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Predictability of earnings, precision of information, and accuracy of earnings expectations

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Abstract

Predictability of Earnings, Precision of Information, and Accuracy of Earnings expectations

By:

Yabing Tang

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This study develops a simple model to explain the relationships among predictability of earnings, precision of information and accuracy of earnings expectations. It also empirically tests the relationships predicted by the model using earnings expectations of two groups of market participants: financial analysts and investors.

For analysts, this study uses a sample of 133,599 analysts' forecasts for 807 firms obtained from the IBES database. The accuracy of investors' earnings expectations is proxied by the variance in price changes during earnings announcements. The test results indicate that analysts'/investors' earnings expectations are relatively more (less) accurate (compared to mechanic time series forecasts) when they possess more (less) precise public and/or private information and when future earnings are less (more) predictable. Thus, the study provides theoretical and empirical evidence suggesting that earnings predictability and the precision of information are fundamental determinants of the accuracy of earnings

expectations.

The evidence also indicates that analysts and investors are able to learn each other's private information by observing public information signals. Analysts can incorporate information contained in price and trading volume movements. Investors, on the other hand, are able to utilize analysts' information through processing analysts' forecasts.

The study uses several proxies for precision of information: variance of price-based earnings forecast errors, standardized trading volumes, dispersion of analysts' forecasts, and incremental accuracy of analysts' forecasts over price-based forecasts. These proxies are developed on the basis of theoretical work, and provide more powerful explanatory power in empirical tests than firm size and its related variables which are used in prior studies. This research finds that size is only weakly associated with information precision and provides little incremental explanatory power to forecast accuracy after the information effect has been captured in the model.

To explain analysts' accuracy, previous studies suggest that analysts possess a timing advantage in addition to information advantage. The results of this study suggest that the timing of forecasts has no effect on the accuracy of forecasts after the information effect is controlled. This means that if the forecasters possess equally precise information about a firm, their forecasts will be equally accurate, regardless of when the forecasts are made.

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Table of Contents

(Table of Contents continued)

Table of Contents - *continued*

(Table of Contents continued)

Table of Contents - *continued*

List of Tables

Chapter 1

Introduction

This study investigates the relationships among the predictability of earnings, the precision of information, and the accuracy of earnings expectations. It provides theoretical and empirical evidence suggesting that the accuracies of analysts'/investors' earnings expectations are determined by the earnings predictability and the precision of their private and public information sources. The study is able to provide unambiguous evidence suggesting that analysts and investors are able to learn each others' private information by observing public information signals. Analysts can incorporate information contained in stock price and trading volume movements. Investors, on the other hand, are able to utilize analysts' information through processing analysts' forecasts. The study uses several proxies for precision of information. These proxies are developed on the basis of theoretical work, and provide more powerful explanatory power in empirical tests than firm size and its related variables, which are used in prior research. The results of this study also suggest that the timing of forecasts has no effect on forecast accuracy after information effect is controlled. This means that if the forecasters possess equally precise information about a firm, their forecasts will be equally accurate, regardless when the forecasts are made.

1.1 Motivation and Objectives

This study addresses four related topics in the accounting literature: (1) the predictive accuracy of analysts' earnings forecasts compared to time series forecasts; (2) the information environment for earnings forecasts; (3) the investors' rationality; and (4) the proxy for market earnings expectations.

1.1.1 Analysts' Forecasts vs. Time Series Forecasts

One motivation of this study is to uncover how analysts' forecast accuracy is affected by the quality of information that analysts use to form their forecasts. Many existing studies have investigated statistical properties of analysts' earnings forecasts and have shown that analysts consistently forecast earnings more accurately than time series models (e.g., Brown et al. [1978, 1987b] and O'Brien [1988]). Little, however, has been done to uncover the sources of this superior predictive accuracy. This study explains analysts' predictive accuracy from an information perspective. The theoretical model and empirical test of this study yield three variables which determine analysts' forecast accuracy. These determinants are precision of public information, precision of analysts' private information, and predictability of earnings. Hereafter, they will be referred to as the fundamental determinants of forecast accuracy or FDFA. Empirical results support the model's prediction.

1.1.2 The Information Environment

Errors in investors' earnings forecasts are usually measured by abnormal stock returns during earnings announcements[1] (e.g., Beaver, Lambert and Morse [1980], Collins and Kothari [1989]). Studies by Atiase [1985,1987], Freeman [1987] and Shores [1990] analyze the relations between abnormal returns during earnings announcements and predisclosure information. This line of research predicts that when there is more (less) precise information available to the market before earnings announcements, more (less) accurate earnings forecasts can be formed, and therefore smaller (larger) abnormal stock returns will be observed when actual earnings are announced. However, existing studies use attributes of the information environment such as firm size, number of analysts' followings, WSJ coverage, etc., as proxies for precision of predisclosure information. These proxies have been criticized because they confound the effects of other factors such as political cost and risk exposure (e.g., Lim [1989] and Schipper [1990]). These confounding effects might introduce serious bias in inference. Instead of using arbitrary attributes, this study uses measures of the FDFA. These determinants directly affect the accuracy of analysts' earnings forecasts, and naturally arise from a theoretical model. In this study, firm size is only weakly related to the precision of information and provides little incremental explanatory power to forecast accuracy after the information effect been captured in the model.

1.1.3 Investors' Rationality

This study provides evidence on whether investors are able to make rational use of the information contained in analysts' earnings forecasts. Answers to this issue will affect the extent to which investors can be viewed as efficient and rational forecasters who incorporate all available information in forming their expectations. A number of studies have shown that investors are actually not rational and do not incorporate all information available to them (e.g., Ball [1992], Bernard and Thomas [1989], [1990], Ou and Penman [1989], and DeBondt and Thaler [1989]). This is evidenced by the predictability of abnormal stock returns, such as post-announcement drift. Analysts' information is an important subset of investors' information set, and it is available to investors either through investors' own information collection activities or through processing analysts' forecasts. Evidence on whether investors are able to make rational use of analysts' information will complement and give a new perspective to the literature in accounting and finance that is reexamining the related anomalies.

1.1.4 The Proxy for Market Earnings expectations

Many researchers prefer analysts' earnings forecasts to time series forecasts as the proxy for market earnings expectations. This preference stems from researchers' proposition that market earnings expectations are likely to incorporate the timely and broad information which is also incorporated in analysts' earnings forecasts. This information, however, is excluded from time series forecasts (e.g., Schipper [1991], Brown et al. [1978, 1978a,b], and Fried and Givoly [1982]). However, existing studies provide mixed evidence on this issue. For example, existing studies use *association tests* to compare the market's reactions to earnings forecast errors based on analysts' forecasts and forecast errors based on mechanical time series models. Brown et al. [1987a] and Fried and Givoly [1982] find that analysts' forecast errors are more strongly associated with abnormal stock returns during earnings announcements. This result is consistent with the proposition. In contrast, O'Brien [1988] finds that forecast errors from a time series model have a stronger association with the abnormal stock returns than do errors based on analysts' forecasts. This is just opposite to the results of Brown et al. and Fried and Givoly, and is against the proposition.

A limitation of an *association test* is that it actually deals with two different issues simultaneously: an information issue (i.e., whether both investors and analysts use the same information source) and a reaction issue (i.e., whether both investors and analysts react to the information in a similar fashion). Finding analysts' forecast errors more strongly associated with abnormal stock returns than with errors from time series forecasts is consistent with the proposition that both analysts and investors use the same information source. However, finding analysts' forecast errors are less strongly associated with abnormal stock returns than errors of time series model will lead to two contradictory explanations: (1) investors and analysts use different information sources; and (2) investors and analysts do use the same information source, but their reactions to the information are different.

Unambiguous interpretation regarding the information issue therefore cannot be obtained by the *association test*. As a result, the issue of whether investors and analysts use the same information source is left as an unanswered question. This study improves the *association test* because it tests whether the *accuracy* of investors' forecasts is associated with the *precision* of information contained in analysts' forecasts. It is easy to understand that if investors incorporate analysts' information into their earnings expectations, then more (less) precise information will lead to more (less) accurate forecasts by investors, despite their differences in degree of reaction. Therefore, the study improves the association test and is able to provide an unambiguous evidence on the information issue.

1.2 The Theoretical Model

This study models the individual analyst as a Bayesian forecaster who searches and processes his/her own private information to form forecasts. In addition to private information, the analyst makes inferences about other market participants' private information by observing stock price and trading volume movements. Three fundamental determinants of analysts' forecast accuracy are identified: (1) the predictability of earnings; (2) the precision of the analyst's private information; and (3) the precision of the analyst's public information. Predictability of earnings is defined as the inverse of the variance of future earnings. Greater predictability means lower variation in earnings which, in turn, means greater ability of past earnings to predict future earnings in the absence of other more timely information. When future earnings are less predictable, the timely information possessed by analysts will be more useful and thus analysts' forecasts will be more accurate when compared with time series forecasts. Precision of analysts' information is defined as the inverse of the variance of noises in the information signals. Precision affects the accuracy of analysts' forecasts because, for instance, analysts know less about future earnings as the variance of noise increases. Therefore, their forecasts will be less accurate if information is less precise. The model suggests that predictability of earnings, precision of analysts' private information and precision of analysts' public information are fundamental determinants of overall analysts' forecast accuracy.

1.3 The Empirical Test

Two regression models are used for the empirical test. The purpose of the first model is to test the predictions of the theoretical model. It regresses a measure of analysts' relative predictive accuracy on measures of the three FDFA. The predictability of earnings is estimated by the variance of past earnings time series based on the random walk model (e.g., Watts [1975], and Lipe [1990]). The precision of public information employed by the analysts is estimated using proxies that measure informativeness of stock price with respect to future earnings. Two alternative measures are employed: (1) the standardized trading volumes before earnings announcements (e.g., Stickel and Verrecchia [1992]); and (2) the variance of forecast errors of a price-based earnings forecast model (e.g., Beaver, Lambert and Morse [1980], and Elger and Murray [1992]). The empirical measure of the precision of analysts' private information is the dispersion of analysts' forecasts (e.g., Lim [1989], and Morse, Stephan and Stice [1991]). The empirical results confirm the theoretical prediction that relative accuracy of analysts' forecasts is inversely related to earnings predictability, and positively related to the precision of public and private information.

The second regression model examines the relationships among the accuracy of investors' earnings expectations, the predictability of earnings, and the precision of investors' information sources. The investors' accuracy is proxied by the squared dollar value of abnormal returns divided by the squared time-series earnings forecast errors. Standardized trading volumes are used to measure the precision of investors' private information (e.g., Kim and Varrecchia [1989, 1991]), squared price-based earnings forecast errors for precision public information, and incremental accuracy of analysts' forecasts over price-based forecasts for precision of analysts' private information. The results show that the slopes of all three variables are significant in the expected direction. The incremental accuracy of analysts' forecasts over price-based forecasts provides significant explanatory power for abnormal returns. This result suggests that (1) analysts' forecasts provide investors with additional information content that is not contained in other public information sources; and that (2) investors are able to incorporate the additional information contained in analysts' forecasts into their own earnings expectations. The test fails, however, to find a significant relationship between abnormal returns and the dispersion of analysts' forecasts. Dispersion of analysts' forecasts is only an *ex anti* measure of forecast accuracy (i.e., dispersion can be viewed as an estimate for variance of forecast errors). The *ex post* measure of forecast accuracy, i.e., analysts' forecast error, has become available when actual earnings are announced. Therefore, it is reasonable to expect investors to revise their beliefs primarily based on the forecast errors, rather than any estimate of it. This might explain why analysts' forecast error has a significant slope coefficient in regression while dispersion does not.

1.4 Contributions

The study contributes to the literature at three levels. First, it deepens the understanding about what are the determinants of the accuracy of earnings expectations of analysts/investors. The determinants proposed in this study have not been tested before. Second, it directly tests whether investors incorporate the information contained in analysts' forecasts in forming their own earnings expectations. The result of the test will enhance our understanding regarding the validity of analysts' forecasts as a proxy for the market's earnings expectations, and regarding the differential ability of incorporating available information into forecasts by investors and analysts. Finally, it refines the methodology in modeling financial analysts' forecasts. It can also be viewed as a logical extension to the literature on information economics (e.g., Holthausen and Verrecchia [1990]) in which the association between precision of information and the accuracy of market agents' beliefs is proposed but not extensively examined and empirically tested.

Chapter 2 provides a brief literature review in the related research. Chapter 3 describes the model and hypotheses development. Chapter 4 discusses empirical models, measurement of variables, sample section, data sources, and descriptive statistics of key variables. Chapter 5 presents test results. Chapter 6 provides a summary of findings and concluding remarks.

Chapter 2

Literature Review

This chapter reviews related research in the areas of (1) information environment and accuracy of earnings expectations; (2) analysts' forecasts as a proxy for market earnings expectations; (3) stock price as a source of information for earnings expectations; and (4) investors' rationality and market anomaly.

2.1 Information Environment and Accuracy of Earnings Forecasts

Accounting researchers prefer financial analysts' earnings forecasts (FAF hereafter) to time-series forecasts (TS hereafter) as the proxy for the market's earnings expectations[2]. The question then arises: what is the source of this preference? The preference seems to stem from two considerations: *accuracy* and *association* with abnormal stock returns during earnings announcements. On the accuracy issue, analysts have consistently been shown to forecast earnings more accurately than mechanical models (e.g., Brown et al. [1978, 1987b] and O'Brien [1988]). The source of this predictive superiority, however, is not well understood.

Albrecht, Johnson, Lookabill, and Watson [1977] proposed (but did not test) a set of firm-specific characteristics that might potentially explain FAF errors. These factors are: year, forecast horizon, industry, firm size, number of lines of business, and variance of firms' earnings. These factors are proposed based on intuition and the result of prior research. Ten years later, Brown, Richardson and Schwager [1987] empirically tested a model that regresses FAF superiority[3] in terms of predictive accuracy on year, forecast horizon, firm size, number of lines of business and dispersion of analysts forecasts. Brown et al. model the FAF superiority as a ratio between the forecast errors of a random walk model and the FAF. However, their theoretical model is simplified and not directly linked to their empirical model. As a result, the variables in their empirical test can hardly be distinguished from what is proposed by Albrecht et al. With a little variation, Kross, Ro and Schroeder [1990] present an empirical test that regresses FAF superiority on forecast horizon, industry, number of lines of business, firm size, the length of WSJ coverage (in inches) and variance of earnings time series.

