Coefficients have been estimated for each year of the sample data from 1984 to 1990. The coefficient values and the p-values of the univariate F-statistic for each variable are shown in Table 5.1. As is apparent in the table, both variables have statistically significant discriminating power. The coefficient of SUM3QEPS has positive values and the coefficient of FEPS has negative values in each estimation period, and both coefficients are significant at a 5% level in each period.

The percentage of correct classifications for each estimation period is presented in Table 5.2. The percentage of negative earnings correctly classified is above 50% in four of the eight estimation samples, reaching a maximum of 75% in the 1984 sample. This improvement comes at the expense of classifying some positive earnings outcomes as negative. With the exception of 1984 and 1990, the overall proportion of correct classifications stays very close to that of the analysts.

The second step in the estimation period involves determining the size of the forecast errors corresponding to the earnings that are predicted as negative. Positive forecasts of positive earnings are quite accurate whereas positive forecasts of negative earnings are grossly over-optimistic. Therefore, forecasts that correspond to a negative earnings number should have the largest forecast error. In order to obtain information on the size of the forecast adjustment, discriminant scores from the analysis are saved and regressed against the forecast errors for the positive forecasts that are relassified as negative by MDA:

$$FCE_{it} = a_t + b_t \, . \, D\_SCORE_{it} + e_{it} \qquad \forall \; SIGNEPS_{it}^{-} \text{ and } \forall \; FEPS_{it} > 0 \quad t = 1984, \ldots, 1990$$

where

FCE_{it}	= forecast error (= EPS - FEPS) for firm i in period t
D_SCORE_{it}	= discriminant score firm i in period t
$SIGNEPS_{it}^{-}$	= sign of earnings per share predicted as negative for firm i in period t

Results presented in Table 5.3 show that discriminant scores have statistically significant explanatory power in predicting the size of the forecast error in each year except 1987. R^2 values range between 4.73% and 91.97%, and the coefficient of D_SCORE is significant at 5% level in each of the sample periods except 1987. The mean value of the forecast error is large and negative in each period indicating that forecasts of earnings that are predicted as negative have an optimistic bias. A positive coefficient for D_SCORE means that the smaller the D_SCORE the more optimistic a forecast is likely to be.

This result gains more significance when the following OLS regression is run for the positive forecasts that are not reclassified:

$FCE_{it} = a_t + b_t \,.\, D\_SCORE_{it} + e_{it} \quad \forall\ SIGNEPS_{it}^{+}$ and $\forall\ FEPS_{it} > 0 \quad t = 1984,\ldots\ldots,1990$

where

$SIGNEPS_{it}^{+}$ = sign of earnings per share predicted as negative for firm i in period t

As is apparent in Table 4.4, the regressions result in small R^2 values and significantly non-zero intercept terms. Also, FCE has a negative and smaller mean compared to the mean in the negative prediction group, whereas the mean of D_SCORE is positive. This suggests that, in contrast to the group of negative earnings prediction, D_SCORE does not explain the variation in FCE as successfully in the sample of positive earnings forecasts that are not reclassified as negative by MDA.

Test Period

In this section, parameters of the discriminant function estimated in one year (the estimation period) are used to predict the sign of earnings in the following year (the test period). Earnings that are predicted as negative are then adjusted using the regression parameters of the forecast error versus the discriminant scores from the estimation period.

The following equation is used to predict the sign of the earnings in the test period:

$$D\_SCORE_{it} = a_{t-1} + b_{t-1} \,.\, SUM3QEPS_{it} + c_{t-1} \,.\, FEPS_{it} \qquad \forall\, FEPS_{it} > 0 \;\; t = 1985,\ldots,1991$$

The D_SCORE that is computed for each observation is compared with the cut-off discriminant score from the estimation period.[1] If the calculated D_SCORE for the test period is greater than the cut-off point, the observation is assigned into the positive earnings group. Otherwise, the observation is classified into the negative earnings group. The classification results for the test period are presented in Table 5.5. For each test period from 1985 to 1991, the percentage of negative earnings correctly classified by MDA is an improvement over analysts' predictions. Correct classification of negative earnings by MDA ranges from 38.89% to 85.29% in the seven test period samples

---

[1] The cut-off discriminant value is obtained from the estimation period sample using a procedure suggested by Altman [1968]. This procedure uses the estimation period discriminant scores to select a cut-off point that minimizes the misclassification error in the “area of ignorance” where distributions of discriminant scores overlap. Hsieh (1993) suggests an alternative method that minimizes the *cost* of misclassification when the costs of misclassification are not symmetric.

between 1985 and 1991. Although it falls below 90.00% in 1985 and 1991, the overall correct classification is still comparable to that of the analysts. With the exception of these two years, probability of incorrectly predicting negative earnings when actual earnings are positive is between 2 and 5 percent of the positive earnings outcomes.

To identify and adjust the forecasts of negative earnings, those observations in the negative earnings group are used with the following equation to predict the size of the forecast error and hence the magnitude of the forecast adjustment (ADJ).

$$ADJ_{it} = a_{t-1} + b_{t-1} \cdot D\_SCORE_{it} \qquad \forall\ SIGNEPS_{it}^{-} \text{ and } \forall\ FEPS_{it} > 0 \quad t = 1985,....,1991$$

Finally, positive forecasts that are predicted by MDA to correspond to negative earnings are adjusted using the following equation:[2]

$$AFEPS_{it} = FEPS_{it} + ADJ_{it} \qquad \forall\ SIGNEPS_{it}^{-} \text{ and } \forall\ FEPS_{it} > 0 \qquad t= 1985,....,1991$$

The improvement in forecast accuracy as a result of these adjustments is presented in Table 5.6. Adjusted forecasts outperform analysts' consensus forecasts in relative forecast accuracy in each period except 1987. Relative forecast accuracy (the ratio of the MSE after adjustment to the MSE before adjustment) ranges between 9.11% and 62.36%

---

[2]Using the conventional measure of forecast error (actual earnings - forecasts) the sign of an over-optimistic forecast error and hence the sign of the adjustment factor will be negative. Adding a negative adjustment factor to the forecast will therefore have the effect of a downward adjustment.

in six test periods, and it is 53.01% in the pooled sample. MSE is reduced by downward adjusting the forecasts of earnings reclassified as negative by MDA. Another important implication of these results pertains to the *positive* forecasts of *positive* earnings that are adjusted as a result of the misclassification by MDA. Despite a classification error, the majority of the positive forecasts of positive earnings that are misclassified as negative earnings forecasts are still overoptimistic. As is apparent in the bottom panel of Table 5.6, the proportion of positive earnings that are overestimated by analysts is around 50% (ranges from 40.72% to 56.33%) in the test period samples. Positive earnings that are classified as negative by MDA are overoptimistic up to 88.24% of the time. This suggests that when SUM3QEPS and FEPS are used as discriminatory variables, MDA can discriminate not only the positive forecasts of negative earnings outcomes but also the optimistic positive forecasts of positive earnings. When the predicted forecast errors are added to the optimistic positive forecasts of positive earnings, this results in a downward adjustment in the correct direction.[3] The proportion of downward adjustments that are in the correct direction ranges between 61.90% and 93.33% in the overall positive forecast sample. Forecasts of positive earnings are correctly downward adjusted at a success rate of above 70% in four of the seven test period samples and 70.69% in the pooled sample. Improvements on these results might be achieved by extending the estimation period by pooling data into two (or more) years.

---

[3] Kwok and Lubecke (1990) use the "correctness" criterion in assessing improvements in foreign exchange forecasts.

Summary

Although security analysts do a relatively good job when they report forecasts for positive earnings that turn out to be positive, they suffer from an optimistic bias when forecasting earnings that turn out to be negative. That is, positive consensus forecasts are fairly symmetrically distributed around actual earnings when they correspond to a positive earnings outcome. Overoptimistic bias in positive forecasts is driven by earnings that turn out to be negative. In this chapter, a methodology is tested to identify and adjust positive forecasts that are predicted to correspond to negative earnings outcomes.

The methodology involves using consensus forecasts of annual earnings with the sum of the first three quarters' earnings to predict the sign of an earnings announcement. First, the coefficients of SUM3QEPS and FEPS and the cut-off discriminant values from Multiple Discriminant Analysis for each annual sample period are estimated between 1984 and 1990. OLS regression parameters of the forecast errors against the discriminant scores are obtained for those earnings predicted as negative by MDA in the estimation period. Coefficient values of the MDA function and cut-off discriminant scores are then used in an out-of-sample test period to predict the sign of actual earnings outcomes. An adjustment factor is obtained by using the previously estimated regression parameters of the forecasts errors versus the discriminant scores. Earnings that are predicted as negative in the test period are then adjusted using the adjustment factor. Test period results indicate that this methodology provides forecasts that outperform security analysts' consensus forecasts. Mean square error before adjustment is greatly reduced in all but one test period.

Table 5.1. Multiple Discriminant Analysis (Estimation of Function Parameters)

$$D\_SCORE_{it} = a_t + b_t \,.\, SUM3QEPS_{it} + c_t \,.\, FEPS_{it} \;\forall\; FEPS_{it} > 0 \qquad t = 1984, \ldots, 1990$$

where

D_SCORE_{it}	=	discriminant score for firm i in fiscal year t
$FEPS_{it}$	=	forecast of earnings per share for firm i in fiscal year t
$SUM3QEPS_{it}$	=	sum of the first three quarters' earnings per share for firm i in fiscal year t

Coefficients for the unstandardized canonical discriminant function are estimated using samples for each year separately from 1984 to 1990. Coefficient estimates for each variable are reported with p-values of their univariate F-ratio statistic underneath. D_SCORES at group centroids denote to the values of the discriminant function evaluated at the group means.

	1984	1985	1986	1987	1988	1989	1990
Number of Observations	371	363	392	408	433	384	490
SUM3QEPS							
. mean	0.07834	0.05927	0.05520	0.06800	0.07058	0.06272	0.06747
. standard deviation	0.04084	0.05196	0.05164	0.04855	0.04102	0.04317	0.04563
FEPS							
. mean	0.10439	0.08259	0.07526	0.08800	0.09433	0.08171	0.08970
. standard deviation	0.05134	0.04041	0.03516	0.04272	0.04382	0.04173	0.04728
Constant term	-1.413313	-0.597556	-1.112169	-0.595092	-0.903005	-0.472532	-0.969966
Coefficient of SUM3QEPS	42.452947	26.163018	22.769653	30.669926	40.876697	38.392046	29.798400
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
Coefficient of FEPS	-18.318795	-11.541054	-1.924142	-16.939243	-21.009982	-23.688394	-11.600678
	(.0018)	(.0009)	(.0000)	(.0120)	(.0018)	(.0392)	(.0018)
D-score at (-) group centroid	-1.80541	-1.69880	-2.08319	-2.49074	-1.84741	-1.85228	-1.260360
D-score at (+) group centroid	0.06035	0.12027	0.14191	0.04981	0.08013	0.07530	0.088060

Table 5.2. Multiple Discriminant Analysis Classification Summary (Estimation Period)

Number of cases correctly classified by analysts and MDA is reported. The significance of gain (loss) in classification accuracy as a result of MDA is evaluated with a binomial test. The p-values of the binomial test are shown in parentheses in the last row.

	1984	1985	1986	1987	1988	1989	1990	1984-90
Correct Classification by analysts	359/371 (96.77%)	339/363 (93.39%)	367/392 (93.62%)	400/408 (98.04%)	415/433 (95.84%)	369/384 (96.10%)	458/490 (93.47%)	2707/2841 (95.28%)
Correct Classification by MDA	335/371 (90.30%)	341/363 (93.94%)	365/392 (93.11%)	397/408 (97.30%)	403/433 (93.07%)	362/384 (94.27%)	418/490 (85.31%)	2621/2841 (92.26%)
. of negative earnings	9/12 (75.00%)	8/24 (33.33%)	13/25 (52.00%)	4/8 (50.00%)	10/18 (55.56%)	7/15 (46.67%)	18/32 (56.25%)	69/134 (51.49%)
. of positive earnings	326/359 (90.81%)	333/339 (98.23%)	352/367 (95.91%)	393/400 (98.25%)	393/415 (94.70%)	355/369 (96.20%)	400/458 (87.34%)	2552/2707 (94.27%)
Gain (Loss) in Classification Accuracy	-24/371 (.0000)	2/363 (.3790)	-2/392 (.3854)	-3/408 (.2040)	-12/433 (.0034)	-7/384 (.0427)	-40/490 (.0000)	-86/2841 (.0000)

Table 5.3. OLS Regressions of Forecast Errors Against Discriminant Scores for the Negative Earnings Classification (Estimation Period)

$$FCE_{it} = a_t + b_t \,.\, D\_SCORE_{it} + e_{it} \qquad \forall\ SIGNEPS_{it}^{-} \text{ and } \forall\ FEPS_{it} > 0 \qquad t = 1984,\ldots,1990$$

where

FCE_{it} = forecast error (= EPS - FEPS) for firm i in period t
D_SCORE_{it} = discriminant score firm i in period t
$SIGNEPS_{it}^{-}$ = sign of earnings per share predicted as negative for firm i in period t

Sample period is 1984-1990. Coefficients of the OLS regression are estimated using the observations from the negative EPS group predicted by the dicsriminant function. This procedure is repeated for samples from each year. Parameters for the intercept (a_t) and slope (b_t) terms are estimated, and their values are reported with the p-value of their t-statistic underneath. For each regression R^2 are reported as well.