The basic hypothesis tested in this line of research is that FAF superiority is related to a firm's *information environment*. The latter is supposed to be related to precision of analysts' information set. Firm size and length of WSJ coverage are used as proxies for the amount of analysts' information. The number of lines of business is used as a proxy for the correlation between information signals about a firm. The industry specialization and year are used as ex post control variables. Regression coefficients of some variables remain insignificant in both of the empirical tests (e.g., number of lines of business). Firm size is found to be significant in Brown et al., but insignificant in Kross et al. The significant variables are size, dispersion of FAF, and forecast horizon in Brown et al.; and variance of time series of earnings, length of WSJ coverage, and forecast horizon in Kross et al. However, the control variables such as industry and year remain consistently significant in both of the studies.

Using firm-specific characteristics as proxies for the analysts' information set in this context is subject to debate since the relationship between these characteristics and analysts' information sets is unclear and arbitrary, confounding many other factors that affect the accuracy of FAF. For example, *precision of information* and *amount of information* are two different concepts. It is obvious that the predictive accuracy of FAF depends on the precision, rather than the amount. The length of WSJ coverage tells much about the amount, but little about the precision, of the information signals. Firm size and length of WSJ coverage might be more closely related to a firm's political cost and risk level than to analysts' information sets. The risk level might be one of the factors that affect analysts' accuracy. These confounding problems suggest insufficient model specification that might introduce serious bias in inference.

2.2 Analysts' Forecasts as Proxy for Market Earnings Expectation

The answer to the question of whether FAF is superior to TS for market earnings expectations is subject to a final test: whether investors incorporate into their earnings expectations the same information as analysts use. The existing *association tests* provide mixed evidence for the question.

The *association test* compares the strength of associations between the market response to earnings and forecast errors based on FAF versus between the market response to earnings and forecast errors generated from mechanical TS models (e.g., Brown et al. [1987a], Fried and Givoly [1982] and O'Brien [1988]). Brown et al. examine the earnings-return relationship using five proxies for market expectation. Four of the proxies are based on statistical models and the fifth is the Value Line forecasts. They report that proxies based on the Value Line forecasts have the highest associations with abnormal returns, especially when the proxies are adjusted for measurement errors. Fried and Givoly evaluate the quality of analysts' forecasts by comparing it with the commonly used prediction models. They also find that analysts' forecast errors are more closely related with security price movement than statistical models. In contrast, O'Brien finds that forecast errors from a quarterly auto-regressive model of earnings have a stronger association with abnormal return than do errors based on analysts' forecasts obtained from IBES. O'Brien interprets this result as anomalous. Her result indicates that investors use the TS model even though there is more timely and precise information that makes accurate forecasts possible. This is inconsistent with the FAF superiority in measuring market earnings expectation. She offered no explanation for the result.

Several problems might exist in the *association test.* First, it deals with *information issue* and *reaction issue* simultaneously. The *reaction issue* also affects the strength of the earnings-return association. There is evidence that investors adjust reported earnings to take into account other information. For example, Lev [1989] finds that in a regression of residual returns on changes in earnings, the explanatory power of the regression increases from .06 to .09 when earnings are adjusted for the effects of early adoption of SFAS 87 (the usual effect of this early adoption was to increase earnings but not cash flows because of the partial write-off of the excess of pension assets over pension liabilities). Secondly, while analysts' forecasts map information into forecasts for earnings in a particular period, investors may look into the effect of the information for earnings of all future periods, not just the current period earnings (e.g., Komendi and Lipe [1987] and Cornell and Landsman [1990]). Last but not least, there is evidence that the usefulness of analysts' forecasts as a proxy for market expectation is enhanced if the researcher adjusts the forecast for information released after the forecast announcement but before the earnings announcement by including the share returns during this interval (e.g., Brown et al. [1987a] and Easton and Zmijewski [1989]). The existence of these problems makes unambiguous interpretation of the *association test* difficult.

2.3 Stock Price as Source Information for Earnings Expectation

Taking a different approach, a number of studies investigated directly what information appears to be impounded in financial analysts' forecasts. These studies attempt to uncover whether analysts appear to make full and rational use of a particular information source.

Lys and Sohn [1990] investigate several aspects of the relationship between analysts' forecast revisions and stock price reactions. They find that while forecast revisions are positively associated with prior share returns and market returns, the association is not complete. This is consistent with the view that while analysts do incorporate in their earnings forecasts the information available in share returns and market returns, they use some other information sources as well. Based on similar regression analyses, Lys and Sohn conclude that analysts' forecasts are based on information that is partly independent across analysts and partly independent of corporate disclosure.

Using a different database and research design to answer somewhat different questions, both Klein [1990] and Abarbanell [1991] confirm the Lys and Sohn results. Abarbanell [1991] finds that there are associations between prior returns and both forecast revisions and forecast errors based on those revisions. He interprets the results in a way that reinforces the interpretations of Lys and Sohn. Klein's research is motivated by the cognitive bias theory as forwarded by DeBondt and Thaler [1987, 1990] to explain what they regard as an overreaction to extremes of earnings changes and returns. She tests whether analysts systematically under-predict earnings following large share price declines and over-predict earnings after large price increases, and finds no evidence that they do.

Holthausen and Verrecchia [1990] theorizes that the individual investor forms expectations based on two sources of information: public information (i.e., price change) and private information. While investors are diversely informed, each individual investor can observe other investors' information through price movement. Holthausen and Verrecchia predict that information signals result in an informedness effect, measured by the variance of investors' expectations upon receiving this signals, and a consensus effect, measured by the correlation coefficient between forecast errors by a pair of investors. While Holthausen and Verrecchia focus on the subsequent effect of informedness and consensus on price and trading volume movement, they do not provide an extensive discussion on how the characteristics of the information set will affect investors' expectations.

Using stock price as an information source for market participants is rooted in the theory that stock price aggregates information and leads accounting earnings (e.g., Beaver, Lambert and Morse [1980], Collins, Kothari and Rayburn [1987], and Elgers and Murray [1992]). These studies examine the predictive power of price-based earnings forecasting models. Using a portfolio approach, Beaver et al. forecast one year ahead accounting earnings based on PE ratio, and compare the forecast accuracy with TS models. They find no clear domination exists by any of the models except for the extreme PE portfolios (in which the price-based model is marginally superior). Elgers et al., on the other hand, forecast one year ahead earnings using a model based on size-adjusted stock return and PE ratio, and suggest no clear domination of their model when compared with FAF. These studies provide strong evidence that stock price contains information about future earnings. Competent earnings forecasts can be made based on the price movements alone[4].

2.4 Investors' Rationality and Market Anomaly

Among the recent studies examining earnings related anomalies[5], Bernard and Thomas [1989, 1990] entertain the possibility that post-announcement drift[6] arises because stock prices fail to reflect the information available. Investors seem to form their earnings expectations based on naive forecast models. As a result, when the subsequent quarters' earnings are announced, stock prices appear to reflect some surprise related to the earnings changes that should have been predictable in advance. Specifically, the short-term (three days) reactions to the announcement of earnings for each of the next four quarters are partially predictable, based on the current quarter's earnings. Even more surprisingly, the sign and the magnitudes of the predictable three-day reactions are related to the auto-correlation structure of earnings, as if stock price failed to reflect the extent to which each firms' earnings series differs from a simple seasonal random walk.

Ou and Penman [1989] and Holthausen and Larcker [1992] document evidence that stock price fails to incorporate the information contained in firms' basic financial statements. They show the possibility of significant abnormal returns to trading strategies that are based on the prediction of the sign of unexpected annual earnings per share and future stock returns. Their prediction model for the sign of unexpected EPS and returns is developed using logit, where the independent variables are traditional financial statement ratios. The market-adjusted stock return for the strategy is as large as 4.3-9.5% (8.3% in Ou and Penman) for a ten-year period by taking a long (short) position in stocks of firms where the prediction model indicates the unexpected earnings/returns is positive (negative).

The above evidence suggests investors' *underreaction* to information. However, DeBondt and Thaler [1985,1987] find the opposite is true: investors *overreact* to the information revealed in current earnings announcements. They provide evidence suggesting that investors overreact to current earnings changes but underreact to the long-run mean reversion in earnings.

While the conflicting evidence of underreaction and overreaction remain to be reconciled[7], both seem to suggest that investors are irrational and fail to incorporate all information available. This evidence has "become one of the most significant anomalies in financial markets research" (Ball [1992]), sparking continuing research.

Chapter 3

The Model and Testable Hypotheses

This chapter develops a simple model to describe the analyst expectation formulation process in order to identify the fundamental determinants of forecast accuracy. Two set of testable hypotheses are proposed.

3.1 Relative Accuracy Index between Analysts' vs. Time Series Forecasts

This study measures the accuracy of forecasts by the inverse of the variance of forecast errors. Focusing on variance, instead of mean level, of FAF is required to examine the relation between accuracy of forecasts and precision of information. Studies that focus on the mean level of FAF, on the other hand, are concerned with systematic errors (the difference between mean forecasts and mean of earnings), i.e., whether FAF is an unbiased estimator for earnings[8]. Since the bias issue is not the major concern of this study, this study assumes that analysts are rational and that they incorporate all the available information into their forecasts[9]. However, the result of the model does not depend on unbiasedness assumption (see Appendix A for proof).

The ultimate objective in this section is to express the relative accuracy between FAF and the TS model in terms of earnings predictability and precision of information. I define the forecast accuracy Θ as the inverse of the variance of forecast errors *V*. Let $\Theta_{FAF,it}$ and $\Theta_{TS,it}$ denote the forecast accuracy for firm *i* and year *t* by analysts and the TS model respectively, then:

$$\Theta_{FAF,it} = (V_{FAF,it})^{-1}; \quad \Theta_{TS,it} = (V_{TS,it})^{-1}$$

where: $V_{FAF,it}$ and $V_{TS,it}$ are the variances of forecast errors for firm *i* and year *t* by analysts and the TS model respectively. To capture the relative accuracy between FAF and the TS model, I construct the relative accuracy index (RAI) between FAF and the TS model as follows:

$$RAI_{it} = \frac{\Theta_{TS,it}}{\Theta_{FAF,it}} = \frac{V_{FAF,it}}{V_{TS,it}}$$

The subscript *it* will be dropped in the rest of the chapter for notational convenience. RAI is similar to the superiority index used by Brown et al. [1987c]. Notice that RAI approaches 0 when FAF become more accurate than TS; and approaches 1 when FAF are less accurate. A value 0 will indicate a perfectly accurate FAF; and 1 indicates FAF and TS are equally accurate[10].

It is worth noting that RAI is a relative measure of FAF accuracy and $\Theta_{FAF,it}$ is an absolute measure. RAI uses the accuracy of TS forecasts as a benchmark to measure the accuracy of FAF. While the determinants of relative and absolute measures are identical, using the relative measure in the model offers several advantages. First, the main interest of this study is to investigate investors' and analysts' ability to incorporate timely information, rather than past earnings information, into their forecasts. Using RAI fits the research purpose better. Second, as a relative measure, RAI is comparable between firms. The absolute measure however does not facilitate meaningful comparison across firms. Finally, to select a surrogate for market expected earnings, researchers make their choice between FAF and TS forecasts. Using RAI is directly related to that choice and to the existing literature.

Brown et al. [1987c] use a random walk model for the TS forecast. The same approach is used here. The early literature on the time-series properties of earnings concluded that annual earnings follow a random walk (e.g., Albrecht et al. [1977], Ball and Watts [1972], and Watts and Leftwich [1977]). The following equation describes the univariate characteristics of earnings:

$$\tilde{u}_t = \tilde{u}_{t-1} + \lambda_t \tag{1}$$

where the stochastic error terms λ_t are a sequence of identically distributed, uncorrelated random variables with a common mean 0 and variance σ. The predictability of earnings at t is captured by the variance of earnings shocks at t or σ. If σ=0, then past earnings predict future earnings perfectly. The ability of past earnings to predict future earnings decreases as σ increases. The majority of the work will be expressing the variance of FAF errors in terms of the precision of analysts' information sets.

To begin, assume a security market with a single stock trading for a single period of time and paying off one liquidation dividend at the end of the period. The unknown liquidation value of the assets, which is set equal to the accounting earnings in this study[11], is represented by a random variable $\tilde{u}$ which has a normal distribution with mean μ and variance σ. The accounting earnings are announced at the end of period when $\tilde{u}=u$ (the tilde is used to distinguish a random variable from its realization).

There are N financial analysts in the market. These analysts are assumed to be Bayesian forecasters (e.g., Easton and Zmijewski [1989], and Morse, Stephan and Stice [1991]) who start with prior knowledge of the probability distribution about earnings and information signals, and update their beliefs using all available information. During the period, analyst a collects and processes his/her private information signal $\tilde{I}_a$. This private information signal is written in the following form[12]:

$$\tilde{I}_a = \tilde{u} + \tilde{n} + \tilde{a}_a \qquad (2)$$

where: ñ is a common noise term that has a normal distribution with a mean zero and variance η; and $\tilde{a}_a$ is an idiosyncratic noise term that has a normal distribution with a mean zero and variance *s*. Since each analyst draws information about a particular firm from a common pool, the information sets are likely to have a noise that is common across analysts. In addition, since each individual analyst draws only samples from the common information pool, each analyst's private information is likely to be different from every other analyst because of idiosyncratic sampling error that is unique to each analyst. The idiosyncratic noise terms, by definition, are independent across analysts: that is $E[\tilde{a}_a, \tilde{a}_b]=0$ for all $a \neq b$. Individual analysts are unable to observe each component of information signal directly. However, the distributions of ũ, ñ and $\tilde{a}_a$ are known to all analysts.

In addition to the private information, analysts also make inferences about other market participants' information through observing stock price movements. The notion that prices convey information about future earnings is pervasive. One of the earliest arguments for the richness of prices in this respect appears in Muth's [1961] seminal essay on rational expectation. Empirical evidence is found in Beaver, Lambert and Morse [1980], Collins, Kothari and Rayburn [1987], Elgers and Murray [1992], and Stickel and Verrecchia [1992], etc. In the spirit of Ohlson [1979, 1988], I write the price equation in the following form[13]:

$$\tilde{P} = \beta(\tilde{u} + \tilde{n}) + \tilde{\varepsilon} \qquad (3)$$

where: β can be characterized as a discount factor which capitalizes earnings information ũ+ñ *into price; and* ε tilde is the unidentified noise term not related to earnings and has a normal distribution with mean 0 and variance δ. The stock price is therefore a function of earnings information that predicts future earnings with some random noise. This particular form of price can also be understood in the literature that considers competitive trading among diversely informed traders (e.g., Holthausen and Verrecchia [1988, 1990], Kim and Verrecchia [1991a,b], and Stikel and Verrecchia [1992]). This literature generally assumes that traders are diversely informed and exchange their assets based on their private information. This exchange of assets implies an equilibrium price which is determined by aggregate demand and supply on the market. Therefore, price aggregates traders' private information, with some noise (e.g., a liquidation shock). Note that although traders are diversely informed, idiosyncratic errors in individual trader's information sets are averaged to zero and disappear in the price equation.