	1984	1985	1986	1987	1988	1989	1990
Number of observations	42	14	28	11	32	21	76
FCE							
. mean	-0.044	-0.128	-0.079	-0.098	-0.056	-0.069	-0.047
. standard deviation	0.085	0.133	0.125	0.149	0.071	0.081	0.088
D_SCORE							
. mean	-1.655	-3.524	-2.300	-3.513	-2.132	-2.241	-1.319
. standard deviation	1.121	3.257	2.705	2.912	1.407	2.300	1.259
Intercept (a_t)	-0.016440 (-0.704)	0.001116 (0.046)	0.023535 (2.598)	-0.001919 (-1.370)	0.024058 (-0.212)	0.032037 (0.261)	0.032962 (-0.233)
Coefficient of D_SCORE_{it} (b_t)	0.016526 (1.409)	0.036772 (7.120)	0.044468 (17.251)	0.012720 (-0.113)	0.009415 (2.980)	0.006291 (9.876)	0.006617 (4.572)
R^2	0.0473	0.8086	0.9197	0.0014	0.2284%	0.8370	0.2202

Table 5.4. OLS Regressions of Forecast Errors Against Discriminant Scores for the Positive Earnings Classification (Estimation Period)

$$FCE_{it} = a_t + b_t \,.\, D\_SCORE_{it} + e_{it} \qquad \forall\ SIGNEPS_{it}^{+} \text{ and } \forall\ FEPS_{it} > 0 \qquad t = 1984,\ldots,1990$$

where

FCE_{it} = forecast error (= EPS - FEPS) for firm i in period t
D_SCORE_{it} = discriminant score firm i in period t
$SIGNEPS_{it}^{+}$ = sign of earnings per share predicted as negative for firm i in period t

Sample period is 1984-1990. Coefficients of the OLS regression are estimated using the observations from the positive EPS group predicted by the dicsriminant function. This procedure is repeated for samples from each year. Parameters for the intercept (a_t) and slope (b_t) terms are estimated, and their values are reported with the p-value of their t-statistic underneath. For each regression R^2 are reported as well.

	1984	1985	1986	1987	1988	1989	1990
Number of observations	329	349	364	397	401	363	414
FCE							
. mean	-0.004	-0.009	-0.008	-0.001	-0.002	-0.005	-0.011
. standard deviation	0.038	0.043	0.041	0.035	0.032	0.029	0.056
D_SCORE							
. mean	0.211	0.141	0.177	0.097	0.170	0.130	0.242
. standard deviation	0.834	0.578	0.640	0.766	0.832	0.776	0.804
Intercept (a_t)	-0.006479	-0.010003	-0.009259	-0.002145	-0.003358	-0.005503	-0.012769
	(-3.098)	(-4.223)	(-4.166)	(-1.266)	(-2.087)	(-3.571)	(-4.493)
Coefficient of D_SCORE_{it} (b_t)	0.009705	0.008206	0.007758	0.012720	0.009415	0.006291	0.006617
	(3.988)	(2.059)	(2.315)	(5.790)	(4.959)	(3.209)	(1.953)
R^2	0.0464	0.0121	0.0146	0.0782	0.0581	0.0277	0.0092

Table 5.5. Multiple Discriminant Analysis Classification Summary (Test Period)

Number of cases correctly classified by analysts and MDA is reported. The significance of gain (loss) in classification accuracy as a result of MDA is evaluated with a binomial test. The p-values of the binomial test are shown in parentheses in the last row.

	1985	1986	1987	1988	1989	1990	1991	1985-91
Correct Classification by Analysts	339/363 (93.39%)	367/392 (93.62%)	400/408 (98.03%)	415/433 (95.84%)	369/384 (96.09%)	458/490 (93.47%)	378/412 (91.75%)	2726/2882 (94.59%)
Correct Classification by MDA	299/363 (82.37%)	363/392 (92.60%)	389/408 (95.34%)	413/433 (95.38%)	356/384 (92.71%)	454/490 (92.65%)	307/412 (74.51%)	2581/2882 (89.56%)
. of negative earnings	15/24 (62.50%)	11/25 (44.00%)	5/8 (62.50%)	7/18 (38.89%)	7/15 (46.67%)	13/32 (40.62%)	29/34 (85.29%)	87/156 (55.77%)
. of positive earnings	284/339 (83.78%)	352/367 (95.91%)	384/400 (96.00%)	406/415 (97.83%)	349/369 (94.58%)	441/458 (96.29%)	278/378 (73.54%)	2494/2726 (91.49%)
Gain (Loss) in Classification Accuracy	-40/363 (.0000)	-4/392 (.2407)	-11/408 (.0001)	-2/433 (.3765)	-13/384 (.0005)	-4/490 (.2518)	-71/412 (.0000)	-145/2882 (.0000)

Table 5.6. Improvement in Forecast Accuracy of Adjusted Positive Forecasts (Test Period)

Analysts' *positive* forecasts of earnings per share are adjusted for bias using the samples of each year from 1985 to 1991. Discriminant function parameters estimated at period t-1 are used together with period t data in order to obtain *a priori* groupings of observations into negative EPS and positive EPS realization. The following equation is then used in adjusting the forecasts pertaining to the negative earnings group:

$$AFEPS_{it} = FEPS_{it} + ADJ_{it} \qquad \forall\ SIGNEPS_{it}^{-} \text{ and } \forall\ FEPS_{it} > 0 \qquad t = 1985,....,1991$$

where

$AFEPS_{it}$ = adjusted forecast for firm i in fiscal year t
ADJ_{it} = forecast adjustment factor for firm i in fiscal year t

Mean square errors before and after the adjustment are computed for each test period. Performance of adjusted forecasts are evaluated using the criterion of relative forecast accuracy (= AMSE / MSE). Percentage of overoptimistic earnings forecasts that are correctly downward adjusted, and the observed analyst overoptimism in the overall sample are also reported.

	1985	1986	1987	1988	1989	1990	1991	1985-91
Mean square forecast error before adjustment (MSE)	.012290	.024622	.022785	.011368	.008581	.023587	.008245	.013052
Mean square forecast error after adjustment (AMSE)	.005954	.002243	.024714	.005551	.001185	.014303	.005142	.006919
Relative Forecast Accuracy (AMSE / MSE)	.4844	.0911	1.0847	.4883	.1381	.6064	.6236	.5301
Correct Downward Adjustment by MDA	51/70 (72.86%)	24/26 (92.31%)	13/21 (61.90%)	12/16 (75.00%)	23/27 (85.18%)	28/30 (93.33%)	100/129 (77.52%)	251/319 (78.68%)
. of forecasts of negative earnings	15/15 (100.00%)	11/11 (100.00%)	5/5 (100.00%)	7/7 (100.00%)	7/7 (100.00%)	13/13 (100.00%)	29/29 (100.00%)	87/87 (100.00%)
. of forecasts of positive earnings	36/55 (65.45%)	13/15 (86.67%)	8/16 (50.00%)	5/9 (55.56%)	16/20 (80.00%)	15/17 (88.24%)	71/100 (71.00%)	164/232 (70.69%)
Earnings Overestimated by Analysts	195/363 (53.72%)	196/392 (50.00%)	195/408 (47.79%)	187/433 (43.19%)	200/384 (52.08%)	290/490 (59.18%)	227/412 (55.10%)	1490/2882 (51.70%)
. negative earnings	24/24 (100.00%)	25/25 (100.00%)	8/8 (100.00%)	18/18 (100.00%)	15/15 (100.00%)	32/32 (100.00%)	34/34 (100.00%)	156/156 (100.00%)
. positive earnings	171/339 (50.44%)	171/367 (46.60%)	187/400 (46.75%)	169/415 (40.72%)	185/369 (50.13%)	258/458 (56.33%)	193/378 (51.06%)	1334/2726 (48.94%)

Chapter 6

A COMPARATIVE ANALYSIS OF ANALYSTS' EARNINGS FORECASTS IN INTERNATIONAL EQUITY MARKETS

Investors who seek to diversify their portfolios through international equity investments face the difficult task of evaluating the market values of stocks in different institutional environments. Valuation of a stock requires estimation of its future cash flow performance. Expectations of market participants on company fundamentals, which serve as measures of future performance, play an important role in driving the market values of stocks.

Research studies of U.S. and other equity markets have shown that analysts forecasts' of earnings proxy for investors' expectations of firms' future performance. For example, Jacques and Rie (1994) examine which company fundamentals are important in determining stock prices in the U.S., the U.K. and Japan. They find that current earnings are important to investors in all three countries and that earnings estimates dominate both current earnings and dividends.

Several studies have documented the association of earnings forecasts with stock prices and returns in international equity markets. Bercel (1994) shows that changes in analysts' earnings per share forecasts and the number of analysts changing their forecasts are related to abnormal stock returns in several international markets. Erickson and Cunniff (1995) find that the appeal of working with consensus forecasts of earnings is even greater for international markets, where differences in accounting standards are significant. In a study that covers quarterly periods between 1988 and 1993, they find that consensus earnings estimates are important, but in varying degrees across different world markets, and that they can effectively contribute to stock selection models. Sultan (1994) examines the relationship between unexpected earnings announcements and stock prices in Japan and shows that firms announcing better than expected earnings outperform those announcing worse than expected earnings. Conroy, Harris and Park (1994) investigate the link between share prices in Japan and earnings forecasts by both analysts and management. Their evidence shows that earnings fundamentals are priced in the Japanese market, and that both analyst and management forecasts convey significant information to the market participants. In spite of important institutional differences between Japanese and U.S. equity markets, this study finds significant value effects of earnings in both markets. Conroy et al. conclude that stock prices react to announcements of recent earnings when actual earnings differ from analysts' forecasts. Elton and Gruber (1989) explore the impact of a change in analysts' forecasts of earnings and sales on the subsequent price performance of a sample of Japanese stocks. Their study finds that changes in earnings and sales estimates affect price and that the impact is incorporated slowly over time.

In light of studies demonstrating the importance of analysts' earnings forecasts in international equity markets, research has increasingly focused on issues of rationality and accuracy in these forecasts. For example, Capstaff, Paudyal and Rees (1995) examine whether forecasts of corporate earnings in the U.K. are formed in a rational manner based on a sample of individual forecasts of annual earnings for the years ending in 1987 and 1991. Their results show that analysts generally provide more accurate forecasts than naive time series models, but that forecast errors are larger when earnings decrease than when earnings increase. These authors also suggest that analysts overreact to recent information when making forecasts. Capstaff, et al. conclude that these results cast considerable doubt on the rationality of earnings forecasting in the United Kingdom. Conroy and Harris (1995) analyze two distinct sources of analysts' earnings forecasts for Japanese stocks, one from sell-side analysts and another from an information provider that does not make stock recommendations. Their results indicate that forecasts from sell-side analysts are more optimistic and less accurate than the second set of forecasts, possibly reflecting analyst incentive structures and traditional role of Japanese securities houses.

Harris, Lang and Moller (1994) compare the value relevance of accounting measures of earnings for U.S. and German firms matched on industry and firm size. Contrary to the notion that accounting data are essentially meaningless for German corporations, the study finds that these data are significantly associated with stock price levels and returns. Harris, et al. also find that the explanatory power of earnings for returns in Germany is comparable to that in the U.S., which suggests that German earnings are not as imprecise as often perceived.

In this chapter, analysts' earnings forecasts in Japan, the United Kingdom, and Germany are investigated to find out whether (1) there exists a bias in analysts' consensus forecasts of earnings per share in these markets, (2) bias (if present) has any systematic component and/or is symmetric across the magnitude of forecasts, (3) negative earnings forecasts differ from positive forecasts in terms of bias, and (4) the U.S. phenomenon of overoptimistic forecasts of negative earnings also appears in these international equity markets.

Data

Data for analysis is gathered using the Institutional Brokers Estimate System (I/B/E/S) International history date tapes. This data base provides information on security analysts' consensus earnings forecasts for over forty countries. The sample is reduced to include Japan, U.K., and Germany to focus on relatively better established international capital markets. Using similar filters as in the U.S. case, a sample of median consensus forecasts of those companies with three or more forecasts of primary earnings per share reported to I/B/E/S during November for a December fiscal year-end is constructed. Earnings per share figures are taken from the Background Data File of the I/B/E/S history tape. Both earnings per share forecasts and actual earnings per share for each firm are divided by beginning-of-year share price in order to scale for cross-sectional differences in the level of earnings and share price. Hereafter, "earnings" and "EPS" refer to the earnings/price ratio and "forecasts" and "FEPS" refer to the ratio of consensus forecasts to price. The final sample covers the period 1987-94 and includes 1,056 observations for Japan, 2,049 for the U.K. and 1,035 for Germany. Tables 6.1-6.3 present descriptive statistics on actual earnings (EPS) and earnings forecasts (FEPS) for Japan, the U.K. and Germany, respectively.

Forecast Bias

Figures 6.1-6.3 plot actual (EPS) against expected (FEPS) earnings over the pooled sample period 1987-94 for Japan, the U.K., and Germany, respectively (Figures 6.4-6.6 provide a more detailed view using a larger scale). As is evident in the figures, analysts in these countries rarely report a negative forecast for earnings that turn out to be positive (about 1% of all observations across all three countries). In fact, forecasts of positive earnings are clustered around a 45-degree line through the origin. (Some U.K. forecasts in the northeast quadrant show a larger deviation from the 45-degree line than those in Japan and Germany). On the other hand, forecasts associated with negative earnings outcomes are located mostly to the right of the 45-degree line, indicating overoptimism by security analysts. The ray of observations scattered along the y-axes in the southeast quadrants of Figures 6.1-6.3 reflect a tendency of analysts to report positive forecasts even when actual earnings are negative. These preliminary observations are similar to those for U.S. forecasts in Table 1.

Tables 6.4-6.6 show the percentage of cases where forecasts overestimate actual earnings on a year-by-year basis and categorized according to the sign EPS and the sign of the FEPS for the three countries.

The pooled sample results in Japan shows that analyst forecasts are overoptimistic 63.87% of the time with a statistically significant forecast bias of (-0.008233). The proportion of optimistic forecasts is 67.50% when forecasts have a negative sign and 63.57% when they have a positive sign. The magnitude of the average forecast error in the pooled sample of negative forecasts (-0.135330) is greater than the magnitude of the average forecast error in the pooled sample of positive forecasts (-0.005493). When analysts report a positive forecast for earnings that turn out to be positive, they are optimistic 62.02% of the time with an average forecast error of (-0.002138). On the other hand, when they issue negative forecasts for earnings that turn out to be negative, this overoptimism is magnified. In this case 85.71% of the earnings are overestimated with a large average bias of (-0.075761). Analysts forecast 39 of the 102 (38.24%) negative earnings outcomes as positive. Analysts report negative forecasts for only 17 of 936 (1.82%) positive earning announcements.

Analysts in the U.K. are also overoptimistic as reported in Table 6.5. Forecasts turn out to be larger than actual earnings 70.52% of the time with an average forecast error of (-0.011660) in the pooled sample. Negative earnings forecasts show an optimistic bias of (0.002231) and the percentage of overestimated earnings is 35.71%. Analysts' negative forecasts of negative earnings have an average forecast bias of (-0.115973). In the case of positive earnings forecasts, the proportion of over-optimistic forecasts is 71.51% and the average forecast bias is (-0.012053). U.K. analysts report positive forecasts for 64 of 96 (66.67%) negative earnings outcomes. On the other hand, they report a negative forecast for 24 of 1943 positive earnings outcomes.

In Germany, analysts overestimate actual earnings 67.64% of the time with an average forecast bias of (-0.010450) in the pooled sample period of 1987-1994. About two-thirds of both negative (66.67%) and positive (67.79%) forecasts are overoptimistic. However, the magnitude of the average bias in negative forecasts (-0.106934) is higher than that of positive forecasts (-0.004913) indicating that negative earnings forecasts contribute proportionally more to bias in the pooled sample. With the exception of 1992 and 1993 analysts in Germany do not report negative forecasts for earnings that turn out to be positive. Nevertheless, 28 out of 71 negative earnings announcements are predicted as positive in the pooled sample of 1987-94.

Are Forecast Errors Symmetric?

To test whether forecast errors are symmetric, the pooled sample is divided into deciles based on the size of the earnings forecasts. Forecast errors and the percentage of forecasts that overestimate actual earnings are calculated for each decile. Then, forecast error and mean square forecast error for equal-sized top and bottom samples based on one or more deciles are compared using a paired sample t-test and analysis of variance.

Results of the analysis are presented in Tables 6.7-6.9 for Japan, the U.K., and Germany, respectively. The top decile of forecasts are compared to the bottom decile of forecasts in the firs row of the table labeled "10%". The top half is compared to the bottom half in the "50%" row of the table.

Results presented in Table 6.7 show that forecasts errors are significantly different from zero in both the bottom and top deciles. Negative signs on the forecast errors indicate that forecasts are optimistic across each sample. In fact, a paired samples t-test cannot reject the hypothesis that forecast errors in corresponding bottom and top deciles are equal. For example, the average forecast error in the bottom half of the sample is (-0.008196). The forecast error for the top half is (-0.009110). The hypothesis that they are equal cannot be rejected at a 5% significance level. Similarly, the hypothesis that mean square forecast errors in the bottom and top halves of the sample are equal cannot be rejected by an analysis of variance at a 5% level of significance. The percentage of forecasts overestimating actual earnings are significantly different from 50% in both bottom and top decile groups where the overestimation rate is higher in the top decile groups. In contrast to the United States (see Table 2.6), large forecast errors do not seem to be driven by the lowest forecasts in Japan. A statistical comparison of the top and bottom deciles fails to reveal any asymmetry in forecast errors in Japan. These results suggest that analysts forecasts of earnings per share in Japan are consistently overoptimistic regardless of the magnitude of the forecasts.

In the United Kingdom (Table 6.8), the percentage of forecasts that overestimate actual earnings is significantly higher than 50% in each sample. Mean forecast errors have a negative sign in each group, indicating consistent overoptimism. However, forecast errors are statistically significant only for the bottom 50 percentile and the top 40-50 percentiles of forecasts. As in Japan, neither average forecast errors nor mean square errors are statistically different for the matching pairs of bottom and top decile groups. These results can be interpreted as an indication that overoptimism is symmetric and consistent across analyst forecasts in the United Kingdom.

Table 6.9 shows the results for Germany. The percentage of forecasts overestimating actual earnings is again significantly different from 50% in both the bottom and top decile groups. A comparison of matched pairs of decile groups reveals that analysts overestimate earnings at a higher proportion in the lower decile groups. As the magnitude of forecasts increases, the number of forecasts overestimating earnings decreases. For example, analysts overestimate earnings 66.67% of the time in the bottom decile, and overestimate earnings 57.14% of the time in the top decile. Average forecast errors are significantly different from zero in each group. The negative signs indicate overoptimism. A comparison of forecast errors in the bottom and top groups with a paired-sample t-test suggests that forecast errors in the bottom groups are significantly greater than the forecast errors in the top groups. A comparison of mean square forecast errors also shows the same result. These findings show that the magnitude of the optimistic bias increases as the forecasts become smaller in this sample of German companies between 1987 and 1994.

Forecast Bias and the Sign of Forecasts

In this section samples of earnings forecasts by analysts in Japan, the U.K. and Germany are investigated to understand whether or not predictions of negative earnings are different from predictions of positive earnings in these countries. The null hypothesis is that analysts' earnings forecasts are accurate and rational, and therefore should lie on a 45-degree line drawn through the origin. In order to test this hypothesis the following OLS regressions are run using samples of Japan, the U.K. and Germany for the period between 1987 and 1994:

$$EPS_{it} = a_t + b_t \,.\, FEPS_{it} + e_{it} \qquad \forall \; FEPS$$

$$EPS_{it} = a_t + b_t \,.\, FEPS_{it} + e_{it} \qquad \forall \; FEPS < 0$$

$$EPS_{it} = a_t + b_t \,.\, FEPS_{it} + e_{it} \qquad \forall \; FEPS \geq 0$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = earnings forecast per share for firm i and fiscal year t

The first regression uses all observations. The second and third regressions use negative FEPS and positive FEPS samples separately to examine whether predictions of negative earnings are different than those of positive earnings. The results are summarized in Tables 6.10-6.12 for each of the three countries.

For the Japanese sample, the first regression yields a significantly negative intercept term (-0.007216) and a slope term (0.913400) that is statistically different from 1. This suggests that forecasts of Japanese earnings have a significant optimistic bias component. A slope term that deviates from the slope of the theoretical relationship indicates a slight inefficiency in the analysts' forecasts of Japanese earnings. An examination of annual samples shows that the intercept term is negative in five of the eight sample periods. With the exception of two annual samples, the intercept term largely deviates from that of a 45-degree line.

In the case of the second regression with the pooled sample of negative FEPS, an intercept term which is negative but not significantly different from zero and a slope term which is significantly larger than one at 10% level indicate that negative forecasts are inefficient in the pooled sample of 1987-1994.

The third regression uses the 1987-1994 pooled sample of positive forecasts. The intercept term in the third regression is significantly different from zero (0.018849) and the slope (.057077) is significantly different from one. A review of Figure 6.1 suggests that this result may be driven by negative forecasts of earnings that turn out to be positive. In fact, the negative slope term for the 1994 sample of positive forecasts is a consequence of overoptimistic positive forecasts of negative earnings.

Table 6.11 presents the regression results for the sample of forecasts in the United Kingdom. In the pooled sample, the intercept term is significantly different from zero and negative (-0.011730) while the slope term is greater than one (1.056217). This suggests both bias and inefficiency in the U.K. analysts' earnings forecasts.

In the case of negative forecasts, the pooled sample of 1987-1994 results in a negative slope term (-0.032981) which is not statistically significant and a slope term of (0.718784). These results imply inefficiency in negative forecasts of the U.K. analysts. A review of Figure 2 suggests that this result is likely to reflect the problem of negative forecasts of earnings that turn out to be positive. Negative forecasts of positive earnings almost equal the number of negative forecasts of negative earnings in the pooled sample. An implication of this result is that, unlike the U.S., Japan and Germany, a negative forecast in the U.K. cannot be presumed as optimistic.

The pooled sample of positive earnings forecasts (the third regression) indicates both bias and inefficiency with a significantly negative intercept term (-0.040993) and a slope term (1.386220) that differs significantly from one. Similar results are observed in six of the eight annual samples with a negative intercept and a slope that is larger than one. The negative intercept is likely to be capturing the impact of negative forecasts of earnings that turn out to be positive, which extend close to the y-axis on the southeast quadrant of Figure 6.2.

In the case of Germany, the first regression provides a negative intercept term of (-0.019978) which is significantly different from zero and a slope term of (1.137615) which is significantly different from one. These results can be interpreted as indication of inefficiency and optimistic bias in the analysts' forecasts of earnings per share in Germany. Regressions that use all observations result in significantly negative intercept terms in five annual samples. The slope is significantly different from one in all annual samples. In this case, too, the negative bias term may reflect the reluctance of analysts to report negative forecasts for some earnings that turn out to be positive.

Regression results in the negative forecast sample exhibit a statistically significant negative intercept term (-0.129640) and a slope term (0.745287) which is less than one at 10% level. These are evidence of optimistic bias as well as inefficiency in the pooled sample of negative earnings forecasts in Germany.

The pooled sample of positive forecasts gives similar regression results where the intercept term (-0.008151) significantly differs from zero. The slope term is close to one (statistically not different from one at 5% level) in the pooled sample and in three of the eight annual samples. This suggests that, in spite of some bias and inefficiency, positive earnings forecasts in the pooled sample of Germany more closely relate to the theoretical relationship of earnings to forecasts designated by a 45-degree line passing through the origin.

Summary

In this chapter, the accuracy of security analysts' median consensus forecasts in Japan, the U.K., and Germany is investigated using a sample that covers the period of 1987-94. Results indicate that analysts' forecasts contain an optimistic bias in all three countries. A majority of negative forecasts are overoptimistic in Japan and Germany where analysts rarely report a negative forecasts for earnings that turn out to be positive, and their negative forecasts of negative earnings are clearly overoptimistic. On the other hand, negative earnings forecasts in the U.K. are on average pessimistic. This is because about half of the negative forecasts in the U.K. pertain to earnings that turn out to be positive (the northwest quadrant of Figure 6.2). This pessimism dominates the other half where the negative forecasts that relate to negative earnings are over-optimistic 62.50% of the time (the southwest quadrant of Figure 6.2). Positive forecasts are on average over-optimistic in all three countries. Large magnitude of forecast errors posed by positive forecasts of negative earnings accounts for a significant portion of this optimistic bias in positive forecasts.

The tests of symmetry suggests that the average forecast error is negative and its magnitude is symmetric regardless of the size of forecasts in Japan and the United Kingdom. On the other hand, the forecast errors become larger and more negative as the forecasts become smaller in Germany.

Regression results show that both negative and positive forecast samples as well as the sample of all forecasts in Japan, the U.K. and Germany deviate from the theoretical relationship between forecasts and actual earnings represented by a 45-degree line passing through the origin. This outcome is magnified in the case of the negative forecast sample where regressions result in intercept and slope terms varying widely from year to year and reflecting bias and/or inefficiency in forecasts. Regressions using the positive forecasts sample also indicate bias and/or inefficiency in all three countries. This result can be attributed to the positive forecasts corresponding to negative earnings outcomes. Especially in the German sample, a majority of positive forecasts tightly cluster around the 45-degree line passing through the origin in Figure 6.3. However, the regression of actual earnings against the forecasts in the positive forecast sample yields a significantly negative intercept term which indicates optimistic bias.

In light of these observations, further research may focus on (1) determining whether this over-optimistic bias observed in forecasts of analysts in Japan, the U.K. and Germany is intentional and (2) developing methods to improve the accuracy of earnings forecasts in these countries.

Figure 6.1. EPS Versus FEPS in Japan

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the Japanese companies in a pooled sample between 1987 and 1994.

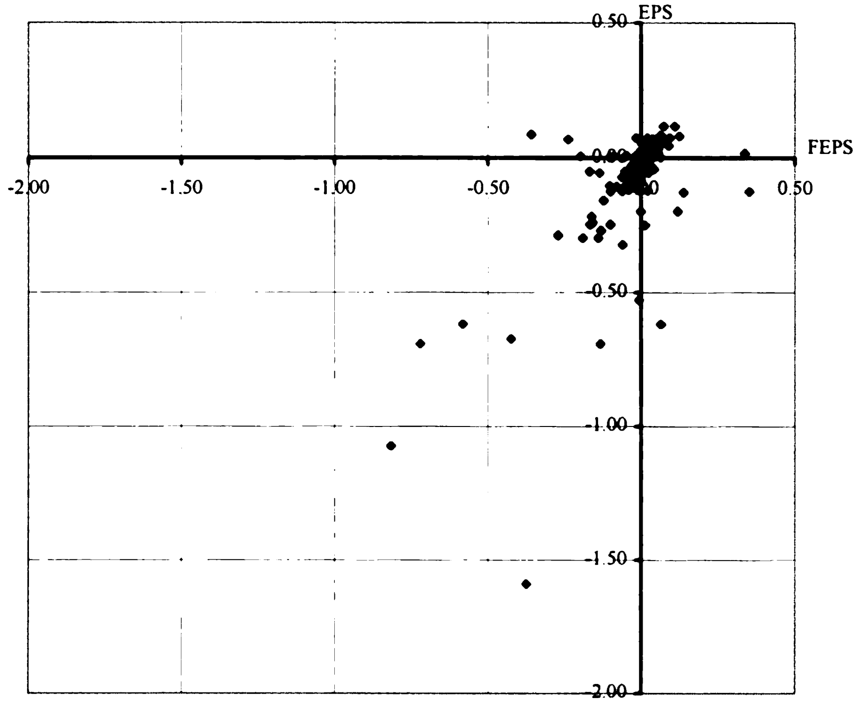


Figure 6.2. EPS Versus FEPS in the United Kingdom

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the U.K. companies in a pooled sample between 1987 and 1994.

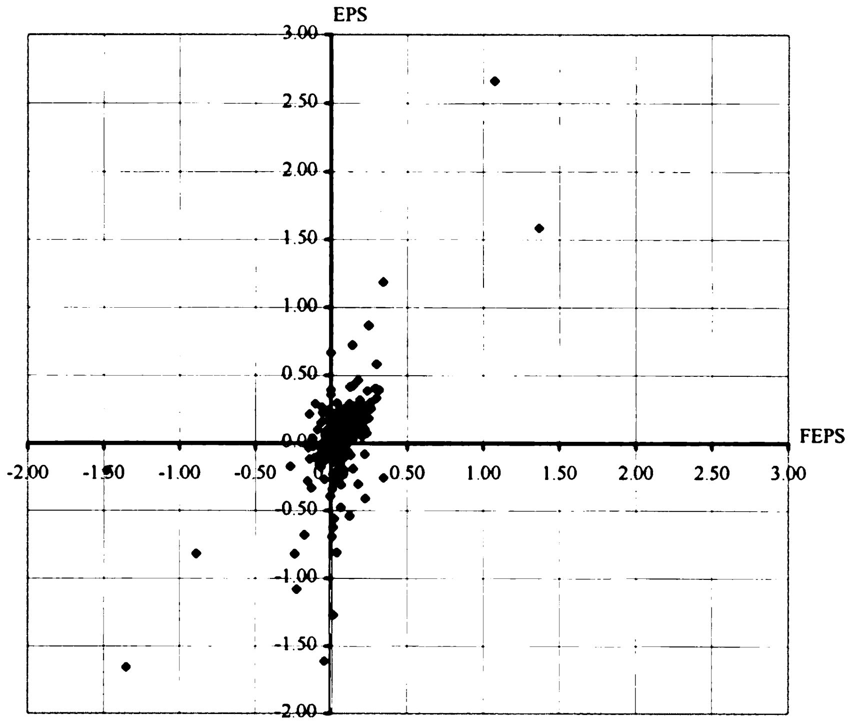


Figure 6.3. EPS Versus FEPS in Germany

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the German companies in a pooled sample between 1987 and 1994.