The variance of earnings, analyst's private information and price, and the covariance between them can be summarized in the following variance-covariance matrix (see Appendix B for proof):

$$\begin{array}{c} \tilde{u} \\ \tilde{I}_a \\ \tilde{P} \end{array} \begin{bmatrix} \sigma & \sigma & \beta\sigma \\ \sigma & \sigma+\eta+s & \beta(\sigma+\eta) \\ \beta\sigma & \beta(\sigma+\eta) & \pi \end{bmatrix}$$

where: π is the variance of price derived from equation (3), and

$$\pi = \beta^2(\sigma+\eta)+\delta \tag{4}$$

Analyst a's earnings forecast is his/her expectation of earnings conditional on observing price (P) and his/her private information set ($\tilde{I}_a$), and expressed as follows[14]:

$$\tilde{F}_a = E[\tilde{u} \mid \tilde{I}_a = I_a, \tilde{P} = P] = \mu+(g,h)[I_a - E(\tilde{I}), P - E(\tilde{P})]' \tag{5}$$

where:

$$E(\tilde{I}_a) = E(\tilde{u}+\tilde{n}+\tilde{\varepsilon}_a) = \mu$$

$$E(\tilde{P}) = E[\beta(\tilde{u}+\tilde{n})+\tilde{\varepsilon}] = \beta\mu$$

and

$$(g,h) = (\sigma,\beta\sigma)\begin{bmatrix}\sigma+\eta+s & \beta(\sigma+\eta)\\ \beta(\sigma+\eta) & \pi\end{bmatrix}^{-1}$$

$$= \frac{[\sigma\delta,\sigma s\beta]}{s(\sigma+\eta)\beta^2+\delta(\sigma+\eta+s)} \tag{6}$$

Notice that this forecast model assumes homogeneous prior beliefs about the distribution (the mean and variance) of future earnings, and noises of both public and private information about a particular firm. From equation (5) one can see that, consistent with Bayesian definition, the analyst's forecast, i.e., the posterior mean of $\tilde{u}$, is a weighted average of the prior mean μ and information $\tilde{I}_a$ and price P tilde. The weights are given by the precision of each source of information[15]. The variance of forecast errors by individual analyst a can be derived as follows:

$$V_{FAF} = E[\tilde{e}_a]^2 = E[\tilde{u}-\tilde{F}_a]^2$$

$$= E\{\tilde{u}-\mu-(g,h)[\tilde{I}_a-E(\tilde{u}),P-E(\tilde{P})]'\}^2$$

$$= \sigma - \frac{\sigma^2[\delta(\sigma+\eta)+s(\pi-\delta)]}{(\sigma+\eta)[s\pi+\delta(\sigma+\eta)]} \tag{7}$$

Since the variance of TS forecasts is by definition σ (i.e., $V_{TS}=\sigma$), the relative accuracy index, RAI, can now be expressed as:

$$RAI = \frac{V_{FAF}}{V_{TS}} = 1 - \frac{\sigma[\delta(\sigma+\eta)+s(\pi-\delta)]}{(\sigma+\eta)[s\pi+\delta(\sigma+\eta)]} \tag{8}$$

3.2 Determinants of Relative Accuracy Index

Expression (8) is the primary result of the model which relates the relative accuracy index between FAF and TS to a set of factors that measures the predictability of future earnings, the precision of analyst private information (i.e., $\sigma+\eta+s$) and precision of public information source [i.e., π and δ]. To obtain an intuitive explanation, substituting equation (4) for π in equation (8) yields:

$$RAI = 1 - \frac{\sigma(\delta+s\beta^2)}{s\delta+(\sigma+\eta)(\delta+s\beta^2)}$$

The second term on the right hand side of above expression is always positive, but less than or equal to 1, i.e.,

$$0 < \frac{\sigma(\delta+s\beta^2)}{s\delta+(\sigma+\eta)(\delta+s\beta^2)} \leq 1$$

Therefore, RAI takes a value from 0 to 1, i.e., RAI$\in$[0,1]. The maximum value of RAI does not exceed 1, indicating that FAF is at least as accurate as random walk forecasts. This is because analysts have direct access to the statistical models and past earnings data themselves. RAI=1 when η and s or η and δ approach infinity. In either case, analysts recognize their private and/or public information contain virtually no information content and will form their expectations based on historical data and mechanical models. On the other extreme, RAI=0 indicates a perfectly accurate FAF. RAI=0 requires that η and s or η and δ approach 0, when σ>0. In either case, analysts have perfect knowledge about future earnings from timely information. RAI will be smaller if the predictability of future earnings decreases (i.e., σ increases) and/or analysts' information sets become more accurate (i.e., η and s or η and δ decrease). RAI smaller than 1 indicates that FAF is superior to the TS model. The basic hypothesis can then be expressed as:

H1: FAF will be relatively more (less) accurate when the predictability of future earnings decreases (increases) and/or the precision of analysts' information increases (decreases).

H1 can be separated into a set of testable hypotheses by examining the relation between RAI and each of the individual factors in expression (8) as discussed in detail below. First, it can be shown that:

$$\frac{\partial RAI}{\partial \sigma} = -\frac{(\delta + s\beta^2)[s\delta + \eta(\delta + s\beta^2)]}{[s\delta + (\sigma + \eta)(\delta + s\beta^2)]^2} < 0$$

This implies that as future earnings become more volatile (i.e., σ increases), future earnings will be less predictable based on historical earnings, and therefore, FAF will be relatively more accurate than the time series model. This result is consistent with Lipe [1990] who suggests that as σ increases, future earnings become harder to predict by a mechanical model based solely on historical earnings data. Timely information before earnings announcements will be more valuable. This suggests the following hypothesis:

H1.1: The relative accuracy of FAF increases (decreases) as earnings predictability decreases (increases);

Second, the partial derivative of RAI with respect to *s*, the variance of idiosyncratic noise term, can be expressed as:

$$\frac{\partial RAI}{\partial s} = \frac{\sigma\delta^2}{[s\delta + (\sigma + \eta)(\delta + s\beta^2)]^2} > 0$$

This implies that FAF accuracy, in relative terms, will decrease (i.e., RAI increases) if the analysts' idiosyncratic error increases (i.e., s increases). This is quite intuitive. When precision of information decreases (i.e., s increases), less is learned about future earnings from the information signal *vis-à-vis* what is known from the past earnings series. As less is learned, the analyst's forecast with the information signal is less likely to be different from the TS forecast that is formed without the information signal. Therefore, relatively larger (smaller) variance in the idiosyncratic error term will lead to a decreased (increased) FAF accuracy. This suggests the following hypothesis:

> *H1.2*: The relative accuracy of FAF decreases (increases) as the variance of analysts' idiosyncratic errors increases (decreases).

Finally, the partial derivatives of RAI with respect to the factors that affect price variance, i.e., η, and δ, can be written as:

$$\frac{\partial RAI}{\partial \eta} = \frac{\sigma^2(\delta + s\beta^2)^2}{[s\delta + (\sigma+\eta)(\delta + s\beta^2)]^2} > 0$$

$$\frac{\partial RAI}{\partial \delta} = \frac{\sigma s^2 \beta^2}{[s\delta + (\sigma+\eta)(\delta + s\beta^2)]^2} > 0$$

and

$$\frac{\partial RAI}{\partial \pi} = \frac{(\sigma+\eta)\sigma\delta s^2}{(\sigma+n)^2[s\delta + (\sigma+\eta)(\delta + s\beta^2)]^2} < 0$$

These three partial derivatives should be examined collectively. First, recall that the variance of stock price in equation (4) consists of two components: $\beta^2(\sigma+\eta)$ and δ. The first component represents the variance of price that is related to earnings information (i.e., $\tilde{u}+\tilde{n}$), and the second measures price variance induced by unidentified non-earnings related noises on the market (i.e., ϵ). The positive partial derivatives of RAI with respect to η and

δ suggest that when η and δ decrease (increase), RAI will decrease (increase) accordingly. This is because when η and δ decrease (increase), stock price is less (more) garbled by noises and will be more (less) informative about future earnings. More (less) informativeness of price will provide analysts with more (less) precise information. As a result, analysts' accuracy increases (decreases). On the other hand, the negative partial derivatives of RAI with respect to π indicate that analysts' superiority increases when π increases, or *vice versa*. This is because when π increases (decreases) while holding the noise term η and δ constant, price variance will be relatively more (less) informative with respect to earnings and less (more) garbled by noises. This will result in an increased (decreased) FAF accuracy.

This result is consistent with the studies by Holthausen and Verrecchia [1990] and Stickel and Verrecchia [1992], who consider how price influences beliefs in noisy rational expectation models of competitive trading. The economic intuition underlying these models is that price aggregates all information about a stock, along with some noise. Consequently, conditioning beliefs over price provides an additional source of information about earnings. On the other hand, Abarbanell [1991], Givoly and Lakonishok [1979] and Brown, Foster, and Noreen [1985] find that the sign and magnitude of analysts' forecast revisions are positively associated with the sign and magnitude of prior security price changes. The following hypothesis is thus formulated:

H1.3: The relative accuracy of FAF will increase (decrease) as the stock price is more (less) informative with respect to future earnings.

3.3 Association between Investors' Accuracy and Precision of Information

The theoretical model reveals that analysts' accuracy is determined by earnings predictability and precision of information sources. Can this conclusion be extended to explain investors' accuracy? Answers to this issue will provide evidence on whether investors are able to utilize the information beyond the time series forecasts. In particular, it will be of interest to know whether investors are able to utilize the information contained in analysts' forecasts. Current literature has not provided an unambiguous answer.

As a forecaster, the individual investor collects private information. He/she also observes financial analysts' forecasts from which he/she learns analysts' private information. The investor observes other public information that is not contained in analysts' forecasts as well. By constructing the relative accuracy index between investors' earnings expectations and TS forecasts similar to equation (8) and using the same theoretical framework as used in the previous section, it can be shown that investors' relative accuracy is inversely related to earnings predictability and positively related to the precision of their information sources. This suggests the following hypothesis:

> *H2*: The relative accuracy of investors' earnings forecasts over TS forecasts increases (decreases) as predictability of earnings decreases (increases), precision of private information increases (decreases), precision of analysts' forecasts increases (decreases), and precision of public information other than analysts' forecasts increases (decreases).

3.4 Investors' Earnings Forecast Error and Abnormal Returns

Since investors' earnings forecast errors are not directly observable, I use the abnormal returns during earnings announcements as a proxy for investors' earnings forecast errors. Theory suggests abnormal returns are product of the earnings response coefficient and earnings forecast errors, and the theoretical expected value of the earnings response coefficient is one (e.g., Beaver, Lambert and Morse [1980], and Collins and Kothari [1985]). In a multiperiod setting, Lipe [1990] shows that unexpected stock returns during period t is[16]:

$$UR_t = \sum_{j=0}^{\infty} \beta^j \frac{E[\tilde{u}_{t+j}|I_t] - E[\tilde{u}_{t+j}|I_{t-1}]}{P_{t-1}} \tag{9}$$

Rearranging this equation, the abnormal stock returns during the earnings announcement period (i.e., from t-τ to t) will be:

$$UR_t = \frac{u - E[\tilde{u}_t|I_{t-\tau}]}{P_{t-\tau}} + \sum_{j=1}^{\infty} \beta^j \frac{E(\tilde{u}_{t+j}|I_t) - E[\tilde{u}_{t+j}|I_{t-\tau}]}{P_{t-\tau}} \tag{10}$$

where: $\tilde{u}_{t+j}$ represents future earnings at jth period from t; E(.) denotes the expectation by investors; I_t and $I_{t-\tau}$ denote the information observed by investors at time t (the earnings announcement date) and t-τ (the latest analyst forecast date before earnings announcement). Notice that $E(\tilde{u}_t|\tilde{I}_t = u) = u$; where u represents earnings realization at t.

Equation (10) shows that the unexpected stock returns are the sum of investors' expectation errors about current period earnings (the first term of the right hand side) and the present value of revisions in expected future earnings based on the current earnings announcement (the second term of the right hand side). Therefore, when using abnormal returns to proxy for earnings forecast errors of the current period, one will benefit by controlling the present value of revisions in expectations of all future periods (the second term). However, OLS coefficients and related statistics will remain unbiased even if the second term is not controlled since the abnormal returns in this study will be used as dependent variable only.

Testing the relationship between stock returns and unexpected earnings during the earnings announcement period while controlling for the effect of revisions in expectations about future period earnings (the second term) has been the focus of much research (e.g., Beaver et al. [1980], Kormendi and Lipe [1987], Easton and Zmijewski [1987], and Cornell and Landsman [1989]). Cornell and Landsman's [1989] approach is straightforward. They regress the abnormal returns during the earnings announcement period on current earnings forecast errors, one quarter ahead and one year ahead forecast revisions. However, they find analysts' revisions for future periods are most significantly related to abnormal stock returns only in quarters other than the fourth quarter. They explain that in quarters other than the 4th quarter, investors' attention is on the prediction of earnings in future periods rather than on the interim earnings announcements that are not audited. In the 4th quarter, the announced audited earnings report is uniquely informative. Therefore, forecast errors revealed through the audited earnings report has the most significant impact on the revision of investors' earnings expectations. Despite the result, I will include one quarter and one year ahead forecast revisions by analysts in the sensitivity test.

Chapter 4

Empirical Design

This chapter discusses the variable measurement, empirical models and data base that will be used to empirically test the hypotheses.

4.1 Measurement of Variables

Hypothesis *H1* suggests that three FDFA will affect financial analysts' forecast accuracy: predictability of earnings, informativeness of stock price with respect to earnings, and precision of analysts' private information. *H2* suggests four factors similar to the three FDFA referenced above which will affect investors' forecast accuracy: predictability of earnings, precision of investors' private information, precision of analysts' information, and precision of public information other than analysts' forecasts. This subsection discusses the empirical measurement of these variables.