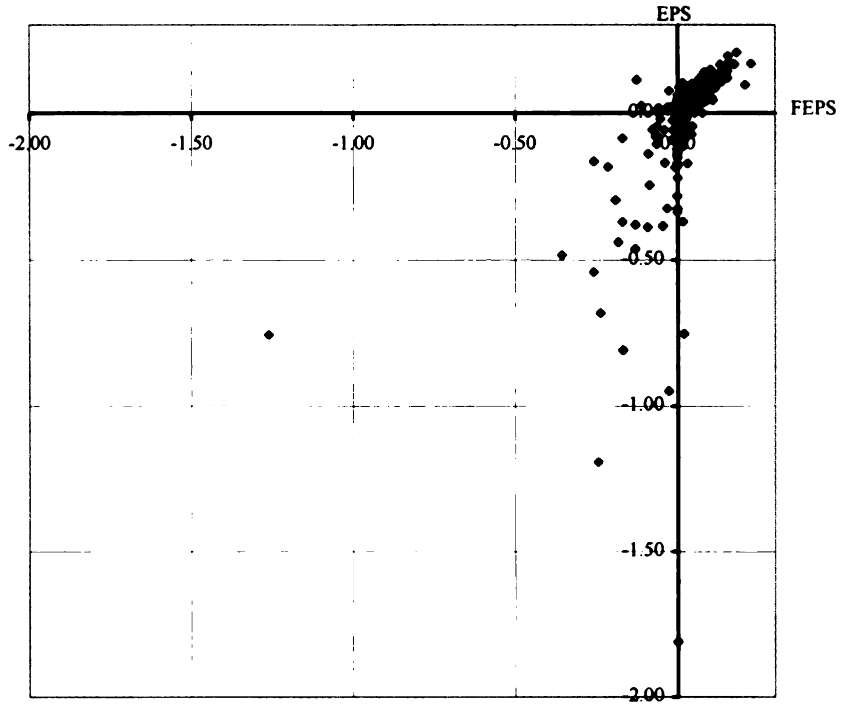


Figure 6.4. EPS Versus FEPS in Japan (Larger Scale Graph)

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the Japanese companies in a pooled sample between 1987 and 1994.

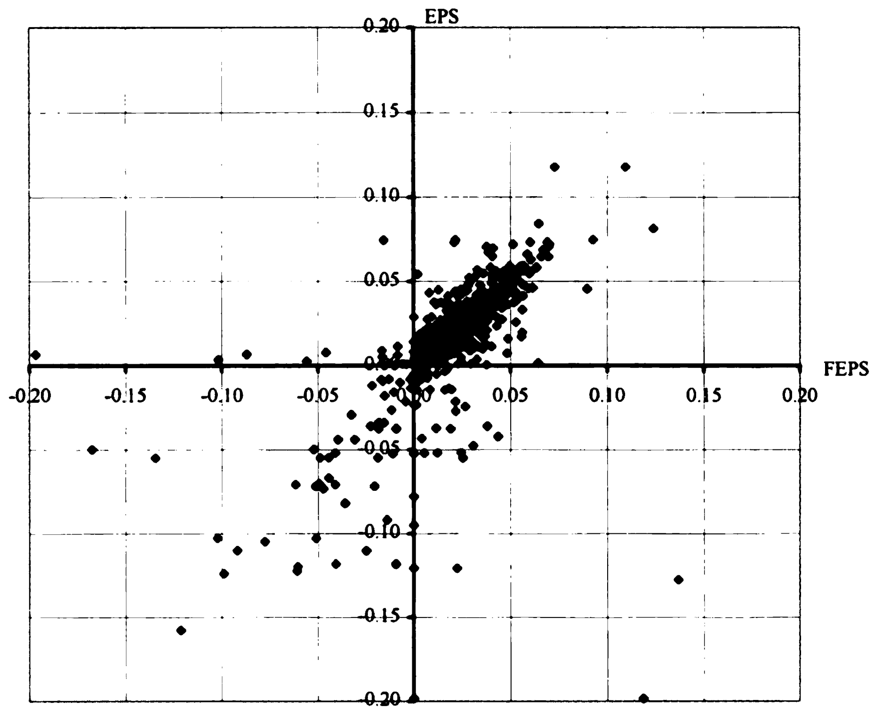


Figure 6.5. EPS Versus FEPS in the United Kingdom (Larger Scale Graph)

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the U.K. companies in a pooled sample between 1987 and 1994.

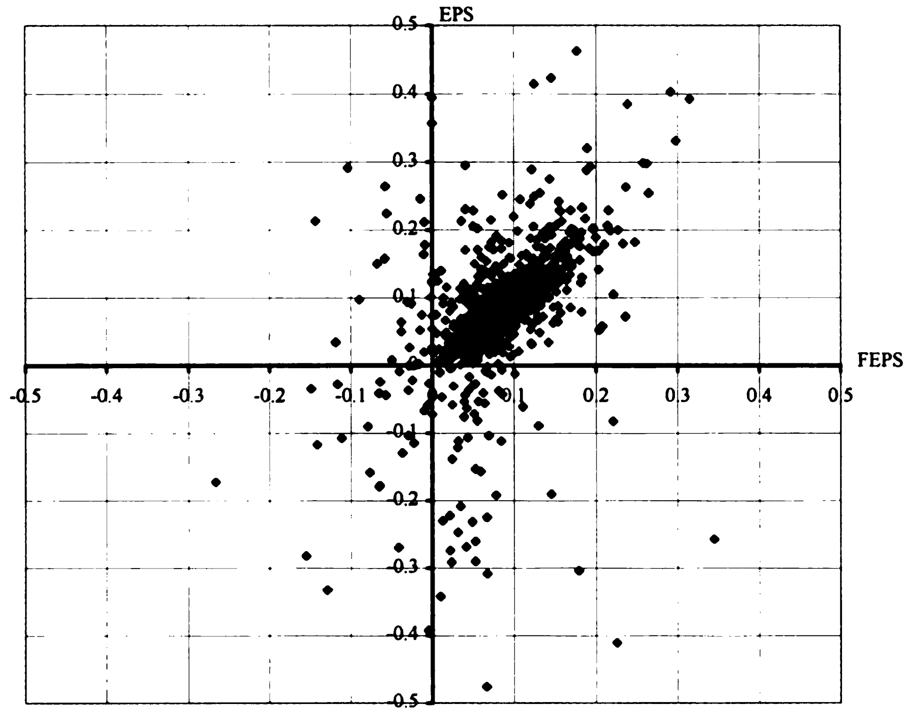


Figure 6.6. EPS Versus FEPS in Germany (Larger Scale Graph)

Annual earnings per share (EPS) are plotted against analysts' forecasts of annual earnings per share (FEPS) for the German companies in a pooled sample between 1987 and 1994.

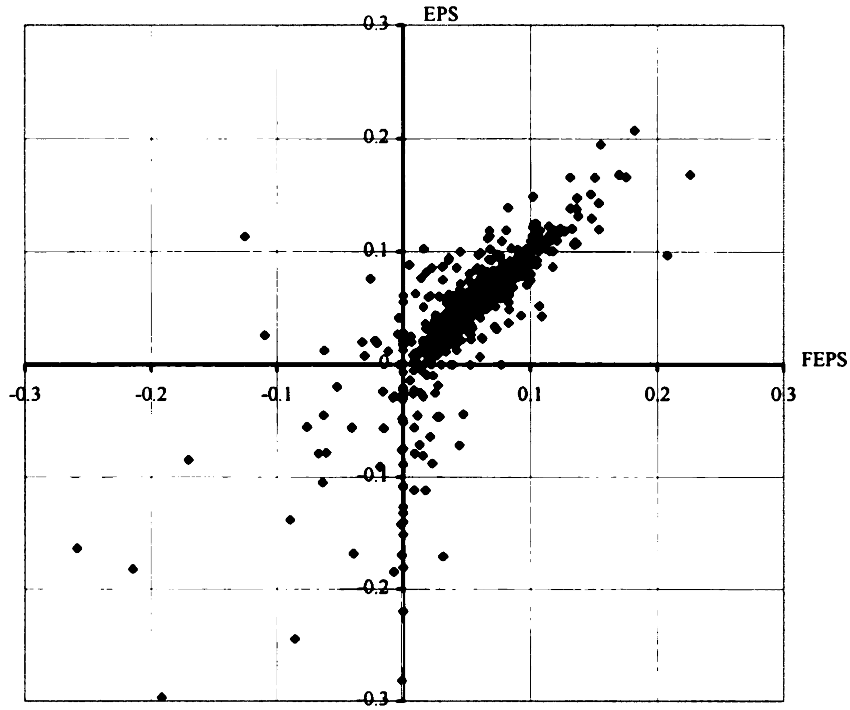


Table 6.1. Descriptive Statistics: Actual Earnings and Analysts' Forecasts of Earnings (Japan)

Descriptive statistics of actual earnings per share (EPS) and analysts' forecasts of earnings per share (FEPS)are reported for samples from each year as well as the pooled sample from 1987 to 1994. Normality of both variables are tested using the Lilliefors test statistic.

	1987	1988	1989	1990	1991	1992	1993	1994	1987-94
EPS									
number of observations	61	89	86	83	174	181	187	195	1056
mean	.018698	.018502	.015018	.022006	.020068	-.004927	-.002169	.000001	.007670
standard deviation	.040789	.017663	.008815	.012932	.030736	.161235	.091414	.081797	.086902
minimum	-.269565	-.091870	-.006032	-.008353	-.249647	-1.590580	-.691760	-.691760	-1.590580
maximum	.081297	.058745	.035340	.054561	.087176	.084167	.117781	.117781	.117781
skewness	-5.96	-2.77	.02	.08	-4.77	-7.48	-5.39	-5.92	-10.49
kurtosis	43.00	16.81	-.31	-.28	37.28	63.64	33.59	43.28	148.18
Lilliefors test statistic . p-value	.3246 (.0000)	.1068 (.0139)	.0513 (.2000)	.0641 (.2000)	.2196 (.0000)	.3864 (.0000)	.3173 (.0000)	.3154 (.0000)	.3588 (.0000)
FEPS									
number of observations	61	89	86	83	174	181	187	195	1056
mean	.024558	.022175	.017807	.021240	.028449	.007101	.005717	.016102	.016298
standard deviation	.027204	.012857	.009870	.013555	.075876	.087830	.077068	.039979	.061212
minimum	-.129674	-.013821	-.005752	-.016824	-.357882	-.816066	-.720225	-.167400	-.816066
maximum	.124085	.057384	.048415	.053801	.848200	.069335	.109688	.351456	.848200
skewness	-2.04	.23	.37	.15	6.97	-6.19	-7.12	1.74	-3.49
kurtosis	19.85	.13	.45	.01	84.24	47.93	59.91	29.18	99.40
Lilliefors test statistic . p-value	.2187 (.0000)	.0546 (.2000)	.0521 (.2000)	.0584 (.2000)	.3186 (.0000)	.3408 (.0000)	.3168 (.0000)	.2164 (.0000)	.3099 (.0000)

Table 6.2. Descriptive Statistics: Actual Earnings and Analysts' Forecasts of Earnings (The United Kingdom)

Descriptive statistics of actual earnings per share (EPS) and analysts' forecasts of earnings per share (FEPS)are reported for samples from each year as well as the pooled sample from 1987 to 1994. Normality of both variables are tested using the Lilliefors test statistic.

	1987	1988	1989	1990	1991	1992	1993	1994	1987-94
EPS									
number of observations	235	269	258	223	254	259	273	278	2049
mean	.070958	.072086	.092495	.133828	.087541	.046702	.032850	.041155	.070529
standard deviation	.041340	.054773	.077168	.209437	.111753	.201015	.097384	.123784	.130255
minimum	-.291489	-.410569	-.811111	-.190476	-.289796	-1.658127	-.692905	-1.613684	-1.658127
maximum	.214833	.160665	.462791	2.662500	1.187598	.724096	.297647	.213043	2.662500
skewness	-2.41	-5.55	-5.59	9.50	5.53	-4.75	-3.71	-9.79	1.11
kurtosis	26.03	41.85	74.73	106.06	48.77	33.16	20.57	120.13	130.39
Lilliefors test statistic	.1111	.1844	.1575	.3036	.2648	.3219	.2904	.3409	.2749
. p-value	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
FEPS									
number of observations	235	269	258	223	254	259	273	278	2049
mean	.084586	.093712	.100219	.120410	.061827	.047252	.055032	.067687	.077881
standard deviation	.032386	.033533	.041409	.117242	.045068	.153606	.039699	.033560	.130255
minimum	-.142857	.004911	-.067647	-.038012	-.141100	-1.477444	-.266249	-.064444	-1.477444
maximum	.214144	.225610	.236842	1.366071	.341654	.299346	.262353	.344882	1.366071
skewness	-1.55	.67	-.11	7.90	.55	-7.67	-1.34	2.32	-4.61
kurtosis	11.16	2.37	1.57	76.46	9.62	68.23	22.79	19.64	191.32
Lilliefors test statistic	.0811	.0644	.0439	.2584	.1462	.3209	.2002	.1325	.2134
. p-value	(.0007)	(.0090)	(.2000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)

Table 6.3. Descriptive Statistics: Actual Earnings and Analysts' Forecasts of Earnings (Germany)

Descriptive statistics of actual earnings per share (EPS) and analysts' forecasts of earnings per share (FEPS)are reported for samples from each year as well as the pooled sample from 1987 to 1994. Normality of both variables are tested using the Lilliefors test statistic.