4.1.1 Informativeness of Stock Price with Respect to Earnings

To measure the informativeness of stock price with respect to earnings, this study proposes two alternative approaches. One approach is found in Kim and Verrecchia [1991a,b] who show that volume reaction to an information release is proportional both to absolute price change and to a measure of average deviation of traders' private information precision. Stickel and Verrecchia [1992] empirically test this prediction and propose that the "standardized volume", defined as the ratio of trading volume to absolute price change (i.e., the raw returns), is positively associated with the amount of earnings information impounded into price. They test two hypotheses. One predicts that price changes accompanied by high abnormal trading volumes contain more information content with respect to future earnings and that price changes not accompanied by high abnormal trading volume are mainly induced by noise and will "bounce back" to its original level. The second hypothesis predicts that the bid-ask spread declines more for the stocks where standardized volume is abnormally low compared to where standardized volume is abnormally high. Their empirical results based on both NASDAQ and NYSE/ASE samples support the two hypotheses. This suggests the following measure for estimating the informativeness of stock price changes (i.e., precision of public information):

$$PP_{it} = PSV_{it} = \frac{STDVOL_{it}}{\frac{1}{K}\sum_{i=1}^{K} STDVOL_{it}} \tag{11}$$

where: $STDVOL_{it}$ is the standardized trading volume for firm i in year t; K is total number of sample firms in year t. PSV_{it} measures the deviation of firm i's standardized volume in year t from the sample mean. Large PSV_{it} represents abnormally high standardized volume that in turn implies stock prices contain more information about earnings; or *vice versa*. Consistent with Stickel and Verrecchia [1992], the standardized volume during the forecast period is computed as:

$$STDVOL_{it} = \frac{\ln[100 \cdot \sum_{d=1}^{T} \frac{v_{itd}}{V_{itd}} + c]}{|\prod_{d=1}^{T}(1+R_{itd}) - 1|}$$

where: v_{itd} is the trading volume of firm i in year t on day d; V_{itd} is the number of shares outstanding on day d; and c is a small constant equal to 0.005 added to preclude computing the natural logarithm of zero. To compute standardized trading volume, both shares outstanding and daily trading volume are adjusted for stock splits and stock dividends that are announced during day d and the latest forecast date t-τ.

An alternative approach to measure the informativeness of stock price with respect to earnings is to estimate the ability of stock price to forecast future earnings. This approach has been used by previous studies, such as Beaver, Lambert, and Morse [1980], Collins, Kothari, and Rayburn [1987] and Elgers and Murray [1992], and etc., to demonstrate that stock price contains information about earnings and leads earnings. The logic is that if stock prices are informative about future earnings, one should be able to forecast future earnings by exploring the information contained in past price movements. Therefore, more (less) accurate forecasts from the price-based model will indicate price is more (less) informative. The following model will be estimated for each firm:

$$\%u_{it-1} = \gamma_{0i} + \gamma_1 PE_{i,t-2} + \gamma_2 (PE_{i,t-1-\tau} - PE_{it-2}) + \gamma_3 CAR_{i,t-1-\tau} + err_{it}$$

where: $\%u_{it-1}$ is the change in firm i's EPS in year t-1; $PE_{i,t-2}$ is the ratio of stock price at the beginning of year t-1 to year t-2 EPS; $PE_{i,t-1-\tau}$ is the ratio of stock price at the latest analyst's forecast date t-1-τ to the previous year's EPS; PE_{i0} is the ratio of price to earnings at the at the previous earnings announcement dates; $CAR_{i,t-1-\tau}$ is the cumulative abnormal returns during the previous forecast period (the date of previous year earnings announcement to latest earnings forecast day t-1-τ in year t-1), and is computed as follows:

$$CAR_{i,t-1-\tau} = \prod_{d=1}^{t-1-\tau} (1 + R_{id} - \hat{\alpha}_i - \hat{\beta}_i R_{md}) - 1$$

where: R_{id} and R_{md} is the daily return of security i and the market return on day d

respectively; and α_i and β_i are the parameters from the CAPM. Both of the price-based measures, $PE_{i,t-1}$ and $CAR_{i,t-1}$, included in the model are relevant to earnings expectation. Abnormal stock returns have been shown by Beaver et al. [1980], Collins et al. [1987] and Elgers et al. [1992] to be associated with the subsequent earnings changes. With respect to the PE ratio, a number of studies (e.g., Beaver et al. [1980]) have demonstrated that price-earnings ratios are highly associated with next-period earnings growth.

The forecasted percentage change from the price-based forecast model, $PBF\%_{i,t}$, is:

$$PBF\%_{i,t} = \varphi_{0i} + \varphi_{1i} PE_{i,t-1} + \varphi_{2i}(PE_{i,t-1} - PE_{i,t-1}) + \varphi_{3i} CAR_{i,t-1}$$

and forecast error in dollar term is:

$$PBFE_{it} = (\%u_{it} - PBF\%_{it}) \cdot EPS_{i,t-1} = [\%u_{it} - \varphi_{0i} - \varphi_{1i} PE_{i,t-1} - \varphi_{2i}(PE_{i,t-1} - PE_{i,t-1}) - \varphi_{3i} CAR_{i,t-1}] \cdot EPS_{i,t-1}$$

$$PBFE_{it} = (\%u_{it} - PBF\%_{it}) \cdot EPS_{i,t-1} = [\%u_{it} - \varphi_{0i} - \varphi_{1i} PE_{i,t-1} - \varphi_{2i}(PE_{i,t-1} - PE_{i,t-1}) - \varphi_{3i} CAR_{i,t-1}] \cdot EPS_{i,t-1} \tag{12}$$

The surrogate for precision of public information used in regression is computed as the squared forecast error divided by the absolute value of last year EPS as:

$$PP^{-1}_{it} = PPBFE_{it} = \frac{(PBFE_{it})^2}{|EPS_{it-1}|} \tag{13}$$

4.1.2 Predictability of Future Earnings

The empirical proxy for predictability of future earnings is measured by the inverse of the coefficient of variation of the earnings time series and is defined as follows:

$$Pred_i^{-1} = \sigma_i = SIGM_i = \frac{Var(EPS_{it})}{|\bar{EPS}_i|} = \frac{\sum_{t=1}^{T}[EPS_{it} - EPS_{i,t-1}]^2}{(T-1) \cdot |\bar{EPS}_i|} \tag{14}$$

The coefficient of variation is thus the variance of earnings TS divided by the absolute value of mean EPS.

4.1.3 Precision of Analysts' Private Information

While the precision of analysts' private information is unobservable, recent studies have used the dispersion (i.e., the cross-sectional variance) of analysts' forecasts as a surrogate for the variance in analysts' private information. For example, Cukierman and Givoly [1982], Cukierman and Wachtel [1979], Holthausen and Verrecchia [1990][17], Brown et al. [1987c,1992], Morse et al. [1991], and Swaminathan [1991], among others, have used the dispersion of analysts' forecasts as a proxy for analysts' private information precision.

The dispersion of analysts' forecasts is measured by the coefficient of variation of the forecasts for particular firm-year (the inverse of private information precision PA_{it}). It can be expressed as follows:

$$PA^{-1}_{it} = DISP_{it} = \frac{Var(\tilde{F}_{ait})}{|\bar{F}_{it}|} = \frac{\sum_{a=1}^{N_{it}} [\tilde{F}_{ait} - \bar{F}_{it}]^2}{(N_{it}-1) \cdot |\bar{F}_{it}|} \tag{15}$$

where: N_{it} is the number of forecasts for firm *i* in year *t*, and *a* indexes individual analysts. Larger (smaller) $DISP_{it}$ would indicate less (more) precise private information.

To investors, precision of analysts' private information is better measured by the variance of forecast errors, rather than dispersion of forecasts. Dispersion of forecasts can be viewed as an estimate for forecast accuracy and therefore is an *ex anti* measure. When actual earnings are announced, an *ex post* measure, i.e., the forecast errors, has been available to investors. The adjustment of Investors' beliefs will be primarily based on the posterior measure of precision, rather than any estimate of it.

Care must be exercised when using the accuracy of analysts' forecasts to proxy for the precision of analysts' private information. I use the incremental accuracy of analysts' forecasts over price-based forecasts to proxy for the precision of analysts' private information. This is because the accuracy of analysts' forecasts is affected by two sources of information, public information and private information. Using incremental accuracy controls the confounding effect of public information precision. Analysts' incremental accuracy is defined as follows:

$$PFAFE_{it} = \frac{(FAFE_{it})^2}{(PBFE_{it})^2} \tag{16}$$

where: $PFAFE_{it}$ denotes precision of analysts' private information for testing investors' accuracy. $FAFE_{it}$ denotes analysts' forecast error and $PBFE_{it}$ denotes the forecast error from the price-based forecast model.

4.2 Empirical Models

The first hypothesis *H1* predicts that analysts' accuracy is determined by (1) the predictability of future earnings; (2) informativeness of stock price with respect to earnings; and (3) precision of analysts' private information. The basic empirical model for testing hypothesis *H1* has the form:

$$RAI_{it} = \theta_{0t} + \theta_{1t} SIGM_i + \theta_{2t} PP_{i,t-1} + \theta_{3t} DISP_{i,t-1} + \xi_{it} \tag{17}$$

Where:

i and *t* index for firm and fiscal year respectively;

RAI is the relative accuracy index of FAF over TS forecasts. Consistent with Brown et al. [1987c], V_{FAF} and V_{TS} are measured by *(FAF error)*^{2} and *(RW error)*^{2} respectively, where *FAF error* is the difference between the analyst's forecast and actual value of earnings for firm *i* and year *t*, and *RW error* is the difference between earnings of year *t* and year *t-1* for firm *i*. Therefore, the empirical surrogate of RAI is defined as the ratio of squared errors:

$$\hat{RAI}_{it} = \frac{e^2_{FAF,it}}{e^2_{RW,it}}$$

$SIGM_i$ is the variance of the earnings distribution for firm *i* at year *t*, and represents the predictability of the earnings as defined in equation (14);

$PP_{i,t-\tau}$ is the informativeness of stock price with respect to future earnings for firm *i* at time $t-\tau$. Two alternative empirical measures are defined in equations (11) and (13);

$DISP_{i,t-\tau}$ is the precision of analysts' private information. The empirical surrogates are defined in equation (15);

ξ_{it} is the unexplained normally distributed residual error.

The second hypothesis *H2* predicts that investors' accuracy should exhibit an association with the precision of investors' information and earnings predictability. The precision of investors' public information is measured by price-based forecast errors and the *incremental precision of financial analysts' forecasts*. The precision of investors' private information is measured by standardized trading volumes as defined before. The basic empirical model for testing hypothesis *H2* takes the following form:

$$RAII_{it} = \Phi_{0t} + \Phi_{1t} SIGM_i + \Phi_{2t} PPBFE_{i,t-\tau} + \Phi_{3t} PFAFE_{it} + \Phi_{4t} PSV_{i,t-\tau} + \varpi_{it} \qquad (18)$$

where:

RAII is the relative accuracy index of investors' (or the market's) earnings forecast accuracy over the accuracy of TS forecasts. Investors' earnings expectations error is defined as the unexpected returns, *CAR*, during the earnings announcement period (i.e., from t-τ to t) multiplied by the stock price at day t-τ. The following empirical surrogate is established for RAII:

$$\hat{RAII}_{it} = \frac{e^2_{mkt,it}}{e^2_{RW,it}} = \frac{[(CAR_{i,t-\tau,t}-1)\cdot P_{it-\tau}]^2}{e^2_{RW,it}} \tag{19}$$

Notice that the numerator is the dollar value of cumulative abnormal returns during the earnings announcement period;

$PPBFE_{it}$ and PSV_{it} are defined in equations (11) and (13);

$PFAFE_{it}$ measures the precision of analysts' private information contained in analysts' forecasts as defined in equation (16);

ω_{it} is the error term; and the other variables are the same as defined previously.

4.3 Databases and Sample Selection

This section discusses the database, sample selection procedure and the effects of sample selection criteria on sample size.

Sample selection criteria and their effects on sample size are summarized in table 1. I start selecting the sample from COMPUSTAT files. I obtain all firms on COMPUSTAT that have a December year end. There is a total of 1,874 firms having a December fiscal year end or 34,846 firm-years. Since the estimation of the time-series model requires at least 20 years of continuous EPS, I exclude the firms that have an earnings history shorter than 20 years. This criterion imposes the most drastic reduction in the sample; 960 firms or 26,384 firm-years remain after applying this criterion. For the 960 firms, I collected additional EPS data from the Moody's Manual. The sample firms have, on average, 27 years of continuous EPS data with a maximum of 32 and minimum of 20 years.

The financial analysts' earnings forecasts are obtained from the Institutional Brokers Estimate System, or IBES, developed by the Lynch, Jones & Ryan brokerage house. 924 firms of sample are found in IBES detailed database. The detailed database consists of individual analysts' forecasts of earnings per share (EPS) made between 1983-1993 by analysts at between 1-134 brokerage houses. Analysts and brokerage houses in the database are identified in the database by code number. The IBES data are updated once per month with new forecasts. Many of the brokerage houses issue forecasts before the start of the year, and update them periodically during the year. Many others issue forecasts for the first time as the EPS announcement approaches. For every firm-year, I select the most recent forecast from each brokerage house that follows the firm. Older forecasts from the same broker are excluded. Two additional restrictions are applied to include a forecast in the sample: (1) a forecast must be made within 365 days before current year earnings announcements; and (2) at least three forecasts must be available for any firm-year in order to compute a meaningful dispersion of the forecasts. As the result, a total of 155,954 current year forecasts (item FY1) for 7,657 firm-years are obtained from IBES detailed files.

The IBES detailed file mainly carries the forecasts for primary EPS. If particular firm is carried in the database as fully-diluted, an indicator and an adjustment factor are provided. I convert the fully-diluted into primary according to the indicator and adjustment factor. If the adjusting factor is missing, I compute the adjusting factor using fully-diluted and primary EPS data from COMPUSTAT.

All the forecasts are adjusted for stock splits and stock dividends announced in the period between the forecast date and the corresponding fiscal period end. The stock split, stock dividend and associated announcement dates are obtained from CRSP daily return and combined file. Data availability on CRSP further reduces the sample size. 117 firms' stocks are not found on CRSP. For the remaining firms, data for a particular year might be unavailable. This reduces the final sample to 5,560 firm-years and a total of 133,599 current year forecasts.