	1987	1988	1989	1990	1991	1992	1993	1994	1987-94
EPS									
number of observations	78	109	117	118	131	159	166	157	1035
mean	.016818	.047613	.049699	.051283	.052551	.032617	.012250	.017908	.034090
standard deviation	.238009	.054101	.032296	.055303	.027829	.160537	.121085	.084047	.112654
minimum	-1.809091	-.324240	-.056452	-.336042	-.028308	-1.192053	-.755968	-.439716	-1.809091
maximum	.151079	.118750	.168244	.207197	.138322	.165803	.113480	.095092	.207197
skewness	-6.50	-3.92	.46	-2.52	.00	-5.53	-4.29	-3.30	-8.28
kurtosis	47.11	22.51	2.28	20.78	.90	34.28	20.26	12.48	98.63
Lilliefors test statistic . p-value	.3908 (.0000)	.1745 (.0000)	.1049 (.0030)	.1841 (.0000)	.0596 (.2000)	.3547 (.0000)	.3077 (.0000)	.2689 (.0000)	.3078 (.0000)
FEPS									
number of observations	78	109	117	118	131	159	166	157	1035
mean	.063422	.059125	.057069	.057677	.052367	.055198	.010911	.043747	.047527
standard deviation	.032901	.029041	.034611	.036486	.025611	.052846	.076699	.032084	.060772
minimum	-.001010	-.001075	-.000314	-.001207	-.016006	-.245033	-1.259947	-.182270	-1.259947
maximum	.147482	.124006	.226078	.182116	.131519	.207978	.119800	.117530	.226078
skewness	.07	.02	1.55	1.23	.03	-2.39	-7.80	-2.83	-10.72
kurtosis	-.03	-.28	4.79	1.94	.32	10.48	77.74	16.56	211.59
Lilliefors test statistic . p-value	.0888 (.2000)	.0594 (.2000)	.1025 (.0042)	.1543 (.0000)	.0430 (.2000)	.1544 (.0000)	.2915 (.0000)	.1250 (.0000)	.1902 (.0000)

Table 6.4. Predictions of Earnings Per Share (Japan)

		FEPS<0				FEPS>0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >0	1987					59	71.19	0.024312	-0.002821	59	71.19	0.024312	-0.002821
	1988					85	65.88	0.020898	[a]-0.001951	85	65.88	0.020898	[a]-0.001951
	1989	1	0.00	0.001062	0.006814	82	75.61	0.015903	[a]-0.002569	83	74.70	0.015724	[a]-0.002456
	1990					80	55.00	0.023002	0.000895	80	55.00	0.023002	0.000895
	1991	5	0.00	0.020231	0.123726	161	58.39	0.024671	-0.008540	166	56.63	0.024537	-0.004556
	1992	4	0.00	0.037885	0.153384	153	58.17	0.027992	-0.000223	157	56.69	0.028244	0.003691
	1993	4	0.00	0.007080	0.039062	145	55.86	0.023927	-0.000724	149	54.36	0.023475	0.000344
	1994	3	0.00	0.004667	0.031407	154	66.23	0.022997	0.000131	157	64.97	0.022647	0.000729
	All	17	0.00	0.017416	[a]0.087615	919	62.02	0.023526	[a]-0.002138	936	60.90	0.023415	-0.000508
EPS<0	1987	1	100.00	-0.269565	-0.139891	1	100.00	-0.024265	-0.051090	2	100.00	-0.146915	-0.095491
	1988	1	100.00	-0.091870	-0.078049	3	100.00	-0.012591	-0.027682	4	100.00	-0.032411	-0.040274
	1989					3	100.00	-0.004511	-0.012009	3	100.00	-0.004511	-0.012009
	1990	1	0.00	-0.008353	0.008471	2	100.00	-0.002666	-0.008264	3	66.67	-0.004562	-0.002686
	1991	3	66.67	-0.032746	-0.008368	3	100.00	-0.139791	-0.204416	6	83.33	-0.086269	-0.106392
	1992	15	93.33	-0.334028	-0.156623	5	100.00	-0.044205	[a]-0.062495	20	95.00	-0.261572	[a]-0.133091
	1993	24	83.33	-0.142011	-0.041249	8	100.00	-0.016120	[a]-0.021225	32	87.50	-0.110538	[a]-0.036243
	1994	18	88.89	-0.124211	-0.066613	14	100.00	-0.091506	[a]-0.143899	32	93.75	-0.109903	[a]-0.100426
	All	63	85.71	-0.176548	[a]-0.075761	39	100.00	-0.054650	[a]-0.084533	102	91.18	-0.129940	[a]-0.079115
TOTAL	1987	1	100.00	-0.269565	-0.139891	60	71.67	0.023502	[a]-0.003625	61	72.13	0.018698	[a]-0.005859
	1988	1	100.00	-0.091870	-0.078049	88	67.05	0.019756	[a]-0.002828	89	67.42	0.018502	[a]-0.003673
	1989	1	0.00	0.001062	0.006814	85	76.47	0.015183	[a]-0.002902	86	75.58	0.015018	[a]-0.002789
	1990	1	0.00	-0.008353	0.008471	82	56.10	0.022376	0.000672	83	55.42	0.022006	0.000766
	1991	8	25.00	0.000365	0.074191	164	59.15	0.021663	[a]-0.012123	172	57.56	0.020672	-0.008109
	1992	19	73.68	-0.255731	-0.091358	158	59.49	0.025707	-0.002194	177	61.02	-0.004504	-0.011765
	1993	28	71.43	-0.120712	-0.029776	153	58.17	0.021833	[a]-0.001796	181	60.22	-0.000218	-0.006124
	1994	21	76.19	-0.105800	-0.052610	168	69.05	0.013455	[a]-0.011872	189	69.84	0.000205	[a]-0.016398
	All	80	67.50	-0.135330	[a]-0.041043	958	63.57	0.020344	[a]-0.005493	1038	63.87	0.008346	[a]-0.008233

[a] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance

Table 6.5. Predictions of Earnings Per Share (The United Kingdom)

		FEPS<0				FEPS>0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >0	1987	2	0.00	0.132730	0.211545	228	90.35	0.073727	[a]-0.013607	230	89.57	0.074240	[a]-0.011649
	1988					263	88.21	0.078626	[a]-0.014214	263	88.21	0.078626	[a]-0.014214
	1989	2	0.00	0.153882	[a]0.216824	255	80.78	0.095557	[a]-0.006182	257	80.16	0.096011	-0.004447
	1990	4	0.00	0.070078	[a]0.098520	213	50.70	0.141278	[a]-0.016517	217	49.77	0.139966	[a]-0.014397
	1991	9	0.00	0.128213	[a]0.153332	230	39.57	0.090885	[a]0.020355	239	38.08	0.092291	[a]0.025363
	1992	4	0.00	0.116438	0.161260	228	52.19	0.086146	[a]0.010846	232	51.29	0.086668	[a]0.013439
	1993	3	0.00	0.114319	[a]0.186739	242	76.03	0.056365	[a]-0.004378	245	75.10	0.057075	-0.002038
	1994					260	80.00	0.060458	[a]-0.008254	260	80.00	0.060458	[a]-0.008254
	All	24	0.00	0.117340	[a]0.159836	1919	70.56	0.084342	-0.004162	1943	69.69	0.084749	-0.002136
EPS<0	1987	1	100.00	-0.036364	-0.007273	4	100.00	-0.090921	-0.129040	5	100.00	-0.080010	-0.104687
	1988					6	100.00	-0.214576	[a]-0.346522	6	100.00	-0.214576	[a]-0.346522
	1989					1	100.00	-0.811111	-0.850000	1	100.00	-0.811111	-0.850000
	1990					5	100.00	-0.110991	[a]-0.189203	5	100.00	-0.110991	[a]-0.189203
	1991	6	16.67	-0.070280	0.003821	4	100.00	-0.154905	-0.200170	10	50.00	-0.104130	-0.077775
	1992	17	70.59	-0.383044	-0.081536	7	100.00	-0.267929	-0.321466	24	79.17	-0.349469	-0.151516
	1993	5	60.00	-0.203400	-0.112821	23	100.00	-0.173834	[a]-0.217051	28	92.86	-0.179114	[a]-0.198439
	1994	3	100.00	-0.635356	-0.592191	14	100.00	-0.171321	[a]-0.248554	17	100.00	-0.253210	[a]-0.309196
	All	32	62.50	-0.309152	-0.115973	64	100.00	-0.186078	[a]-0.248659	96	87.50	-0.227103	[a]-0.204430
TOTAL	1987	3	33.33	0.076365	0.138606	232	90.52	0.070888	[a]-0.015597	235	89.79	0.070958	[a]-0.013629
	1988					269	88.48	0.072086	[a]-0.021626	269	88.48	0.072086	[a]-0.021626
	1989	2	0.00	0.153882	[a]0.216824	256	80.86	0.092015	[a]-0.009478	258	80.23	0.092495	-0.007724
	1990	4	0.00	0.070078	[a]0.098520	218	51.83	0.135492	-0.020478	222	50.90	0.134313	-0.018334
	1991	15	6.67	0.048816	[a]0.093528	234	40.60	0.086683	[a]0.016585	249	38.55	0.084402	[a]0.021220
	1992	21	57.14	-0.287905	-0.035289	235	53.62	0.075599	0.000947	256	53.91	0.045780	-0.002025
	1993	8	37.50	-0.084255	-0.000486	265	78.11	0.036385	[a]-0.022836	273	76.92	0.032850	[a]-0.022181
	1994	3	0.00	-0.635356	-0.592191	274	81.02	0.048615	[a]-0.020532	277	81.23	0.041208	[a]-0.026723
	All	56	35.71	-0.126370	0.002231	1983	71.51	0.075614	[a]-0.012053	2039	70.52	0.070067	[a]-0.011660

[a] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance

Table 6.6. Predictions of Earnings Per Share (Germany)

		FEPS<0				FEPS>0				TOTAL			
	Year	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias	N	% Over	Mean EPS	Average Bias
EPS >0	1987					71	66.20	0.066417	[a] -0.003000	71	66.20	0.066417	[a] -0.003000
	1988					98	74.49	0.059733	[a] -0.004322	98	74.49	0.059733	[a] -0.004322
	1989					112	83.04	0.052902	[a] -0.006641	112	83.04	0.052902	[a] -0.006641
	1990					111	69.37	0.058821	-0.001688	111	69.37	0.058821	-0.001688
	1991					123	65.85	0.055794	0.000365	123	65.85	0.055794	0.000365
	1992	1	0.00	0.111696	0.023392	142	57.04	0.068450	0.000414	143	56.64	0.068752	0.000575
	1993	10	0.00	0.036450	[a] 0.080109	127	47.24	0.049229	[a] 0.004223	137	43.80	0.048296	[a] 0.009762
	1994					129	75.19	0.047789	[a] -0.005629	129	75.19	0.047789	[a] -0.005629
	All	11	0.00	0.043291	[a] 0.074953	913	66.70	0.056980	[a] -0.001811	924	65.91	0.056817	-0.000898
EPS<0	1987	2	100.00	-0.165025	-0.164198	1	100.00	-0.752772	-0.772727	3	100.00	-0.360941	-0.367041
	1988	1	100.00	-0.169892	-0.168817	2	100.00	-0.032407	-0.069506	3	100.00	-0.078235	-0.102610
	1989	1	100.00	-0.031447	-0.031132	1	100.00	-0.056452	-0.065136	2	100.00	-0.043950	-0.048134
	1990	3	100.00	-0.162313	-0.161760	2	100.00	-0.009637	-0.016515	5	100.00	-0.101243	-0.103662
	1991	2	100.00	-0.026146	-0.014851	1	100.00	-0.018405	-0.046012	3	100.00	-0.023566	-0.025238
	1992	8	100.00	-0.524352	[a] -0.407769	3	100.00	-0.038582	-0.058503	11	100.00	-0.391869	[a] -0.312515
	1993	19	63.16	-0.237960	-0.050963	2	100.00	-0.047442	-0.073849	21	66.67	-0.219815	-0.053143
	1994	7	100.00	-0.242262	[a] -0.189303	16	100.00	-0.080084	[a] -0.099393	23	100.00	-0.129443	[a] -0.126757
	All	43	83.72	-0.267035	[a] -0.153463	28	100.00	-0.085846	[a] -0.106050	71	90.14	-0.195580	[a] -0.134765
TOTAL	1987	2	100.00	-0.165025	-0.164198	72	66.67	0.055039	-0.013691	74	67.57	0.049092	-0.017758
	1988	1	100.00	-0.169892	-0.168817	100	75.00	0.057890	[a] -0.005626	101	75.25	0.055635	[a] -0.007241
	1989	1	100.00	-0.031447	-0.031132	113	83.19	0.051934	[a] -0.007159	114	83.33	0.051203	[a] -0.007369
	1990	3	100.00	-0.162313	-0.161760	113	69.91	0.057609	-0.001950	116	70.69	0.051922	-0.006083
	1991	2	100.00	-0.026146	-0.014851	124	66.13	0.055196	-0.000009	126	66.67	0.053904	-0.000245
	1992	9	88.39	-0.453680	[a] -0.359862	145	57.93	0.066236	-0.000805	154	59.74	0.035851	[a] -0.021789
	1993	29	41.38	-0.143336	-0.005766	129	48.06	0.047730	0.003013	158	46.84	0.012661	0.001401
	1994	7	100.00	-0.242262	[a] -0.189303	145	77.93	0.033679	[a] -0.015975	152	78.95	0.020971	[a] -0.023958
	All	54	66.67	-0.203821	[a] -0.106934	941	67.69	0.052730	[a] -0.004913	995	67.64	0.038807	[a] -0.010450

[a] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance

Table 6.7. Matched Pair Test of Symmetry in Forecast Errors (Japan)

The pooled sample of 1987-94 is divided into deciles with respect to the size of the earnings forecasts. Forecast error and the percentage of forecasts that overestimate actual earnings are calculated for each decile. Then, forecast error and mean square forecast error for corresponding top and bottom deciles are compared using a paired sample t-test and analysis of variance. Numbers in parentheses denote to the p-value of a binomial test in the "% over", the value of the t-statistic in the "Mean error" and "Me_b -ME_t", and the value of the F-statistic in the MSE_b/MSE_t columns.

		Bottom group			Top group			Bottom vs Top group	
Bottom vs top forecasts	N	% over	Mean error (ME)	MSE	% over	Mean error (ME)	MSE	ME_b - ME_t	MSE_b/MSE_t
10%	106	59.43 (.0650)	-.025968 (-1.74)	.023968	66.98[a] (.0007)	-.031994[b] (-2.68)	.015957	.006026 (.31)	1.502 (.23)
20%	212	60.85[a] (.0000)	-.018002[b] (-2.27)	.013648	68.87[a] (.0000)	-.017829[b] (-2.94)	.008082	-.000173 (-.02)	1.689 (.44)
30%	318	58.80[a] (.0020)	-.012566[b] (-2.33)	.009344	66.98[a] (.0000)	-.012579[b] (-3.09)	.005416	.000013 (.00)	1.725 (.49)
40%	424	59.43[a] (.0001)	-.009678[b] (-2.39)	.007031	67.45[a] (.0000)	-.010523[b] (-3.40)	.004165	.000845 (.17)	1.688 (.46)
50%	525	59.24[a] (.0000)	-.008196[b] (-2.50)	.005696	68.57[a] (.0000)	-.009110[b] (-3.62)	.003399	.000914 (.22)	1.676 (0.45)

[a] The null hypothesis H_0 : (% over) = 50% is rejected by a binomial test with 5% significance
[b] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance

Table 6.8. Matched Pair Test of Symmetry in Forecast Errors (The United Kingdom)

The pooled sample of 1987-94 is divided into deciles with respect to the size of the earnings forecasts. Forecast error and the percentage of forecasts that overestimate actual earnings are calculated for each decile. Then, forecast error and mean square forecast error for corresponding top and bottom deciles are compared using a paired sample t-test and analysis of variance. Numbers in parentheses denote to the p-value of a binomial test in the "% over", the value of the t-statistic in the "Mean error" and "Me_b -ME_t", and the value of the F-statistic in the MSE_b/MSE_t columns.

		Bottom group			Top group			Bottom vs Top group	
Bottom vs top forecasts	N	% over	Mean error (ME)	MSE	% over	Mean error (ME)	MSE	ME_b - ME_t	MSE_b/MSE_t
10%	204	57.84[a] (.0300)	-.009767 (-.62)	.050172	65.20[b] (.0000)	-.000061 (-.00)	.030694	-.009706 (-.50)	1.634 (.88)
20%	408	63.48[a] (.0000)	-.009702 (-1.12)	.030532	68.87 (.0000)	-.005669 (-.90)	.016211	-.004033 (-.38)	1.883 (1.63)
30%	612	66.01[a] (.0000)	-.006516 (-1.12)	.020690	68.95 (.0000)	-.007399 (-1.69)	.011822	.000883 (.12)	1.750 (1.39)
40%	816	69.00[a] (.0000)	-.008000 (-1.81)	.016008	69.85 (.0000)	-.006672[b] (-2.00)	.009095	-.001328 (-.24)	1.760 (1.50)
50%	1022	69.96[a] (.0000)	-.007720[b] (-2.17)	.013011	70.55 (.0000)	-.007023[b] (-2.60)	.007520	-.000697 (-.16)	1.730 (1.48)

[a] The null hypothesis H_0 : (% over) = 50% is rejected by a binomial test with 5% significance
[b] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance

Table 6.9. Matched Pair Test of Symmetry in Forecast Errors (Germany)

The pooled sample of 1987-94 is divided into deciles with respect to the size of the earnings forecasts. Forecast error and the percentage of forecasts that overestimate actual earnings are calculated for each decile. Then, forecast error and mean square forecast error for corresponding top and bottom deciles are compared using a paired sample t-test and analysis of variance. Numbers in parentheses denote to the p-value of a binomial test in the "% over", the value of the t-statistic in the "Mean error" and "Me_b -ME_t", and the value of the F-statistic in the MSE_b/MSE_t columns.

		Bottom group			Top group			Bottom vs Top group	
Bottom vs top forecasts	N	% over	Mean error (ME)	MSE	% over	Mean error (ME)	MSE	ME_b - ME_t	MSE_b/MSE_t
10%	105	66.67[a] (.0009)	-.098050[b] (-3.89)	.075555	57.14 (.1719)	-.004894[b] (-2.45)	.000439	-.093156[c] (-3.66)	172.107[d] (4.98)
20%	210	66.19[a] (.0000)	-.053509[b] (-4.07)	.039030	58.10[a] (.0228)	-.003914[b] (-3.38)	.000295	-.049595[c] (-3.76)	132.305[d] (5.20)
30%	315	67.62[a] (.0000)	-.036625[b] (-4.11)	.026300	61.59[a] (.0000)	-.003694[b] (-3.97)	.000286	-.032931[c] (-3.69)	91.958[d] (5.24)
40%	420	66.90[a] (.0000)	-.028109[b] (-4.18)	.019760	64.28[a] (.0000)	-.003303[b] (-4.54)	.000233	-.024806[c] (-3.65)	84.807[d] (5.23)
50%	515	69.13[a] (.0000)	-.023650[b] (-4.30)	.016141	65.82[a] (.0000)	-.003338[b] (-4.94)	.000246	-.020312[c] (-3.64)	65.610[d] (5.20)

[a] The null hypothesis H_0 : (% over) = 50% is rejected by a binomial test with 5% significance
[b] The null hypothesis H_0 : (Mean error) = 0 is rejected by a t-test at 5% level significance
[c] The null hypothesis H_0 : (ME_b - ME_t) = 0 is rejected by a t-test at 5% level significance
[d] The null hypothesis H_0 : $MSE_{top} = MSE_{bot}$ is rejected by an analysis of variance at 5% level significance

Table 6.10. OLS Regressions of EPS Against FEPS (Japan)

$$EPS_{it} = a_t + b_t * FEPS_t + e_{it}$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = analysts' forecasts of earnings per share for firm i and fiscal year t

Sample period is 1987-1994. Coefficients of OLS regression are estimated separately using flags for negative FEPS and positive FEPS as well as without flags (all observations). This procedure is repeated for samples from each year, and for the pooled sample from 1987 to 1994. Parameters for the intercept (a_t) and slope (b_t) terms are estimated, and their values are reported with their t-values underneath. The intercept term is tested against zero, and the slope term is tested against one with a one-sample t-test. For each regression r^2 are reported as well.

	FEPS<O				FEPS>0				ALL OBSERVATIONS			
YEAR	N	a	b	r^2	N	a	b	r^2	N	a	b	r^2
1987	1				60	.005766	.653804	.5632	61	-.013612	1.315664	.7699
						(2.328)	(-4.579)			(-3.985)	(3.371)	
1988	1				88	.002749	.753073	.4960	89	-.002818	.961454	.4898
						(1.307)	(-3.016)			(-1.046)	(-.366)	
1989	1				85	.002389	.707413	.6028	86	.002560	.699613	.6136
						(1.855)	(-4.642)			(2.079)	(-4.959)	
1990	1				82	.004874	.806404	.6919	83	.004896	.805545	.7128
						(3.210)	(-3.218)			(3.427)	(-3.423)	
1991	8	-.020380	-.280994	.5873	164	.021692	-.000878	.0000	174	.020303	-.008251	.0004
		(-1.584)	(-13.321)			(8.610)	(-30.922)			(8.134)	(-32.650)	
1992	19	.005552	1.589582	.5617	158	-.000942	.955152	.4855	181	-.015693	1.516002	.6820
		(.064)	(1.731)			(-.376)	(-.570)			(-2.308)	(6.668)	
1993	28	-.035258	.939719	.6895	153	-.002333	1.022725	.8043	187	-.008059	1.030306	.7545
		(-1.522)	(-.487)			(-1.960)	(.554)			(-2.420)	(.701)	
1994	21	-.002850	1.935527	.3553	169	.023844	-.415618	.0462	195	-.010403	.646142	.0997
		(-.068)	(1.564)			(4.191)	(-9.687)			(-1.731)	(-2.532)	
1987-94	80	-.020743	1.215310	.5029	959	.018849	.057077	.0041	1056	-.007216	.913400	.4139
		(-.860)	(1.574)			(15.315)	(-32.714)			(-3.404)	(-2.587)	

Table 6.11. OLS Regressions of EPS Against FEPS (The United Kingdom)

$$EPS_{it} = a_t + b_t * FEPS_t + e_{it}$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = analysts' forecasts of earnings per share for firm i and fiscal year t

Sample period is 1987-1994. Coefficients of OLS regression are estimated separately using flags for negative FEPS and positive FEPS as well as without flags (all observations). This procedure is repeated for samples from each year, and for the pooled sample from 1987 to 1994. Parameters for the intercept (a_t) and slope (b_t) terms are estimated, and their values are reported with their t-values underneath. The intercept term is tested against zero, and the slope term is tested against one with a one-sample t-test. For each regression r^2 are reported as well.

	FEPS<O				FEPS>0				ALL OBSERVATIONS			
YEAR	N	a	b	r^2	N	a	b	r^2	N	a	b	r^2
1987	3	-.024159	-1.615107	.8028	232	-.018595	1.034667	.2094	235	.016628	.642298	.2532
		(-.357)	(-3.267)			(-2.978)	(.503)			(2.541)	(-4.950)	
1988					269	.048642	.250169	.8231	269	.048642	.250169	.0235
						(4.948)	(-7.591)			(4.948)	(-7.591)	
1989	2				256	-.024837	1.151334	.9031	258	-.004246	.965300	.2683
						(-2.255)	(1.493)			(-.393)	(-.348)	
1990	4	.094569	.861084	.3696	218	-.064395	1.615992	.8927	223	-.056071	1.577107	.7794
		(3.922)	(-.175)			(-6.740)	(10.943)			(-5.919)	(10.226)	
1991	16	.111677	1.508690	.2054	234	-.060735	2.103031	.5205	254	.010228	1.250483	.2543
		(2.469)	(.641)			(-5.665)	(8.050)			(.992)	(1.857)	
1992	21	-.124693	.646087	.3505	235	-.041276	1.565594	.6684	259	.006529	.850186	.4221
		(-1.262)	(-1.754)			(-2.697)	(3.082)			(.656)	(-2.414)	
1993	8	-.081918	.027901	.0001	265	-.043603	1.350660	.2914	273	-.022897	1.012995	.1705
		(-.730)	(-.990)			(-3.782)	(2.004)			(-2.488)	(.096)	
1994	3	-.616401	.439128	.0001	274	.036492	.175332	.4204	278	-.018837	.886323	.0577
		(-.328)	(-.014)			(3.463)	(-5.942)			(-1.157)	(-.527)	
1987-94	57	-.032981	.718784	.2579	1983	-.040993	1.386220	.4288	2049	-.011730	1.056217	.4004
		(-.662)	(-1.711)			(-12.307)	(11.549)			(-3.725)	(1.968)	

Table 6.12. OLS Regressions of EPS Against FEPS (Germany)

$$EPS_{it} = a_t + b_t * FEPS_t + e_{it}$$

where

EPS_{it} = actual earnings per share for firm i and fiscal year t
$FEPS_{it}$ = analysts' forecasts of earnings per share for firm i and fiscal year t

Sample period is 1987-1994. Coefficients of OLS regression are estimated separately using flags for negative FEPS and positive FEPS as well as without flags (all observations). This procedure is repeated for samples from each year, and for the pooled sample from 1987 to 1994. Parameters for the intercept (a_t) and slope (b_t) terms are estimated, and their values are reported with their t-values underneath. The intercept term is tested against zero, and the slope term is tested against one with a one-sample t-test. For each regression r^2 are reported as well.

	FEPS<O				FEPS>0				ALL OBSERVATIONS			
YEAR	N	a	b	r^2	N	a	b	r^2	N	a	b	r^2
1987	2				72	-.056781	1.626962	.2094	78	-.197892	3.385448	.2190
						(-2.024)	(1.659)			(-3.782)	(3.253)	
1988	1				104	-.006699	1.006198	.8231	109	-.033663	1.374645	.5445
						(-2.153)	(.134)			(-4.208)	(3.082)	
1989	1				113	.000871	.864123	.9031	117	-.000956	.887597	.9048
						(.478)	(-5.057)			(-.534)	(-4.187)	
1990	3	-.204557	-76.339255	.0867	114	-.004914	1.038557	.8927	118	-.018028	1.201717	.6286
		(-1.133)	(-.312)			(-2.082)	(1.133)			(-3.084)	(2.352)	
1991	2				125	.010280	.807730	.5205	131	.009793	.816503	.5647
						(2.467)	(-2.751)			(2.663)	(-2.907)	
1992	9	-.118215	3.302960	.3745	145	.001639	.963546	.6684	159	-.102589	2.449467	.6502
		(-.570)	(1.427)			(.394)	(-.642)			(-9.376)	(10.108)	
1993	30	-.044227	.708781	.5229	131	.011311	.805577	.2914	166	.003309	.819426	.6573
		(-1.307)	(-2.276)			(2.178)	(-1.758)			(.597)	(-3.908)	
1994	7	-.151036	1.722577	.5231	146	-.050636	1.695852	.4204	157	-.077299	2.176327	.6902
		(-2.591)	(.982)			(-5.710)	(4.194)			(-12.181)	(10.045)	
1987-94	55	-.129640	.745287	.2457	950	-.008151	1.052032	.4288	1035	-.019978	1.137615	.3766
		(-3.541)	(-1.420)			(-3.240)	(1.319)			(-5.688)	(3.022)	

Chapter 7

CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

This study investigates bias in security analysts' forecasts of annual earnings per share. Forecasts reported to the Institutional Brokers Estimate System (I/B/E/S) of Lynch, Jones and Ryan are examined for U.S. firms with December fiscal year-ends. Methods to identify bias and to improve the accuracy of analyst forecasts are suggested and tested. Earnings forecasts of firms in Japan, the U.K., and Germany are also examined for bias.

In Chapter 2, analysts median consensus forecasts of earnings per share are evaluated for forecast bias in a sample of November forecasts from 1984 through 1991. Negative earnings forecasts are found to be overoptimistic. Analysts overestimate earnings 71.71% of the time when they report negative forecasts, and out of the 258 negative forecasts only 14 correspond to a positive earnings outcome. Positive forecasts of earnings per share, however, overestimate actual earnings only 54.19% of the time. Positive forecasts of positive earnings are overoptimistic only 50.50% of the time. However, 5.16% of these positive forecasts grossly over-estimate earnings that actually turn out negative.

In terms of the magnitude of bias, negative earnings forecasts are more optimistic than positive earnings forecasts. Negative earnings forecasts have an average bias of (-0.074176) and positive earnings forecasts have an average bias of (-0.010772) in the pooled 1984-91 sample. For both negative and positive forecast samples, bias is optimistic every year from 1984 to 1991.