The one-year ahead forecasts (FY2) and one-quarter ahead forecasts (FQ1) for the firm-years in final sample are obtained from IBES. Ideally, these forecasts should be made during the period between the latest current year forecast and the earnings announcement. But too few forecasts would be available if this restriction were applied since fewer analysts provide one-year and one-quarter ahead forecasts and the forecasts are updated less frequently. I therefore selected the most recent forecast from each brokerage house that is made or updated after the third quarter earnings announcement but before the annual earnings announcement. The approximate length of the period is about 90 days. As a result, 80,033 one-year ahead forecasts and 7,610 one quarter ahead forecasts are obtained for the sample firm-years. For any firm-year that has no one-year and/or one-quarter ahead forecasts available, missing values are assigned.

Panel B of table 1 contains three descriptive statistics of the sample: age of forecasts, number of forecasts per firm-year, and firm size. The age of forecast is defined as the difference, in calendar days, between the forecast date and the earnings announcement date. The sample forecasts have a average age of 124 days with a standard deviation of 92 days. The median age is 91 days. The median age indicates that nearly half of the sample forecasts are made after third quarter earnings announcements. The older forecasts made before 90 days may indicate analysts' failure to incorporate new information such as third quarter earnings announcements, but need not. For example, announced third quarter EPS may be indistinguishable from the analyst's expectation. In this case, no new information is conveyed to the analysts and a revision of the annual EPS forecast is unnecessary. For this reason, older forecasts also included in the sample.

The sample has on average 22 forecasts per firm-year. This average is considerably larger than the IBES database overall average of 13 analysts' following a firm. This is because the sample firms are relatively large in size and the number of analysts' followings is positively correlated with firm size. Firm size is defined as the market value of a firm at end of the fiscal year. The average size of the sample firm-year is 3,339 million dollars, but more than half of the sample firms have a size below 1 billion.

4.4 Descriptive Statistics of Key Variables

This section discusses descriptive statistics of the variables that will be used to test hypotheses.

4.4.1 Stock Returns and Standardized Trading Volume

Table 2 contains descriptive statistics of the main variables. Panel A of table 2 presents descriptive statistics of abnormal stock returns and parameters of CAPM. I measure the abnormal stock returns using the market adjusted stock returns by estimating following CAPM equation:

$$R_{itd} = \alpha_{it} + \beta_{it} \cdot Rm_{itd} + \epsilon_{itd}$$

where *it* indexes for firm *i* and year *t*; *d* indexes trading date. The parameters are estimated for each firm using 240 trading days before the previous earnings announcement date. The estimated intercept and slope coefficient are then used to estimate the abnormal return of each trading day during the current year. The distribution of estimated parameters including intercept, slope, R^2, and abnormal returns are presented.

Abnormal returns are cumulated for two different periods in the current year: the *forecast period* and the *earnings announcement period*. The forecast period is defined as the interval from the previous year's earnings announcement date (day *0*) to the latest forecast date (day *t-τ*). The earnings announcement period is from the latest forecast date (day *t-τ*) to 3 days after the current year's earnings announcement date (day *t*). $CAR_{0,t-\tau}$ denotes the cumulative abnormal returns for the forecast period and $CAR_{t-\tau,t}$ is the cumulative abnormal returns for the earnings announcement period. If the latest forecast date is the same date as the current year earnings announcement date, *t-τ* is assigned a date that is one day before the earnings announcement date.

The mean intercept is not significantly different from zero. The mean slope coefficient, so called "beta", is not significantly different from unity. The mean R-squared is 13.6%. The mean of cumulative abnormal returns during the forecast period is above 1 while the mean of cumulative abnormal returns for the earnings announcement period is less than one. This indicates that $CAR_{0,t-\tau}$ is positively skewed and $CAR_{t-\tau,t}$ is negatively skewed. This result is consistent with previous studies that show cumulative abnormal returns during earnings announcements are negatively skewed (i.e., McNichols [1988]).

$PSV_{0,t-\tau}$ in panel A of table 2 is the standardized trading volume in forecast period. Standardized trading volume is estimated using equation [11]. Daily trading volume and shares outstanding during the forecast period is adjusted for stock splits and stock dividends that are announced between each trading day and the fiscal year end.

4.4.2 Earnings Forecast Errors

Panel B of table 2 lists the distribution of earnings forecast errors from three different earnings forecast models: time series forecast error (TSFE), price-based forecast error (PBFE), and financial analysts' forecast error (FAFE). The forecast error (FE) in general is computed as:

$$FE_{it} = EPS_{it} - E(EPS_{it}|I_{it})$$

where EPS_{it} denotes the actual EPS and $E(.)$ denotes conditional expectation.

For financial analysts' forecasts, I used actual EPS contained in the IBES database rather than the EPS from COMPUSTAT. Using actual EPS from the IBES provides an easier match with the forecasts. This is particularly true when it is not known with certainty whether analysts forecasts EPS before or after extraordinary items. IBES provides no specific instructions to individual analysts about the treatment of "extraordinary" items, and no indication is given in the database. However, IBES does provide the latest available actual EPS and associated fiscal year as of the forecasting date. Presumably, this actual EPS matches the scope of forecasts for particular firm-year better than the actual EPS from COMPUSTAT.

The price-based forecast model in equation (12) is estimated for each firm. To forecast year *t*'s earnings change, I first estimate the regression coefficients using data excluding year *t*. Then the estimated parameters are used to predict year *t*'s forecasted earnings. The forecast error is then calculated based on that forecast. This procedure is repeated for each year for every firm in the sample.

The distributions of the forecast errors confirm many previous studies (e.g., O'Brien [1988], and Brown et. al. [1985]). The mean and median of TSFE and PBFE are approximately zero, while the mean and median of FAFE are -.2377 and -0.035. The negative mean and median indicates that most of the analysts provide a forecast greater than the actual. This confirms the well known negative skewness of FAFE and the optimistic bias by financial analysts. However, despite the bias, financial analysts forecasts are the most accurate forecasts compared to both TS forecasts and price-base forecasts. The mean of absolute and squared FAFE (0.5167 and 1.3838) is less than half of the magnitude of absolute and squared TSFE (1.0648 and 3.8719) as well as absolute and squared PBFE (0.9498 and 3.4664). Also, the absolute and squared FAFE is smaller than that of TSFE and PBFE on every fractile.

On the other hand, the absolute and squared forecast errors from the price-based forecast model are smaller than these of TSFE. This is judged not only on the mean, but on the magnitude of forecast errors on every fractile. Price-based forecasts are in general more accurate than TS model, but less accurate than analysts' forecasts. This is what should be expected because the price-based forecast utilizes an information set that is smaller than analysts' information, but broader than the information a TS model can incorporate.

4.4.3 Precision of Analysts' Private Information

Panel C of table 2 presents the descriptive statistics for the variance of financial analysts' forecasts and their incremental accuracy over price based forecast.

STDFY1 denotes the variance of analysts' forecasts, and STDFDATE denotes the standard deviation of forecast date for each firm year. Ideally, the variance of analysts' forecasts should be measured over the forecasts that are issued on the same date. However this is not practical. The forecasts for any particular firm-year spread over 365 days a year. The mean deviation of forecast date per firm-year in my sample is about 119 days. Different information may be impounded into the forecasts when the forecast date differs. Computing the variance of forecasts over the forecasts that are made at different dates might bias the variance upwards, and the problem might be more pronounced when the deviation of forecast date increases. To prevent the bias, I divided the variance of forecasts by the standard deviation of forecast date for each firm-year. The distribution of resulting dividends are reported in the third column of panel C of table 2. This deflated standard deviation of forecasts is used to compute DISP as specified in equation [15][18].

PFAFE denotes the incremental accuracy of financial analysts' forecasts over price-based forecasts, as defined in equation (16). The mean and median of this variable shows its value is generally less than 1, indicating analysts' forecasts are more accurate than price-based forecasts. The smaller value indicates that analysts' private information is more precise, or *vice versa*.

4.4.4 Forecast Revisions for One-year & One-quarter Ahead EPS

Panel D of table 2 presents the descriptive statistics of the one-year and one-quarter ahead forecast revisions from the IBES database. The forecast revisions for both the quarterly and annual forecasts demonstrate substantial negative skewness. On average, a forecast is revised downwards by 10 cents for the one-year ahead forecast and about 5 cents for the one-quarter ahead forecasts. This is consistent with the result of previous studies which show that analysts start with optimistic forecasts and revise them down as earnings announcement approaches (e.g., DeBondt and Thaler [1990]). I also present the ratio of forecast revisions, which is defined by dividing the absolute value of the revision by the absolute value of the old forecast. The percentage revision is substantial. On average, analysts revised their one-year and one-quarter ahead forecasts by 24.61% and 35.31% respectively.

Chapter 5

Empirical Results

This chapter discusses the test results.

5.1 Correlations

Table 3 presents the one-way correlations among the variables that will be used in regression analysis. These variables are the relative accuracy indices of investors and analysts (RAI_{it} and $RAII_{it}$), predictability of earnings ($SIGM_i$), two measures of precision of public information ($PPBFE_{it}$ and PSV_{it}), precision of analysts' private information (PSV_{it}), analysts' one-year and one-quarter forecast revisions ($REV_{i,t+y1}$ and $REV_{1,t+q1}$), number of analysts' following ($NFAF_{it}$), firm size ($SIZE_{it}$), and mean number of days between forecasts and earnings announcement dates (TAU_{it}).

Consistent with hypotheses *H1* and *H2*, both RAI and RAII have significantly negative correlations with SIGM. This indicates that as earnings become less predictable (i.e., variance of earnings time-series increases), relative accuracy indices of analysts and investors fall (i.e., analysts and investors are relatively more accurate than TS forecasts), or *vice versa*.

Standardized trading volumes (PSV) and price-based forecast errors (PPBFE) are proxies for precision of information impounded in stock price. PSV is a direct measure for precision of information, while PPBFE is an inverse measure. The correlation between the two is, as expected, significantly negative. However, this correlation is far from -1. This indicates that PSV and/or PPBFE measure the precision of information with error. PSV has negative correlations with RAI and RAII. PPBFE has positive correlations with RAI and RAII. All the correlations are significant in the predicted direction. The association of RAI and RAII with PPBFE is much stronger than with PSV, suggesting that PSV is a noisier measure than PPBFE.

The correlation between RAII and PFAFE is positive but insignificant. However, the slope of PFAFE turns out positively significant in the multiple regression test discussed later. This indicates that analysts' private information is only one of the many sources of information investors use. Investors' accuracy will be significantly correlated with the precision of this particular source of information only when the precision of other information sources is also present in the model. The correlation between DISP and RAII is positive but not significant. The slope of DISP in the multiple regression test remains insignificant. This indicates that the *ex anti* measure of precision of analysts' information is a poor proxy to explain abnormal returns. However, both DISP and PFAFE are positively correlated with RAI with high significance.

It is also interesting to note that PSV, PPBFE, PFAFE and DISP exhibit negative correlations with both SIZE and NFAF, except for correlations between DISP and SIZE and between PSV and NFAF. But most of the coefficients are insignificant. The significance level of correlation between these variables and NFAF is higher than with SIZE. This indicates that firm size is an even poorer proxy for precision of information than the number of analysts' followings.

5.2 Regression Analysis

To test hypotheses *H1* and *H2*, I estimate the regressions as presented in equations (17) and (18). Regressions are run for each year cross-sectionally. The means of the estimated OLS coefficients are calculated and reported in table 4-9. The significant test for each slope coefficient is based the t-test under the null hypothesis of mean equal to zero. Running the regression by year cross-sectionally instead of on pooled data avoids the well-known cross dependence problem which might bias the test towards significance. For both analysts' and investors' forecasts, I first start with the basic model. Several variations of the basic model are also tested by adding the other relevant variables, such as SIZE, NFAF, and TAU, as a sensitivity check.

5.2.1 Regression Analysis of Analysts' Forecast Accuracy

This section discusses the result of regression tests in which the relative accuracy index of financial analysts (RAI) is regressed on the earnings predictability (SIGM) and precision of public and private information (PPBFE, PSV and DISP). Table 4 presents the results of the regressions in which precision of public information is represented by the price-based earnings forecast errors (PPBFE). Table 5 contains the results of regressions in which the precision of public information is represented by the standardized trading volumes (PSV). The tests start with the basic models, marked as "Model 1" in both tables, and then SIZE, NFAF, and TAU are added to the model to test the sensitivity of the basic model. Adding these variables can reveal whether these variables alter the results of the basic model and whether these variables add any additional explanatory power.

Hypothesis *H1* (i.e., *H1.1-H1.3*) is strongly supported by the result of the basic model. In the basic model (i.e., Model 1 in table 4 and 5), the slope coefficients of all the three fundamental determinants have the predicted sign and are highly significant. In table 4, PPBFE is used as the proxy for precision of public information. Its slope is significantly positive (0.0654). In table 5, PSV is used as the proxy for precision of public information. It has a negative slope coefficient (-0.7787). This is exactly what should be expected since

PPBFE is an inverse measure of precision of public information while the PSV is a direct measure. The slope coefficient of SIGM is negative in both table 4 and table 5 (-0.1667 and -0.0986 respectively). Its sign and significance level do not depend on which proxy is used for precision of public information, PPBFE or PSV. The slopes for DISP are positive (0.1619 in table 4 and 0.3382 in table 5) and are highly significant.

It is interesting to note that slope coefficient of PSV is less significant than that of PPBFE (4.07 vs. 8.46), although both of them are highly significant. The mean adjusted R-squared is more than 12% when PPBFE is used. It reduces to about 5% when PSV is used. This confirms the discussion in the previous subsection that PSV is a much noisier measure for precision of public information than PPBFE.

It is worth noting that the magnitudes and significance levels of slopes for the variables SIGM, PPBFE, PSV and DISP hardly change when other variables such NFAF, SIZE and TAU are added to the regression. They remain almost unaltered. This indicates that the test results regarding the basic model are not sensitive to other variables.

Model 2 in tables 4 and 5 adds variable TAU into the regression. The slope of TAU is positive (0.0037 and 0.0045) but not significant (t-value is 0.97 and 1.23 respectively). TAU adds little incremental explanatory power to the model. In particular, when PPBFE is used, adding TAU does not increase but reduces the overall model significance (adjusted R-squared reduces from 0.1226 to 0.1225). The insignificance of TAU remains unaltered when SIZE and NFAF are further added as reported in Models 5 and 6. This result suggests that the timing advantage of analysts, as suggested by the previous literature (i.e., Fried and Givoly [1982], Brown et al. [1987], and Kross et al. [1990]), is not supported. It is interesting to note that TAU is significantly correlated with both RAI and RAII as shown by the Pearson correlations in table 3. It is no longer significant in the multiple regression. This suggests that when information effects are well captured and controlled for, the timing effect no longer exists. Intuitively, it is easy to understand that two equally experienced analysts will provide equally accurate forecasts if they are equally informed, even if they are informed at different points of time during the year.