An examination of empirical regression lines in Chapter 2 reveals that the relationship of forecasts and actual earnings deviates from the 45-degree line through the origin. This deviation is most apparent for the negative forecast sample in the form of large optimistic biases. Regressions using the positive forecast sample result in parameter estimates that reflect bias and inefficiency.

The findings in the chapter suggest that the observed overoptimism is mostly driven by the forecasts of companies with negative earnings. The percentage of earnings overestimated is 50.32% and average bias is (-0.002439) in the positive earnings sample. On the other hand, analysts are overoptimistic 86.69% of the time with an average bias of (-0.117492) in the negative earnings sample.

The main conclusions of Chapter 2 are that (1) forecasts are on average optimistic, (2) biases in negative forecasts and in negative earnings are more obvious than those in positive forecasts and earnings, (3) positive forecasts that overestimate negative earnings are the biggest source of forecast error, (4) optimistic bias in forecasts seems to be driven by firms with negative earnings.

In light of these observations, Chapter 3 investigates methods to improve the accuracy of negative earnings forecasts. Chapters 4 develops a methodology to predict the sign of actual earnings. Chapter 5 corrects positive earnings forecasts that are likely to be associated with negative earnings.

The first part of Chapter 3 provides information on the increase in relative forecast accuracy (measured by mean square error) one might expect from adjusting negative forecasts downward by various amounts. Since security analysts are likely to be measured by more than just forecast accuracy, this chapter also investigates how downward adjustments of varying amounts affect (1) the probability of being closer to actual earnings than the consensus, and the (2) probability of underestimating actual earnings. These additional two measures will be of interest to those analysts (1) rewarded for "beating the consensus", and (2) exposed to criticism by corporate management for underestimating earnings.

Results in Chapter 3 show that adjustments of up to 1% of share price result in improved forecast accuracy, an increased probability of beating the consensus forecast, and little increase in the probability of underestimating actual earnings. Forecast adjustments of between 1% and 2% of share price consistently beat consensus forecasts and continue to improve forecast accuracy, although there is an increasing risk of underestimating earnings. Relative forecast accuracy continues to improve for adjustments of up to 5% of share price. While the probability of beating the consensus is still on average greater than one-half for adjustments of up to 5% of share price, the extent to which forecasts can be adjusted and still beat the consensus more than half the time exhibits a good deal of year-to-year variation. The maximum adjustment before the probability of beating the consensus falls below one-half in the yearly samples ranged from 2% to 11% of share price. Beyond an adjustment of 2% of share price there is substantial risk of underestimating earnings. Forecast adjustments of up to 11% of share price are still likely to be superior to unadjusted forecasts on forecast accuracy, although by this point one has probably overshot the mark. The probability of beating the consensus and the probability of underestimating earnings are both unacceptably high.

Each analyst must make an individual decision on how much to adjust negative earnings forecasts according to the incentives and penalties they face in their individual circumstance. Small downward adjustments can improve forecast accuracy as well as the probability of beating the consensus forecast. Larger adjustments continue to improve forecast accuracy at the expense of an increasing probability of under-estimating earnings and a lower probability of beating the consensus forecast.

In Chapter 4, firm-specific variables that can help predict the sign of an annual earnings outcome are tested in samples of positive forecasts between 1985 and 1991. Using Multiple Discriminant Analysis (MDA) and Logistic Regressions (LR), observations are classified into negative and positive earnings groups and the correct classification rates of each method is evaluated against a benchmark of correct classification by security analysts. Both MDA and LR outperform security analysts in the prediction of negative earnings outcomes. MDA performs better than both LR and analysts in correctly predicting negative earnings outcomes. In terms of the overall correct classification, LR tops the list while analysts and MDA come second and third, respectively.

The best variables in terms of explanatory power in MDA are the sum of the first three quarterly earnings (SUM3QEPS), the magnitude of the consensus forecast (FEPS), and the percentage change in share price during the year (PRICECHG). Although LR gives results that agree with MDA for the inclusion of SUM3QEPS and PRICECHG, FEPS is not a significant explanatory variable.

MDA is chosen to be the methodology for adjusting positive forecasts in Chapter 5 because of its better performance in explaining negative earnings outcomes.

Chapter 5 involves (1) obtaining MDA parameters in an estimation period, (2) using these parameter estimates in a hold-out test period to predict the sign of earnings, and (3) adjusting those forecasts that correspond to the negative earnings group using an adjustment factor obtained in the estimation period. Out-of-sample tests are performed to assess the power of the model in predicting negative earnings outcomes. Also, forecast improvement is evaluated using the same out-of-sample tests. Although security analysts do a relatively good job when they report positive consensus forecasts, these forecasts suffer from an optimistic bias stemming from overoptimistic positive forecasts of negative earnings. Positive consensus forecasts are fairly symmetrically distributed around actual earnings when they correspond to a positive earnings outcome. On the other hand, overoptimistic bias in positive forecasts is heavily driven by earnings that turn out to be negative.

The methodology developed in Chapter 5 uses consensus forecasts of annual earnings (FEPS) with the sum of the first three quarters' earnings (SUM3QEPS) in MDA to predict the sign of an earnings announcement. First, the coefficients of SUM3QEPS and FEPS and cut-off discriminant values for each annual sample period are estimated between 1984 and 1990. OLS regression parameters of forecast errors against discriminant scores are also obtained for the earnings predicted as negative in the estimation period. Then, coefficient values of the MDA function and cut-off discriminant scores are used in an out-of-sample test period to predict the sign of actual earnings. An adjustment factor is obtained by using the previously estimated regression parameters of forecasts errors versus discriminant scores. Earnings that are predicted as negative in the test period are then adjusted using the adjustment factor. Test period results indicate that this methodology outperforms security analysts' consensus forecasts in predicting negative earnings outcomes. Mean square forecast error is greatly reduced in all but one test period. The methodology also predicts the optimistic positive forecasts of positive earnings at a success rate of up to 88.24% while the observed probability of an optimistic positive forecast is about 50.00% across the test period.

In Chapter 6, the accuracy of security analysts' median consensus forecasts in Japan, the U.K., and Germany is investigated using a sample that covers the period 1987-94. Results indicate that analysts' forecasts contain an optimistic bias in all three countries. A majority of negative forecasts are overoptimistic in Japan and Germany, where analysts rarely report negative forecasts for earnings that turn out to be positive. Negative forecasts of negative earnings are clearly overoptimistic in Japan and Germany.

In contrast, negative earnings forecasts in the U.K. are on average pessimistic. This is because about half of the negative forecasts in the U.K. pertain to earnings that turn out to be positive. Positive forecasts are also on average over-optimistic in all three countries. The large magnitude of forecast errors posed by positive forecasts of negative earnings accounts for a significant portion of this optimistic bias in positive forecasts.

Tests of symmetry suggest that the average forecast error is negative and its magnitude is symmetric regardless of the size of forecasts in Japan and the United Kingdom. On the other hand, the forecast errors become larger and more negative as the forecasts become smaller in Germany.

Regression results show that both negative and positive forecast samples as well as the sample of all forecasts in Japan, the U.K. and Germany deviate from the theoretical relationship between forecasts and actual earnings represented by a 45-degree line passing through the origin. This outcome is magnified in the case of the negative forecast sample where regressions result in intercept and slope terms varying widely from year to year and reflecting bias and/or inefficiency in forecasts. Regressions using the positive forecasts sample also indicate bias and/or inefficiency in all three countries. This result can be attributed to the positive forecasts corresponding to negative earnings outcomes. Especially in the German sample, a majority of positive forecasts tightly cluster around the 45-degree line passing through the origin. However, the regression of actual earnings against the forecasts in the positive forecast sample yields a significantly negative intercept term which indicates optimistic bias.

In light of the findings of this study, further research should focus on (1) investigating the association of adjusted forecast errors to the post announcement stock price changes in the U.S., (2) determining the underlying institutional implications of over-optimistic bias observed in forecasts of analysts in Japan, the U.K. and Germany, and (2) developing methods to improve the accuracy of earnings forecasts in these countries.

APPENDIX

APPENDIX

DECOMPOSITION OF THE FORECAST ERROR

At this point, it is useful to reconsider the multiple regression model employed in Chapter 2:

$$EPS = a + b \,.\, FEPS + e$$

where

EPS	=	actual earnings per share
FEPS	=	earnings forecast per share

Using this model, the sources of forecast error in the composition of mean square error (MSE) can be reviewed. The forecast error (FCE) can be computed as:

$$FCE = EPS - FEPS$$

The variance of the forecast error is $\sigma^2(FCE)$ and r^2 is the coefficient of determination of the regression model. Applying the method suggested by Theil (1966) (see also Mincer (1969)), the mean square error of the forecast can be decomposed as follows:

$$\begin{aligned} MSE &= E(EPS - FEPS)^2 = E(FCE)^2 = [E(FCE)]^2 + \sigma^2(FCE) \\ &= [E(FCE)]^2 + [\sigma^2(FCE) - \sigma^2(e)] + \sigma^2(e) \\ &= [E(FCE)]^2 + (1 - b)^2 \,.\, \sigma^2(FEPS) + (1 - r^2) \,.\, \sigma^2(EPS) \\ &= \text{bias} \quad + \quad \text{inefficiency} \quad + \quad \text{error} \end{aligned}$$

Bias in the prediction of EPS relates to the difference between the actual mean EPS and the mean FEPS. In line with a rational expectations framework, an unbiased estimate involves an average FEPS ($\overline{\text{FEPS}}$) which is equal to average EPS ($\overline{\text{EPS}}$). In this case, the regression equation passes through the point:

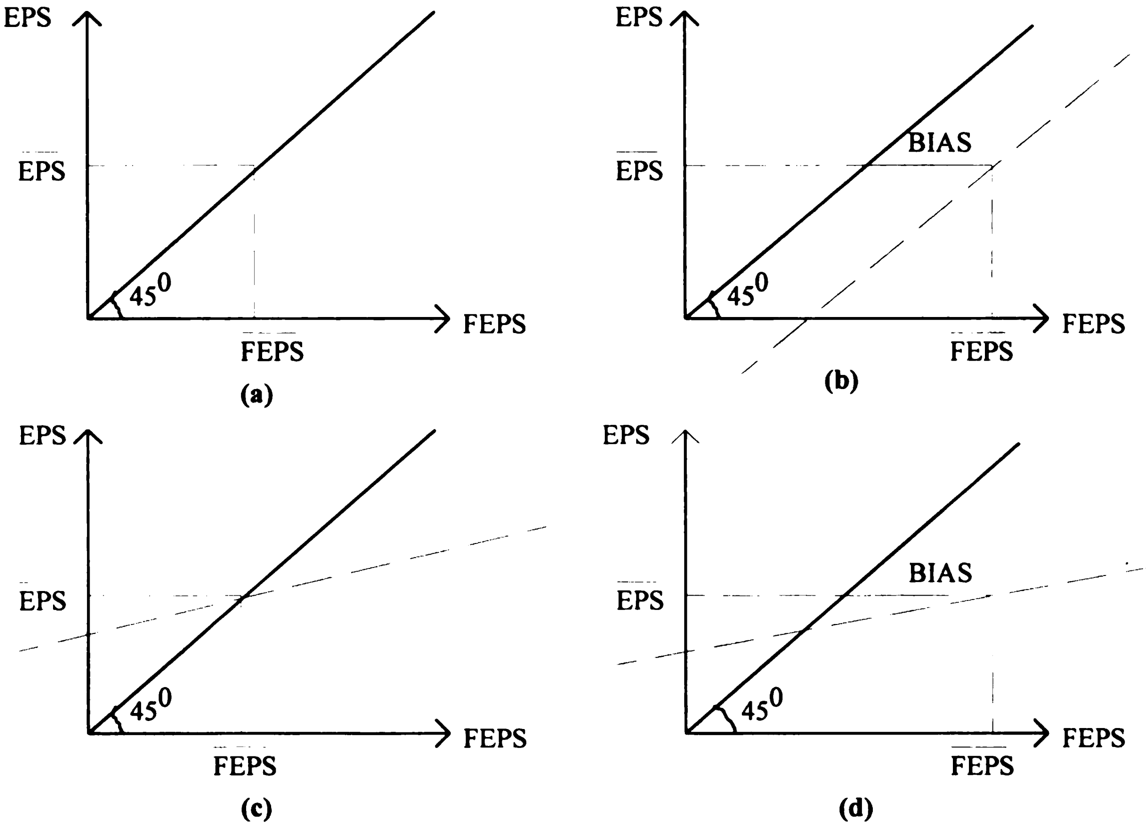
$$(x,y) = (\overline{\text{FEPS}}, \overline{\text{EPS}})$$

on the 45-degree line of perfect fit.

The inefficiency of the forecast is represented by the magnitude of σ^2(FCE) relative to the residual variance σ^2(e) in the regression equation. When the forecast error (FCE) is uncorrelated with the FEPS, the slope coefficient (b) must be equal to unity. This implies that $\sigma^2(\text{FCE}) = \sigma^2(\text{e})$ and the EPS prediction is efficient. If, however, the FCE is related to the FEPS, then the forecast is inefficient. In this case, b is not equal to unity and σ^2(FCE) is different from σ^2(e).

Figure A.1 demonstrates four different cases where (a) the forecast is unbiased and efficient although a random estimation error exists, (b) forecast exhibits only bias, (c) forecast is inefficient, and (d) forecast is both biased and inefficient.

Figure A.1. Decomposition of Mean Square Forecast Error of EPS Forecasts



BIBLIOGRAPHY

BIBLIOGRAPHY

Abarbanell, Jeffrey S., 1991, "Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes", *Journal of Accounting and Economics*, Vol. 14, Iss. 2, June 1991, pp. 147-165.

Affleck-Graves, John, Larry R. Davis and Richard Mendenhall, 1990, "Forecasts of Earnings Per Share: Possible Sources of Analyst Superiority and Bias", *Contemporary Accounting Research*, Spring 1990, pp. 501-517.

Ali, Ashiq, April Klein and James Rosenfeld, 1992, "Analysts' Use of Information About Permanent and Transitory Earnings Components in Forecasting Annual EPS", *Accounting Review*, Vol. 67, Iss. 1, January 1992, pp. 183-198.

Altman, E. I., 1968, "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *The Journal of Finance*, 23, 589-609.

Altman, E. I., R. G. Haldeman and P. Narayanan, 1977, "Zeta Analysis: A New Model to Identify Bankruptcy Risk of Corporations", *Journal of Banking and Finance*, 1, 29-54.