Model 3 and Model 4 add NFAF or SIZE to the basic model, and Model 5 and 6 add the two variables while TAU is also in the model. The coefficient of NFAF and SIZE have the expected sign in all the models where they are present. This is true regardless of which proxy (PPBFE or PSV) is used in the basic model. However only NFAF is significant. SIZE is never significant in either Models 4 or 6 of tables 5 and 6, despite the fact that RAI and SIZE exhibit marginally significant Pearson correlation. NFAF remains significantly negative in every model where it is added. This suggests that forecasts are more accurate when there is a large number of analysts following the same firm. This is true even when effect of precision of information is controlled. Possible explanations are: (1) the empirical proxies used in the basic model do not capture the entire effect of precision of information, and some of the left-over effects are recaptured by the NFAF; and/or (2) NFAF might captures the effect that are not related to information. For example, more experienced analysts might follow large firms because it is more profitable to follow a large firm than a small one. These analysts might produce more accurate forecasts even if they are given the same amount of information as the less experienced analysts. Whatever the reason, NFAF provides only limited incremental explanatory power to the basic model. The adjusted R-squared improves by merely 0.4% on basis of model 1.

5.2.2 Regression Analysis of Investors' Forecast Accuracy

5.2.2.1 The Basic Model

This section discusses the test results for the second hypothesis *H2*. Table 6 presents the main test results. The results strongly support hypothesis *H2*. The basic model

(model 5 in table 6) regresses the accuracy of investors' forecasts on predictability of earnings (SIGM), precision of public information other than analysts' forecasts (PPBFE), precision of analysts' information (PFAFE), and precision of investors' private information (PSV). SIGM has significantly negative slope which suggests investors are relatively more accurate than time series model when future earrings are less predictable (i.e., future earnings are more volatile). Slopes of both PPBFE and PFAFE are significantly positive. This suggests (1) financial analysts' forecasts provide additional information that is not captured in price-based forecasts; and (2) investors are able to incorporate public information and analysts' private information into their own earnings expectation. The significant negative slope coefficient of PSV indicates that errors in investors earnings expectations falls (rises) as the precision of investors' private information increases (decreases).

I also present some variations of the basic model, model 1-4 and 6-7, in table 6. Model 1-4 examine whether individual variables PPBFE, PFAFE or PSV alone can explain the accuracy of investors expectation with the expected direction and significance. I find the answers are positive. Each individual variables show significant explanatory power with the predicted direction. It is interesting to note that PFAFE (In model 2, PFAFE is defined as squared analysts' forecast error divided by absolute mean of actual EPS) has slightly stronger association with RAII than PPBFE. Model 6 and 7 add analysts' one-year and one quarter ahead revision to the basic model. I find the slope of RVFY2, one-year ahead forecast revision, is only significant in model 6. When RVFQ1, one-quarter ahead revisions, is further introduced in model 7, both of the revision variables become insignificant (due to high correlation between the two). Although it is theoretically sound to include revisions of future earnings expectations in the model, my test fails to provide a significant result. This is consistent with Cornell and Landsman [1989] who suggest the audited annual earnings reports are uniquely informative and investors adjust their expectation primary based on forecast errors revealed through audited earnings report in the 4th quarter. Changes in earnings expectations for future period has relatively weaker effects.

5.2.2.2 Size Effect and Timing Effect

Table 7 presents tests for the effect of firm size (model 1-4) and number of analysts' followings (model 5-8). Although the slopes of SIZE and NFAF shows expected negative sign in almost every model, none of them are significant. SIZE is only marginally significant when PPBFE and PFAFE are absent from the regression (model 3). Their negative signs are consistent with previous studies that use SIZE and NFAF as proxies for precision of information.

In all models presented in table 6 and 7, I include the mean age of analysts' forecasts (TAU) as a control variable. The slopes of TAU remains consistently significant for every model I tested. However, this does not suggest timing effect as discussed earlier. The positive and significant slope coefficient of TAU only suggests that the magnitude of the abnormal return is correlated with the length of the period over which the abnormal return is cumulated. The abnormal return accumulation period for the test is the latest analysts' forecast date to earnings announcement date. TAU is positively correlated with the length of accumulation period. To verify this conjecture, I deflate the abnormal return by the length of accumulation period and re-estimate the regression models. The results are presented in table 8. Model 1, 3, and 5 shows the slope of TAU is no longer significant. Models 2, 4, and 6 drop variable TAU from models 1, 3, and 5 respectively. Dropping TAU does not alter the sign, magnitude and significance level of the remaining variable.

5.2.2.3 Dispersion of Analysts' Forecasts

Table 9 presents the regression results where the dispersion of financial analysts' forecasts (DISP) is added on the basis of the models included in table 6. The tests fail to find any significant relationship between RAll and DISP. The slope of DISP is, at best, only marginally significant as in models 1 and 3. In all other models the slope of DISP is insignificant. While this seems to suggest investors are not concerned with precision of analysts' private information, this may not necessarily true. Dispersion of analysts' forecasts is only an *ex anti* measure of forecast accuracy (i.e., dispersion can be viewed as an estimate for forecast errors). When actual earnings are announced, the *ex post* measure of forecast accuracy, i.e., analysts' forecast errors, has become available. Therefore, it is reasonable to expect investors to revise their beliefs primarily based on the forecast errors, rather than any estimate of forecast errors. This may explain why analysts' forecast errors (PFAFE) has significant slope while DISP does not.

Chapter 6

Summary and Conclusion

This study develops a simple model to explain the relationships among predictability of earnings, precision of information and accuracy of earnings expectations. It also empirically tests the relationships predicted by the model using earnings expectations of two groups of market participants: *financial analysts and investors*.

For analysts, this study uses a sample of 133,599 analysts' forecasts for 807 firms obtained from the IBES database. The accuracy of investors' earnings expectations is proxied by the variance in price changes during earnings announcements. The test results indicate that analysts'/investors' earnings expectations are relatively more (less) accurate (compared to mechanic time series forecasts) when they possess more (less) precise public and/or private information and when future earnings are less (more) predictable. Thus, the study provides theoretical and empirical evidence suggesting that earnings predictability and the precision of information are fundamental determinants of the accuracy of earnings expectations.

The evidence also indicates that analysts and investors are able to learn each others' private information by observing public information signals. Analysts can incorporate information contained in price and trading volume movements. Investors, on the other hand, are able to utilize analysts' information through the observation of analysts' forecasts.

The study uses several proxies for precision of information: price-based earnings forecast errors, standardized trading volumes, dispersion of analysts' forecasts, and incremental accuracy of analysts' forecasts over price-based forecasts. These proxies are developed on the basis of theoretical work, and provide more powerful explanatory power in empirical tests than firm size and its related variables which are used in prior studies. This study finds that size is only weakly associated with information precision and provide little incremental explanatory power to forecast accuracy after the information effect has been captured in the model.

To explain analysts' accuracy, previous studies suggest that analysts possess a timing advantage in addition to information advantage (e.g., Brown et al. [1977]). The results of this study suggest that the timing of forecasts has no effect on the accuracy of forecasts after the information effect is controlled. This means that if the forecasters possess equally precise information about a firm, their forecasts will be equally accurate, regardless of when the forecasts are made.

Future extensions of research on the subject could, first, attempt to incorporate a cost-benefit constraints in modelling analysts' and investors' forecasting process. There are costs in collecting and processing information, and forecasters will decide when to stop searching additional information according to cost-benefit consideration. Incorporating this constraint into the model could help answer questions such as in what situation the precision of private information will equal, less or exceed the precision of public information sources. The cost-benefit constraints will also affect how forecasters assign the weight among different sources of information.

Secondly, there is a need to incorporate financial analysts and investors into a single model to formally examine the effect of leaning each others' private information on their forecast accuracy. This study includes investors and analysts in two separate models. An integrated model would help identify new openings for research on the subject.

Last, but not least, two prior studies have predicted a nonmonotonic relationship between dispersion of analysts' forecasts and precision of their private information (e.g., Im [1989] and Barry et al. [1992]), although none have provided strong empirically evidence. This study also fails to find any evidence supporting the nonmonotonic hypothesis. More powerful and refined research design is needed to prove the nonmonotonic hypothesis. Empirically identifying the turning point in the nonmonotonic relationship between dispersion and precision of analysts' private information will certainly help improve the power of the tests in this study.

Table 1

Sample Selection and Descriptive Statistics

Panel A: Sample Selection Criteria & Sample Size

Criteria		No. of Observation	No. of Firm	No. of Firm-Year
(1)	Total number of Firm and Year on COMPUSTAT that have December Yearend	34,846	1,874	34,846
(2)	At Least a 20 Years of EPS Time-Series Available on Compustat or Moody's Manual	26,384	960	26,384
(3)	Number of Most Resent Forecasts from Each Brokerage House on IBES Detailed Files For Firm and Years in (2)	155,954	924	7,657
(4)	Stock Price, Return, Trading Volume and Stock dividends and Splits Available on CRSP Daily Return and Master Combined Files	133,599	807	5,560

Panel B: Selected Statistics for Forecasts: Age[1], Number of Forecasts Per Firm-Year and Size

Fractiles	Number of Days Between Forecast Dates & Earnings Announcement Date	Number of Forecasts Per Firm-Year[2]	Market Value of Firms (in Million $)
Mean	124	22	3,339
Std. Dev.	92	15	13,427
90%	275	42	6,095
75%	178	33	2,718
50%	91	20	981
25%	57	9	314
10%	28	5	105

Note:

[1] The Age of Forecasts if defined as number of calendar days between the forecast date and earnings announcement day.

[2] Since I keep the most recent forecast from each broker for every firm-year, the number of forecasts per firm-year is equivalent to the number of analysts' followings.

Table 2
Descriptive Statistics of Key Variables

Panel A: Distribution of CAPM Parameters, Cumulative Abnormal Returns, and Standardized Trading Volume

	Intercept	Beta	R-Squared	$CAR_{0,+1}$	$CAR_{-1,+1}$	$PSV_{0,+1}$ [1]
Mean	-0.0000	0.9579	0.136	1.0130	0.98826	4.7197
Std. Dev.	0.0011	0.5207	0.103	0.3802	0.10746	2.3783
95%	0.0016	1.8640	0.329	1.6144	1.15628	8.0632
90%	0.0011	1.6257	0.278	1.4084	1.09703	6.8369
75%	0.0005	1.2577	0.195	1.1710	1.03383	5.3084
50%	-0.0000	0.8783	0.113	0.9684	0.98336	4.2838
25%	-0.0007	0.5497	0.053	0.7930	0.93276	3.5634
10%	-0.0014	0.3302	0.021	0.6322	0.87695	2.9640
5%	-0.0019	0.2286	0.010	0.5254	0.83671	2.6072

Panel B: Distribution of TSFE[2], PBFE[3], and FAFE[4]

	Actual-Forecasted			Absolute Forecast Error			Squared Forecast Error		
	TSFE	PBFE	FAFE	TSFE	PBFE	FAFE	TSFE	PBFE	FAFE
Mean	0.0042	-0.0074	-0.2377	1.0648	0.9498	0.5167	3.8719	3.4664	1.3838
Std. D	1.8015	1.6914	1.0496	1.6548	1.6015	1.0569	14.7725	14.5869	8.1869
95%	2.2569	1.9438	0.6116	4.3054	3.7490	2.2166	18.5361	14.0551	4.9132
90%	1.4311	1.0934	0.3521	2.6540	2.4325	1.2985	7.04348	5.91718	1.6860
75%	0.5499	0.3523	0.1016	1.1545	1.0185	0.4670	1.33291	1.03734	0.2181
50%	0.0923	0.0046	-0.0350	0.4777	0.3809	0.1753	0.22820	0.14513	0.0307
25%	-0.3728	-0.4079	-0.2689	0.2010	0.1374	0.0633	0.04041	0.01889	0.0040
10%	-1.4508	-1.5108	-1.0528	0.0758	0.0506	0.0225	0.00575	0.00256	0.0005
5%	-2.8725	-2.7969	-1.9294	0.0388	0.0239	0.0100	0.00150	0.00057	0.0001

Panel C: Distribution of Financial Analysts' Forecasts Dispersion

	STDFY1[5]	STDFDATE[6]	STDFY1/STDFDATE[7]	PFAFE
Mean	0.51662	119	0.00529	0.40741
Std. Dev.	1.92875	41	0.01863	5.53043
95%	1.56143	188	0.01723	8.76250
90%	1.02701	167	0.01050	2.47624
75%	0.53079	142	0.00508	1.09440
50%	0.26327	119	0.00236	0.17265
25%	0.12976	97	0.00110	0.02353
10%	0.07258	64	0.00057	0.00259
5%	0.05000	43	0.00039	0.00066

(table 2 continued on next page)

(Table 2 Continued)

Panel D: Distribution of Analysts' One-Year Ahead & One-Quarter Ahead Forecast Revisions				
	Revision of One-year Ahead Forecasts		Revision of One-quarter Ahead Forecasts	
	RVFY2	RVFY2%[9]	RVFQ1	RVFQ1%[10]
M	-0.1031	0.2461	-0.0466	0.3531
STD	1.2894	2.5475	0.2132	2.7846
95%	0.4398	0.5003	0.2031	1.5623
90%	0.2486	0.2941	0.1000	0.7661
75%	0.0600	0.1309	0.0271	0.3176
50%	-0.0590	0.0539	-0.0338	0.1222
25%	-0.2000	0.0230	-0.1000	0.0525
10%	-0.4130	0.0090	-0.2010	0.0244
5%	-0.6100	0.0044	-0.3254	0.0145

Note:

1. $PSV_{0,t}$, denotes for standardized trading volume from last year earnings reporting date to the latest earnings forecast date for current year;

2-4. TSFE denotes the random walk earnings forecast error; PBFE denotes the earnings forecast error from the price based forecast model; FAFE denotes the earnings forecast errors by financial analysts. All forecast errors are defined as actual EPS minus forecasted EPS.

5. Standard deviation of financial analysts' current year forecasts.

6. Standard deviation of financial analysts' forecast dates.

8. dispersion of forecast deflated by standard deviation of forecast dates.

9-10. RVFY2% and RVFQ1% denote the relative revision for one-year and one-quarter ahead forecast revision by financial analysts. They are defined as absolute revision divided by analysts previous forecasts.

Table 3

Pearson Correlation Coefficients and Significance Level (p-value) among Key Variables

	RAI_{it}	$SIGM_i$	PSV_{it}	$PPBFE_{it}$	$PFAFE_{it}$	$DISP_{it}$	$RVF2_{it}$	$RVQ1_{it}$	$NFAF_{it}$	$SIZE_{it}$	TAU_{it}
$RAII_{it}$	.2921	-.1363	-.1408	.0838	.0284	.0972	.0421	.0542	-.0349	-.0162	.0823
	.000	.000	.000	.000	.166	.340	.111	.157	.035	.326	.000
RAI_{it}		-.0354	-.0299	.2591	.1652	.2064	-.0055	.0099	-.0762	-.0229	.0287
		.018	.044	.000	.000	.015	.718	.674	.000	.127	.017
$SIGM_i$			.2137	.0426	-.0332	.1357	.0829	.0113	.0048	-.0155	-.0491
			.000	.007	.053	.000	.000	.000	.708	.257	.000
PSV_{it}				-.0295	-.0312	.0527	.1954	.0423	.0195	-.1124	-.0345
				.068	.083	.256	.000	.067	.226	.000	.009
$PPBFE_{it}$					-.0775	.0175	-.0091	-.0116	-.0237	-.0016	-.0145
					.000	.254	.561	.622	.124	.916	.345
$PFAFE_{it}$						.0215	-.0076	-.0334	-.0353	-.0046	.0350
						.004	.658	.202	.036	.787	.038
$DISP_{it}$							-.1197	-.0461	-.0341	.0019	.0037
							.062	.097	.008	.891	.779
$RVFY2_{it}$								.2603	-.0371	-.0202	.0038
								.001	.006	.143	.778
$RVFQ1_{it}$									-.0288	-.0227	-.0176
									.165	.279	.398
$NFAF_{it}$										.3102	-.0994
										.000	.000
$SIZE_{it}$											-.0596
											.000

Variable definitions:
RAI_{it} -squared analysts' forecast error divided by squared time series forecast errors;
$RAII_{it}$-a ratio between squared \$ abnormal return & squared time series forecast error for firm *i* in year *t*;
$SIGM_i$-the coefficient of variation of earnings of firm *i*, defined as variance divided by absolute mean;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$PFAFE_{it}$-square analysts' forecast error divided by squared price-based forecast errors;
PSV_{it} -standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$DISP_{it}$-variance of analysts' forecasts divided by absolute value of mean forecasts;
$NFAF_{it}$-number of analysts following divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm i in year t divided by the mean market value of all firm in year t;
$RVFY2_{it}$-squared one-year ahead forecast revision divided by absolute value of previous forecasts;
$RVFQ1_{it}$-squared one quarter ahead forecast revision divided by absolute value of previous forecasts.

Table 4

Mean Estimated OLS Coefficients Showing Relationship Between Accuracy of Analysts' Earnings Forecasts and Precision of Information for Year of 1983-1992, Variance of Price-Based Forecast Errors as Proxy for Precision of Public Information
Dependant Variable: $RAI_{it}=(FAFE_{it})^2/(TSFE_{it})^2$

Indep. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$Intercept_t$	1.6311	1.1338	2.3805	1.7088	1.9620	1.2786
	(6.37)***	(2.63)***	(6.62)***	(6.02)***	(4.64)***	(2.84)***
$SIGM_i$	-0.1667	-0.1674	-0.1640	-0.1690	-0.1642	-0.1694
	(-4.45)***	(-4.24)***	(-4.28)***	(-4.51)***	(-4.10)***	(-4.30)***
$PPBFE_{it}$	0.0654	0.0650	0.0651	0.0654	0.0646	0.0649
	(8.46)***	(8.31)***	(8.30)***	(8.44)***	(8.18)***	(8.29)***
$DISP_{it}$	0.1619	0.1726	0.1421	0.1636	0.1515	0.1718
	(2.45)***	(2.50)***	(2.38)***	(2.49)***	(2.32)***	(2.36)***
TAU_{it}	-	0.0037	-	-	0.0028	0.0031
	-	(0.97)	-	-	(0.82)	(0.84)
$NFAF_{it}$	-	-	-0.0303	-	-0.0290	-
	-	-	(-4.36)***	-	(-4.24)***	-
$SIZE_{it}$	-	-	-	-0.0968	-	-0.1003
	-	-	-	(-1.54)	-	(-1.61)
Adjusted R^2	0.1226	0.1225	0.1267	0.1232	0.1275	0.1228

Variable definitions:
RAI_{it}-squared analysts' forecast error and squared time series forecast error for firm *i* in year *t*;
$SIGM_i$-the variance of earnings time series of firm *i* divided by absolute mean;
PSV_{it}-standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$DISP_{it}$-variance of analysts' earnings forecasts divided by the absolute value of mean forecasts;
$NFAF_{it}$-number of analysts following firm *i* divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm *i* in year *t* divided by the mean market value of all firm in year *i*.

Numbers in parenthesis is the t-value using mean divided by standard error of ten-year time series of regression coefficients.

*** P-value < 0.05
** 0.1<P-value<0.05

Table 5

Mean Estimated OLS Coefficients Showing Relationship Between Accuracy of Analysts' Earnings Forecasts and Precision of Information for Year of 1983-1991, Standardized Trading Volume as Proxy for Precision of Public Information
Dependant Variable: $RAI_{it}=(FAFE_{it})^2/(TSFE_{it})^2$

Indep. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$Intercept_t$	2.8533	2.1178	3.4118	2.9945	2.7767	2.3276
	(8.32)***	(2.85)***	(10.17)***	(7.61)***	(4.08)***	(2.95)***
$SIGM_i$	-0.0986	-0.0976	-0.1001	-0.1005	-0.0985	-0.0997
	(-2.40)***	(-2.39)***	(-2.39)***	(-2.43)***	(-2.38)***	(-2.42)***
PSV_{it}	-0.7787	-0.7817	-0.7217	-0.8448	-0.7351	-0.6430
	(-4.07)***	(-3.87)***	(-3.66)***	(-4.08)***	(-3.66)***	(-3.90)***
$DISP_{it}$	0.3382	0.3647	0.3299	0.3531	0.3533	0.3768
	(2.30)***	(2.70)***	(2.33)***	(2.40)***	(2.70)***	(2.77)***
TAU_{it}	-	0.0054	-	-	0.0045	0.0048
		(1.23)			(1.04)	(1.10)
$NFAF_{it}$	-	-	-0.0258	-	-0.0242	-
			(-3.69)***		(-3.45)***	
$SIZE_{it}$	-	-	-	-0.1131	-	-0.1044
				(-1.58)		(-1.59)
Adjusted R^2	0.0464	0.0501	0.0503	0.0458	0.0537	0.0502

Variable definition:
RAI_{it}-squared analysts' forecast error and squared time series forecast error for firm *i* in year *t*;
$SIGM_i$-the variance of earnings time series of firm *i* divided by absolute mean;
PSV_{it}-standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$DISP_{it}$-variance of analysts' earnings forecasts divided by the absolute value of mean forecasts;
$NFAF_{it}$-number of analysts following firm *i* divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm *i* in year *t* divided by the mean market value of all firm in year *i*.

Numbers in parenthesis is the t-value using mean divided by standard error of nine-year time series of regression coefficients.

*** P-value < 0.05

** 0.1<P-value<0.05

Table 6

Mean Estimated OLS Coefficients Showing Relationship Between Accuracy of Investors' Earnings expectations and Precision of Information for Year of 1983-1991, Basic Models

Dependant Variable: $RAII_{it}=(\$AR_{it})^2/(TSFE_{it})^2$

Indep. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$Intercept_t$	3.7061	5.0922	9.6319	2.0001	6.9391	7.6512	3.9473
	(6.94)***	(6.36)***	(10.92)***	(1.83)**	(9.82)***	(6.79)***	(2.02)**
$SIGM_i$	-0.7981	-0.7549	-0.6229	-0.7409	-0.6074	-0.5703	-0.7803
	(-10.00)***	(-7.44)***	(-5.95)***	(-5.96)***	(-4.55)***	(-5.02)***	(-3.12)***
$PPBFE_{it}$	0.2121	-	-	0.2674	0.2706	0.2902	0.6251
	(3.23)***	-	-	(5.28)***	(5.19)***	(4.91)***	(3.82)***
$PFAFE_{it}$[1]	-	0.2898	-	0.0723	0.0516	0.0561	0.0525
	-	(3.08)***	-	(3.12)***	(3.09)***	(3.00)***	(2.87)***
PSV_{it}	-	-	-4.0507	-	-4.8764	-4.5141	-3.3150
	-	-	(-6.35)***	-	(-4.34)***	(-4.48)***	(-3.73)***
$RVFY2_{it}$	-	-	-	-	-	2.0157	2.2548
	-	-	-	-	-	(1.96)**	(1.32)
$RVFQ1_{it}$	-	-	-	-	-	-	1.3098
	-	-	-	-	-	-	(1.21)
TAU_{it}	0.0320	0.0249	0.0235	0.0399	0.0389	0.0323	0.0425
	(12.93)***	(4.96)***	(8.96)***	(4.23)***	(4.38)***	(4.81)***	(3.82)***
Adjusted R^2	0.0400	0.0293	0.0392	0.0415	0.0562	0.0536	0.0806

[1] For model 2, PFAFE is defined as squared analysts' forecast error divided by absolute actual EPS.

Variable definitions:

$RAII_{it}$-a ratio between squared \$ abnormal return & squared time series forecast error for firm *i* in year *t*;
$SIGM_i$-the coefficient of variation of earnings of firm *i*, defined as variance divided by absolute mean;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$PFAFE_{it}$-square analysts' forecast error divided by squared price-based forecast errors;
PSV_{it} -standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$NFAF_{it}$-number of analysts following divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm *i* in year *t* divided by the mean market value of all firm in year *t*;
$RVFY2_{it}$-squared one-year ahead forecast revision divided by absolute value of previous forecasts;
$RVFQ1_{it}$-squared one quarter ahead forecast revision divided by absolute value of previous forecasts.

Numbers in parenthesis is the t-value using mean divided by standard error of nine-year time series of regression coefficients.

*** P-value < 0.05

** P-value < 0.10

Table 7

Mean Estimated OLS Coefficients Showing Relationship Between Accuracy of Investors' Earnings expectations and Precision of Information for Year of 1983-1991. Effect of Firm Size and Number of Analysts' Following

Dependant Variable: $RAII_{it}=(\$AR_{it})^2/(TSFE_{it})^2$

Indep. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$Intercept_t$	3.7656	5.0256	9.8850	6.9057	4.4315	5.7756	7.5811	7.0752
	(6.83)***	(5.58)***	(11.54)***	(7.93)***	(6.01)***	(5.42)***	(6.19)***	(6.83)***
$SIGM_i$	-0.8003	-0.7467	-0.6244	-0.5917	-0.8008	-0.7459	-0.6328	-0.5825
	(-10.09)***	(-7.72)***	(-5.95)***	(-4.89)***	(-10.17)***	(-7.58)***	(-5.16)***	(-4.45)***
$PPBFE_{it}$	0.2120	-	-	0.2851	0.2143	-	-	0.2866
	(3.25)***	-	-	(4.88)***	(3.26)***	-	-	(5.20)***
$PFAFE_{it}$[1]	-	0.2899	-	0.0320	-	0.2803	-	0.0422
	-	(3.08)***	-	(2.86)***	-	(3.12)***	-	(2.98)***
PSV_{it}	-	-	-4.1469	-4.9218	-	-	-4.0612	-4.9247
	-	-	(-6.59)***	(-4.78)***	-	-	(-6.16)***	(-4.20)***
$NFAF_{it}$	-	-	-	-	-0.5369	-0.5057	-0.4917	-0.1186
	-	-	-	-	(-1.58)	(-1.28)	(-1.46)	(-0.20)
$SIZE_{it}$	-0.0235	-0.1451	-0.0772	0.1859	-	-	-	-
	(-0.60)	(-0.53)	(-1.80)**	(0.59)	-	-	-	-
TAU_{it}	0.0318	0.0246	0.0230	0.0385	0.0312	0.0238	0.0225	0.0390
	(12.40)***	(4.49)***	(8.90)***	(3.98)***	(11.49)***	(4.37)***	(8.01)***	(4.07)***
Adjusted R^2	0.0399	0.0293	0.0399	0.0568	0.0404	0.0299	0.0395	0.0560

[1] For model 2 & 6, PFAFE is defined as squared analysts' forecast error divided by absolute EPS.

The variables are defined as follows:

$RAII_{it}$-a ratio between squared \$ abnormal return & squared time series forecast error for firm *i* in year *t*;
$SIGM_i$-the coefficient of variation of earnings of firm *i*, defined as variance divided by absolute mean;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$PFAFE_{it}$-square analysts' forecast error divided by squared price-based forecast errors;
PSV_{it} -standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$NFAF_{it}$-number of analysts following divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm *i* in year *t* divided by the mean market value of all firm in year *t*;
$RVF2_{it}$-squared one-year ahead forecast revision divided by absolute value of previous forecasts;
$RVQ1_{it}$-squared one quarter ahead forecast revision divided by absolute value of previous forecasts.

Numbers in parenthesis is the t-value using mean divided by standard error of nine-year time series of regression coefficients.