Altman, E. I. and R. Eisenbeis, 1978, "Financial Applications of Discriminant Analysis: A Clarification", *Journal of Financial and Quantitative Analysis*, 185-195.

Anthony, Joseph H. and K. Ramesh, 1992, "Association Between Accounting Performance Measures and Stock Prices: A Test of the Life Cycle Hypothesis, *Journal of Accounting and Economics*, Vol. 15, Iss. 2,3, June/September 1992, pp. 203-227.

Atiase, R. K., 1980, "Predisclosure Informational Asymmetries, Firm Capitalization, Financial Reports, and Security Price Behavior", *Ph. D. Dissertation*, University of California, Berkeley.

Atiase, R. K., 1985, "Predisclosure Information, Firm Capitalization, and Security Price Behavior Around Earnings Announcements", *Journal of Accounting Research*, Vol. 23, Iss. 1, Spring 1985, pp. 21-36.

Atiase, R. K., 1987, "Market Implications of Predisclosure Information: Size and Exchange Effects", *Journal of Accounting Research*, Vol. 25, Iss. 1, Spring 1987, pp. 168-176.

Ball, R. and P. Brown, 1968, "An Empirical Evaluation of Accounting Income Numbers", *Journal of Accounting Research*, 6, pp. 159-78.

Barrondale, I. and A. Young, 1966, "A Note on Numerical Procedures For Approximation by Spline Functions", *Computer Journal*, 9, pp. 318-320.

Beaver, W. H., 1968, "The Information Content of Annual Earnings Announcements", *Empirical Research in Accounting: Selected Studies*, pp. 67-100.

Benesh, Gary A. and Pamela P. Peterson, 1986, "On the Relationship Between Earnings Changes, Analysts' Forecasts and Stock Price Fluctuations", *Financial Analysts Journal*, Vol. 42, Iss. 6, November/December 1986, pp. 29-39.

Bercel, Anthony, 1994, "Consensus Expectations and International Equity Returns", *Financial Analysts Journal*, Vol. 50, Iss. 4, July/August 1994, pp. 76-80.

Bhardwaj, Ravinder K. and LeRoy D. Brooks, 1992, "Stock Price and Degree of Neglect as Determinants of Stock Returns", *Journal of Financial Research*, Vol. 15, Is. 2, Summer 1992, pp. 101-112.

Bhushan, Ravi, 1989, "Firm Characteristics and Analyst Following", *Journal of Accounting and Economics*, Vol. 11, Iss. 2-3, July 1989, pp. 255-274.

Brennan, Michael J. and Patricia J. Hughes, 1991, "Stock Prices and Supply of Information", *Journal of Finance*, Vol. 46, Iss. 5, December 1991, pp. 1665-1691.

Brown, Lawrence D., 1993, "Earnings Forecasting Research: Its Implications for Capital Market Research", *International Journal of Forecasting*, 9, pp. 295-320.

Brown, Lawrence D., 1996, "Analyst Forecasting Errors and Their Implications for Security Analysis: An Alternative Perspective", *Financial Analysts Journal*, January/February 1996, pp. 40-47.

Brown, Lawrence D. and Michael S. Rozeff, 1978, "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings", *Journal of Finance*, March 1978, pp. 1-16.

Brown, Lawrence D. and Michael S. Rozeff, 1979, "Adaptive Expectations, Time-Series Models, and Analyst Forecast Revision", *Journal of Accounting Research*, Autumn 1979, pp. 341-351

Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin and Mark E. Zmijewski, 1987, "Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings", *Journal of Accounting and Economics*, April 1987, pp. 61-87.

Brown, Stewart L., 1978, "Earnings Changes, Stock Prices, and Market Efficiency", *Journal of Finance*, Vol. 33, Iss. 1, March 1978, pp. 17-28.

Capstaff, John, Krishna Paudyal and William Rees, 1995, "The Accuracy and Rationality of Earnings Forecasts by UK Analysts", *Journal of Business Finance and Accounting*, Vol. 22, Iss. 1, January 1995, pp. 67-85.

Chambers, Anne E. and Stephen H. Penman, 1984, "Timeliness of Reporting and the Stock Price Reaction to Earnings Announcements, *Journal of Accounting Research*, Vol. 22, Iss. 1, Spring 1984, pp. 21-47.

Collins, Daniel W. and S. P. Kothari, 1989, "An Analysis of Intertemporal and Cross-Sectional Determinants of Earnings Response Coefficients", *Journal of Accounting and Economics*, Vol. 11, Iss. 2,3, July 1989, pp. 143-181.

Collins, William A. and William S. Hopwood, 1980, "A Multivariate Analysis of Annual Earnings Forecasts Generated fro Quarterly Forecasts of Financial Analysts and Univariate Time-Series Models", *Journal of Accounting Research*, Autumn 1980, pp. 390-406.

Conroy, Robert M. and Robert S. Harris, 1995, "Analysts' Earnings Forecasts in Japan: Accuracy and Sell-Side Optimism", *Pacific-Basin Finance Journal*, Vol. 3, Iss. 4, December 1995, pp. 393-408.

Conroy, Robert M., Robert S. Harris and Young S. Park, 1994, "Earnings Forecasts and Share Prices in Japan: The Role of Analyst and Management Predictions, *Working Paper*, February 1994.

Crichfield, Timothy, Thomas Dyckman and Josef Lakonishok, 1978, "An Evaluation of Security Analysts' Forecasts", *Accounting Review*, July 1978, pp. 651-668.

Damodaran, Aswath, 1987, "The Impact of Information Structure on Common Stock Returns", *Journal of Portfolio Management*, Vol. 13, Iss. 3, Spring 1987, pp. 53-58.

Dorfman, J. R., 1991, "Analysts Devote More Time to Selling as Firms Keep Scorecard on Performance", *The Wall Street Journal*, October 29, 1991, C1-2.

Dowen, Richard J., 1989, "The Relation of Firm Size, Security Analyst Bias and Neglect", *Applied Economics*, January 1989, pp. 19-23.

Dreman, David N. and Michael A. Berry, 1995, "Analyst Forecasting Errors and Their Implications for Security Analysis", *Financial Analysts Journal*, Vol. 51, No. 3, May/June 1995, pp. 30-41.

Dugar, Amitabh and Siva Nathan, 1995, "The Effect of Investment Banking Relationships on Financial Analysts' Earnings Forecasts and Investment Recommendations", *Contemporary Accounting Research*, Fall 1995.

Edmister, R. C., 1972, "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction", *Journal of Financial and Quantitative Analysis*, Vol. 7, Iss. 2, March 1972, p. 1477.

Eisenbeis, R. A., 1977, "Pitfalls in the Application of Discriminant Analysis: A Clarification", *Journal of Financial and Quantitative Analysis*, pp. 185-195.

Elton, Edwin J. and Martin J. Gruber, 1989, "Expectational Data and Japanese Stock Prices", *Japan and the World Economy*, Vol. 1, No. 4, November 1989, pp. 391-425.

Elton, Edwin J., M. J. Gruber and M. Gultekin, 1981, "Expectations and Share Prices", *Management Science*, 27, pp. 975-87.

Erickson, Hans L. and John M. Cunniff, 1995, "A Comparative Look at Consensus Earnings in World Markets", Journal of Investing, Vol. 4, No. 1, Spring 1995, pp 19-28.

Francis, Jennifer and Donna Philbrick, 1992, "The Association Between Value Line Earnings Forecasts and Value Line Recommendations", *Working Paper*, University of Chicago.

Francis, Jennifer and Donna Philbrick, 1993, "Analysts' Decisions as Product of a Multi-Task Environment", *Journal of Accounting Research*, Vol. 31, Iss. 2, Autumn 1993, pp. 216-230.

Freeman, R.N., 1987, "The association Between Accounting Earnings and Security Returns for Large and Small Firms", *Journal of Accounting and Economics*, 9, pp. 195-228.

Fried, D. and D. Givoly, 1982, "Financial Analysts' Forecasts of Earnings: A Better Surrogate for Market Expectations", *Journal of Accounting and Economics*, 4, pp. 85-107.

Givoly, D. and J. Lakonishok, 1979, "The Information Content of Financial Analysts' Forecasts of Earnings: Some Evidence on Semi-Strong Inefficiency", *Journal of Accounting and Economics*, 3, 165-85.

Grant, Edward B., 1980, "Market Implications of Differential Amounts of Interim Information", *Journal of Accounting Research*, Vol. 18, Iss. 1, Spring 1980, pp. 255-268.

Guerard, John B., Jr., 1987, "Linear Constraints, Robust-Weighting and Efficient Composite Modeling", *Journal of Forecasting*, July-September 1987, pp. 193-199.

Harris, Trevor S., Mark Lang and Hans P. Moller, 1994, "The Value Relevance of German Accounting Measures: An Empirical Analysis", *Journal of Accounting Research*, Vol. 32, Iss. 2, Autumn 1994, pp. 187-209.

Hsieh, Su-Jane, 1993, "A Note on the Optimal Cutoff Point in Bankruptcy Prediction Models", *Journal of Business Finance and Accounting*, 20, pp. 457-464.

Huberts, Lex C. and Russell J. Fuller, 1995, "Predictability Bias in the U.S. Equity Market", *Financial Analyst Journal*, March-April 1995, pp. 12-28.

Jacques, William and Dan Rie, 1994, "Valuation Factors Across Countries", *The Handbook of Corporate Earnings Analysis*, Probus Publishing, 1994.

Joy, D. M. and J. O. Tollefson, 1975, "On the Financial Applications of Discriminant Analysis", *Journal of Financial and Quantitative Analysis*, pp. 723-739.

Joy, D.M. and J.O. Tollefson, 1978, "Some Clarifying Comments on Discriminant Analysis", *Journal of Financial and Quantitative Analysis*, pp. 197-199.

Klecka, W.R., 1980, *Discriminant Analysis*, Beverly Hills, CA: Sage Publications, Inc.

Klein, A., 1990, "A Direct Test of the Cognitive Bias Theory of Share Price Reversals", *Journal of Accounting and Economics*, 12, July 1990, pp. 155-166.

Kwok, C. C. Y. and T. H. Lubecke, 1990, "Improving the Correctness of Foreign Exchange Forecasts Through Composite Forecasting", *Management International Review*, 30, pp. 331-352.

Lin, H. W. and M. McNichols, 1991, "Underwriting Relationships and Analysts' Earnings Forecasts", *Working Paper*, Stanford University.

Lipe, R., 1990, "The Relation Between Stock Returns and Accounting Earnings Given Alternative Information", *The Accounting Review*, 65, pp. 49-71.

Lobo, Gerald J., 1992, "Analysis and Comparison of Financial Analysts', Time Series, and Combined Forecasts of Annual Earnings", *Journal of Business Research*, May 1992, pp. 269-280.

Lobo, Gerald J. and Amal A. W. Mahmoud, 1989, "Relationship Between Differential Amaounts of Prior Information and Security Return Variability", *Journal of Accounting Research*, Vol. 27, Iss. 1, Spring 1989, pp. 116-134.

Mincer, Jacob, ed., 1969, *Economic Forecasts and Expectations*, National Bureau of Economic Research, Columbia University Press, New York, pp. 1-46.

Moses, O. D., 1990, "On Analysts' Earnings Forecasts for Failing Firms", *Journal of Business Finance and Accounting*, 17, pp. 101-118.

Niederhoffer, Victor and Patrick Regan, 1972, "Earnings Changes and Stock Prices", *Financial Analysts Journal*, Vol. 28. Iss. 3, May/June 1972, pp. 65-71.

O'Brien, Patricia C., 1988, "Analysts' Forecasts as Earnings Expectations", *Journal of Accounting and Economics*, Vol. 10, pp. 53-83.

O'Brien, Patricia C., 1994, "Corporate Earnings Forecasts and the Macroeconomy", *Working Paper*, January 1994.

Ohlson, J. A., 1980, "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research*, 18, pp. 109-131.

Pincus, Morton, 1983, "Information Characteristics of Earnings Announcements and Stock Price Behavior", *Journal of Accounting Research*, Vol. 21, Iss. 1, Spring 1983, pp. 155-183.

Poirier, D. J., 1976, *The Econometric of Structural Change*, North Holland/American Elsevier, New York, pp. 9-11.

Potter, Gordon, 1992, "Accounting Earnings Announcements, Institutional Investor Concentration, and Common Stock Returns", *Journal of Accounting Research*, Vol. 30, Iss. 1, Spring 1992, pp. 146-155.

Press, S. J. and S. Wilson, 1978, "Choosing Between Logistic Regression and Discriminant Analysis", *Journal of the American Statistical Association*, 73, pp. 699-705.

Rendleman, Richard J., Charles P. Jones and Henry A. Latane, 1982, "Empirical Anomalies Based on Unexpected Earnings and the Importance of Risk Adjustments", *Journal of Financial Economics*, Vol. 10, Iss. 3, November 1982, pp. 269-287.

Sicinolfi, M., 1992, "At Morgan Stanley, Analysts Were Urged to Soften Harsh Views", *The Wall Street Journal*, July 14, 1992, A1 and A6.

Sicinolfi, M., 1995, "Incredible 'Buys': Many Companies Press Analysts to Steer Clear of Negative Ratings", *The Wall Street Journal*, July 19, 1995, A1 and A6.

Sultan, Asad, 1994, "Earnings Surprise in Japan", *Journal of Investing*, Vol. 3, No. 4, Winter 1994, pp. 32-38.

Theil, Henri, 1966, *Applied Economic Forecasting*, Chicago.

Trueman, Brett, 1990, "On the Incentives for Security Analysts to Revise Their Earnings Forecasts", *Contemporary Accounting Research*, Fall 1990, pp. 203-222.

Trueman, Brett, 1994, "Analysts Forecasts and Herding Behavior", *Review of Financial Studies*, Spring 1994, pp. 97-124

Weston, J. F. and T. E. Copeland, 1986, *Managerial Finance*, New York, NY: The Dryden Press.

Zavgren, C. V., 1983, "The Prediction of Corporate Failure: The State of the Art", *Journal of Accounting Literature*, 2, pp. 1-35.

Zavgren, C. V., 1985, "Assessing the Vulnerability To Failure of American Industrial Firms: A Logistic Analysis", *Journal of Business Finance and Accounting*, 12, pp. 19-45.