*** P-value < 0.05
** P-value < 0.10

Table 8

Mean Estimated OLS Coefficients Showing Relationship Between Accuracy of Investors' Earnings expectations and Precision of Information for Year of 1983-1991

Timing Effect

Dependant Variable: $RAII_{it}=(\$AR_{it}/ARLEN)^2/(TSFE_{it})^2$

Indep. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$Intercept_i$	0.0713	0.0713	0.0722	0.0705	0.0726	0.0725	0.0644	0.0690
	(5.92)***	(5.76)***	(6.06)***	(5.79)***	(6.42)***	(5.74)***	(6.67)***	(4.50)***
$SIGM_i$	-0.0061	-0.0061	-0.0057	-0.0057	-0.0061	-0.0061	-0.0060	-0.0059
	(-8.04)***	(-9.21)***	(-7.93)***	(-8.75)***	(-7.90)***	(-8.94)***	(-7.22)***	(-8.29)***
$PPBFE_{it}$	0.0025	0.0024	0.0025	0.0024	0.0025	0.0025	0.0026	0.0025
	(3.30)***	(3.25)***	(3.27)**	(3.23)**	(3.34)***	(3.29)**	(3.43)***	(3.38)***
$PFAFE_{it}$	0.0025	0.0026	0.0026	0.0026	0.0025	0.0025	0.0025	0.0025
	(2.87)***	(2.93)***	(2.89)***	(2.94)***	(2.85)***	(2.90)***	(2.81)***	(2.88)***
PSV_{it}	-0.0358	-0.0357	-0.0344	-0.0340	-0.0371	-0.0370	-0.0385	-0.0388
	(-3.61)***	(-3.59)***	(-3.57)***	(-3.53)***	(-3.77)***	(-3.71)***	(-3.87)***	(-3.96)***
$DISP_{it}$	-	-	0.0038	0.0042	-	-	-	-
	-	-	(1.16)	(1.68)	-	-	-	-
$SIZE_{it}$	-	-	-	-	0.0003	0.0001	-	-
	-	-	-	-	(0.36)	(0.14)	-	-
$NFAF_{it}$	-	-	-	-	-	-	-0.0047	-0.0045
	-	-	-	-	-	-	(-0.57)	(-0.53)
TAU_{it}	0.0000	-	-0.0000	-	0.0000	-	0.0000	-
	(0.10)	-	(-0.00)	-	(0.07)	-	(0.36)	-
Adjusted R^2	0.0148	0.0151	0.0147	0.0149	0.0146	0.0148	0.0148	0.0151

Variables definitions:

$RAII_{it}$-a ratio between squared \$ abnormal return & squared time series forecast error for firm *i* in year *t*;
$ARLEN_{it}$-number of days between latest forecast dates and earnings announcement dates;
$SIGM_i$-the coefficient of variation of earnings of firm *i*, defined as variance divided by absolute mean;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$PFAFE_{it}$-square analysts' forecast error divided by squared price-based forecast errors;
PSV_{it} -standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$DISP_{it}$-variance of analysts' earnings forecasts divided by the absolute value of mean forecasts;
$NFAF_{it}$-number of analysts following divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm *i* in year *t* divided by the mean market value of all firm in year *t*;
$RVFY2_{it}$-squared one-year ahead forecast revision divided by absolute value of previous forecasts;
$RVFQ1_{it}$-squared one quarter ahead forecast revision divided by absolute value of previous forecasts.

Numbers in parenthesis is the t-value using mean divided by standard error of nine-year time series of regression coefficients.

*** P-value < 0.05

** P-value < 0.10

Table 9

Mean Estimated OLS Coefficients Showing Relationship Between Accuracy of Investors' Earnings expectations and Precision of Information for Year of 1983-1991, Adding DISP to basic models
Dependant Variable: $RAII_{it}=(\$AR_{it})^2/(TSFE_{it})^2$

Indep. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$Intercept_t$	4.0528 (6.63)***	5.3143 (6.65)***	9.3944 (11.03)***	2.3918 (2.22)***	6.6573 (9.54)***	7.6753 (6.83)***	4.0342 (2.14)**
$SIGM_i$	-0.7282 (-8.77)***	-0.7091 (-6.72)***	-0.5938 (-5.86)***	-0.6831 (-5.23)***	-0.5761 (-4.22)***	-0.5470 (-4.73)***	-0.7578 (-3.03)***
$PPBFE_{it}$	0.2158 (3.26)***	- -	- -	0.2730 (5.40)***	0.2746 (5.37)***	0.2963 (5.01)***	0.6546 (3.48)***
$PFAFE_{it}$	- -	0.2893 (3.04)***	- -	0.0708 (2.86)***	0.0498 (2.50)***	0.0552 (2.38)**	0.0492 (2.33)***
PSV_{it}	- -	- -	-3.7329 (-4.39)***	- -	-4.7461 (-3.96)***	-4.4069 (-4.16)***	-2.7633 (-2.82)***
$DISP_{it}$	0.6154 (1.09)	0.2957 (0.88)	0.2116 (1.23)	0.7347 (1.67)	0.4081 (1.15)	0.3966 (0.29)	0.5793 (0.64)
$RVFY2_{it}$	- -	- -	- -	- -	- -	1.5916 (1.66)	1.9707 (1.22)
$RVFQ1_{it}$	- -	- -	- -	- -	- -	- -	1.3538 (1.25)
TAU_{it}	0.0310 (12.07)***	0.0243 (4.82)***	0.0237 (9.27)***	0.0382 (4.10)***	0.0382 (4.14)***	0.0316 (4.60)***	0.0394 (3.29)***
Adjusted R^2	0.0415	0.0313	0.0400	0.0434	0.0571	0.0544	0.0804

[1] For model 2, PFAFE is defined as squared analysts' forecast error divided by absolute actual EPS.

Variables definitions:
$RAII_{it}$-a ratio between squared \$ abnormal return & squared time series forecast error for firm *i* in year *t*;
$SIGM_i$-the coefficient of variation of earnings of firm *i*, defined as variance divided by absolute mean;
$PPBFE_{it}$-squared price-based forecast error divided by absolute value of actual earnings;
$PFAFE_{it}$-square analysts' forecast error divided by squared price-based forecast errors;
PSV_{it} -standardized trading volume of firm *i* divided by the mean standardized trading volume in year *t*;
$DISP_{it}$-variance of analysts' earnings forecasts divided by the absolute value of mean forecasts;
$NFAF_{it}$-number of analysts following divided by the mean number of analysts following in year *t*;
TAU_{it}-average number of days between earnings announcement dates and analysts' forecast dates;
$SIZE_{it}$-market value of firm *i* in year *t* divided by the mean market value of all firm in year *t*;
$RVFY2_{it}$-squared one-year ahead forecast revision divided by absolute value of previous forecasts;
$RVFQ1_{it}$-squared one quarter ahead forecast revision divided by absolute value of previous forecasts.

Numbers in parenthesis is the t-value using mean divided by standard error of nine-year time series of regression coefficients.

*** P-value < 0.05
** P-value < 0.10

Appendix A

This appendix demonstrates that relaxation of unbiasedness assumption does not alter the prime result of the model. Define analysts' mean bias for a particular firm as a constant *bias*. Then, analyst *a*'s forecast as defined in equation (5) can be written as:

$$\tilde{F}_a = E[\tilde{u} \mid \tilde{I}_a = I_a, \tilde{P} = P] = \mu + (g,h)[I_a - E(\tilde{I}), P - E(\tilde{P})]' + bias$$

The posterior variance of residual errors is:

$$V_{FAF} = E[\tilde{e}_a]^2 = E[\tilde{u} - \tilde{F}_a]^2$$

$$= E\{\tilde{u} - \mu - (g,h)[\tilde{I}_a - E(\tilde{u}), P - E(\tilde{P})]' - bias\}^2$$

$$= \sigma - \frac{\sigma^2[\delta(\sigma+\eta) + s(\eta-\delta)]}{(\sigma+\eta)[s\eta + \delta(\sigma+\eta)]} + bias^2$$

Comparing this expression with equation (7), the only difference is the term *bias*^{2}. Since *bias*^{2} is a positive constant, it will not alter the sign of any partial derivatives shown in the text.

The bias, if significant, will cause the intercepts θ_{0i} and ϕ_{0i} in regression model (18) and (19) to deviate from their expected value one. This is because in the absence of timely information, the variance of analysts' forecasts is the variance of TS model plus the variance of the bias. For example,

$$E[\theta_{0i}] = 1 + \frac{bias^2}{\sigma}$$

Appendix B

This appendix derives the three covariances used in the variance-covariance matrix. Covariance between earnings and analyst's private information ($\tilde{I}_a$) is derived as follows:

$$Cov(\tilde{u},\tilde{I}_a) = E\{(\tilde{u}-\mu)*[\tilde{I}-E(\tilde{I}_a)]\} = E\{(\tilde{u}-\mu)*(\tilde{u}+\tilde{n}+\tilde{\delta}_a-\mu)\} = E(\tilde{u}-\mu)^2 = \sigma$$

Covariance between earnings and stock price is:

$$Cov(\tilde{u},\tilde{P}) = E\{(\tilde{u}-\mu)*[\tilde{P}-E(\tilde{P})]\} = E\{(\tilde{u}-\mu)*(\tilde{P}-\beta\mu)\}$$
$$= E\{(\tilde{u}-\mu)*[\beta(\tilde{u}+\tilde{n})+\tilde{\varepsilon}-\beta\mu]\} = \beta E(\tilde{u}-\mu)^2 = \beta\sigma$$

Covariance between analyst's private information & stock price is:

$$Cov(\tilde{I}_a,\tilde{P}) = E\{(\tilde{I}_a-\mu)*(\tilde{P}-\beta\mu)\} = E\{(\tilde{u}+\tilde{n}+\tilde{\delta}_a-\mu)*[\beta(\tilde{u}+\tilde{n})+\tilde{\varepsilon}-\beta\mu]\}$$
$$= E[\beta(\tilde{u}-\mu)^2+\beta\tilde{n}^2] = \beta[E(\tilde{u}-\mu)^2+E(\tilde{n})^2] = \beta(\sigma+\eta)$$

Endnotes

[1] The abnormal stock returns during earnings announcement is defined as the investors' earnings forecast errors multiplied by the *earnings response coefficients* (see Beaver, Lambert and Morse [1980]). The theoretical expected value of this coefficient is 1.

[2] Refer to Schipper [1991] for a literature review in this area.

[3] Brown et al. [1987c] use the ratio of variance of random walk forecast model to the FAF forecasting error as proxy for FAF superiority. Kross et al. [1990] use the difference between the forecast errors of the two forecast models as proxy for FAF superiority.

[4] Notice that both Beaver et al. [1980] and Elgers et al. [1992] study the prediction accuracy in terms of earnings changes, not the earnings prediction. As Elgers et al. point out, "the result cannot be generalized to earnings prediction" [pp. 315, last paragraph].

[5] See Ball [1992] and Bernard [1991] for a literature review in this area.

[6] Post announcement drift is the phenomenon whereby estimated cumulative abnormal returns continue to drift upward (downward) after the announcement of earnings increases (decreases).

[7] For detailed discussion of this area, refer to Ball [1992] and Bernard [1991].

[8] For example, DeBondt and Thaler [1990] and Klein [1990] focus on the possible cognitive bias in FAF. DeBondt and Thaler [1990] provide evidence suggesting that FAF include a cognitive bias, i.e., FAF are overly pessimistic (optimistic) predictions of future earnings during periods of extreme share price declines (increases). Klein [1990] uses a more direct test and finds no such bias exists. Research on the bias issue is related to a broader research area that is reexamining efficient market hypothesis, and is out of the scope of this study. Interested readers should refer to Ball [1992] and Bernard [1991] for a detailed critical review of research in this area.

[9] Muth [1961] criterion for rationality states that expectations should be generated by the same stochastic process that generates the variables to be forecasted. Most tests for the Muthian hypothesis, however, have employed a somewhat weaker condition, namely, that rational expectation should fully reflect all the information that is available. Therefore, rational expectation should be unbiased and have the minimal variance, and the forecast errors should be serially uncorrelated.

[10] The smaller RAI indicates FAF is more accurate. This inversely defined index will greatly simplify the mathematic presentation of the model.

[11] Previous studies in this context normally define stock price as the present value of expected future dividend, as Ohlson [1988, p29] points out, "ultimately only payoffs count, and dividends alone can be consumed." In this study, the actual and expected dividends are set equal to the actual and expected accounting earnings. While this setting presents no problem in the single period case of this study, the assumption will not hold exactly in the

multi-period settings, and some errors might be introduced. However, as Lipe [1990] points out that without knowing exactly how the revisions in expectations of accounting earnings and dividend differ, it is impossible to accurately predict the magnitude or even the direction of the effect.

[12] Holthausen and Verrecchia [1988, 1990] and Lundholm [1988], among others, also model private information with both a common and idiosyncratic components of noise. Holthausen and Verrecchia point out that the idiosyncratic noise term need not necessarily be interpreted as errors in analysts' private information. It is also appropriate to interpret the idiosyncratic error as an error made by individual analyst in interpreting and processing public information. For example, when analysts receive a public information signal (e.g., management earnings forecast), it is likely to have idiosyncratic noise because each analyst might interpret the signal differently.

[13] Ohlson [1979, 1988] present theoretical models that are used widely to derive response coefficient for information variables (for example, ERC for earnings) in previous research. These model demonstrate that (stock) price is a function of all information variables that predict dividends. The model in this study assumes a single trading period and set the dividend equal to accounting earnings. Therefore, the price equation takes much simpler form.

[14] The forecast is called a posterior forecast in the sense that it is conditioned upon information observation and analyst's prior beliefs. For example, when X and Y are both normally distributed, the expected value of Y given X can be written as:

$$E[Y|X] = \bar{Y} + \frac{cov(x,y)}{var(x)}[X - \bar{X}]$$

[15] This can be seen by substituting equation (6) into (5) and rearranging:

$$F_e = \frac{[\eta\beta^2 + \delta(\eta + s)]\mu + \sigma\delta\bar{i}_e + \sigma s\beta\bar{p}}{s(\sigma + \eta)\beta^2 + \delta(\sigma + \eta + s)}$$

[16] Lipe [1990] analytically separates stock returns into two components, expected returns ER and unexpected returns UR, as follows:

$$R_t = \frac{P_t - P_{t-1} + D_t}{P_{t-1}} = \frac{E[P_t|I_{t-1}] - P_{t-1} + E[D_t|I_{t-1}]}{P_{t-1}} + \frac{P_t - E[P_t|I_{t-1}] + D_t - E[D_t|I_{t-1}]}{P_{t-1}} = ER + UR$$

where: D_t is the dividend at period t; and I_t and I_{t-1} represent the information observed by investors at t and t-1 respectively. He defines price as the present value of expected future dividends as:

$$P_t = \sum_{s=1}^{\infty} \beta^s E[D_{t+s}|I_t]$$

where *s* represents the number of period in future starting from current period *t*. Lipe then sets future dividends equal to future earnings, and substitutes P_t into the expression of UR to arrive equation (9) above.

[17] Holthausen and Verrecchia [1990] predict a consensus effect which is measured by correlation coefficient of residual errors between two agents. They assert there is a inverse and monotonic relation between correlation coefficient and variance of agent's private

information. This is equivalent to asserting a positive and monotonic relation between dispersion and variance of analysts' forecasts because there is a functional relationship between dispersion and correlation coefficients based on statistics theory.

[18] Test result is not changed if this deflating procedure is not applied.

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