THE INCREMENTAL PREDICTIVE ABILITY OF INDIVIDUAL
FINANCIAL ANALYSTS

BY

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ABSTRACT

Financial analysts are among the most influential group of users of financial accounting information. Because the FASB has advocated usefulness as the "overriding criterion" (FASB, 1980, p.26) to judge accounting choices, accountants have a stake in understanding this important group of financial statement users. The majority of existing accounting research concerning financial analysts focuses on aggregated analysts' earnings forecasts rather than individual analysts' forecasts. Studies in accounting have documented the superiority of aggregated analysts' earnings forecasts relative to models. This is in contrast to the robust result from years of judgment/decision making (JDM) research that human predictions are inferior to statistical model predictions. Prior accounting studies have also documented that analysts exhibit optimism when forecasting earnings.

Humans can make a significant contribution to accurate forecasting in spite of cognitive limitations. Some skills people bring to bear are cue identification, rapid adaptability to environmental changes and the evaluation of qualitative factors. Although statistical models are not well-equipped to utilize qualitative factors and be adaptable, they do offer consistency and significant computational power. Thus, the strengths of humans and statistical models in forecasting are complementary.

This research documents the incremental predictive ability of both individual financial analysts and statistical models in forecasting earnings. It also provides evidence that both individual financial analysts' and statistical models' incremental predictive ability varies between industries. In addition, tests show a pessimistic bias for individual

analysts, contrary to prior studies. Additional evidence is presented regarding forecast accuracy for four different forecast generation methods.

To Marianne

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CHAPTER I

INTRODUCTION AND MOTIVATION

Over the last two decades, interest in forecasts of corporate earnings has grown significantly. Forecasting earnings is one of the vital services performed by financial analysts (Knutson, 1993). Today, thousands of analysts earn their livelihood from monitoring, studying and forecasting earnings in addition to other activities (e.g. selecting stocks).[1] An indication of this increasing interest is the substantial growth in commercially available earnings forecasting services since 1967.[2]

There are several reasons for this increased attention. Among the most significant reasons is that accurate earnings forecasts are valued by investors. Another is the development of valuation models that use future earnings as inputs. Similarly, academic researchers are interested in obtaining accurate proxy measures for the market's expectation of future earnings. Since analysts' forecasts are generally more accurate than time-series forecasts, they are a prime candidate for use as a proxy (Brown & Rozeff, 1978; Brown, et al, 1987a).

In the accounting literature, most research concerning earnings forecasts focuses on

[1] Evidence of this is the "All-Star Analysts Survey" done by Dow Jones & Company, Inc. This annual survey was started in 1993 and is reported in the Wall Street Journal (see the WSJ, June 29, 1994). Analysts are ranked according to the accuracy of their earnings forecasts as well as their stock-picking success.

[2] In 1967, Standard & Poor's started providing The Earnings Forecaster, a service that listed forecasted earnings for large companies.

commercially available forecasts.[3] Most studies utilize summary forecasts (combinations of multiple individual analysts' forecasts). The literature tells us much about the characteristics of summary forecasts, but relatively little about individual analysts' forecasts (Lys & Sohn, 1990).

This study contributes to the accounting literature in at least two ways. First, it provides insight regarding the amount of overlap of information useful to earnings forecasting that is extracted by analysts and models from available data sources. This is accomplished by testing whether individual analysts possess incremental predictive ability relative to statistical models and conversely, whether statistical models possess incremental predictive ability relative to individual analysts. Furthermore, the incremental predictive ability of individual analysts and models will be examined between industries to identify differential performance. In addition, individual analysts' forecast accuracy relative to other forecast methods is examined in order to positively establish differences in accuracy between forecast generation methods for the specific sample used in the study. Investigations studying individual analysts' forecasts are needed because findings relating to summary analysts' forecasts may not hold true for individual analysts' forecasts. Second, ideas from the judgment and decision making (JDM) literature (e.g. cue identification and adaptability) will be drawn upon to propose explanations as to why individual analysts' are able to perform well relative to models.

This study also extends the JDM literature. Evidence indicating that analysts'

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[3] For example, the Institutional Brokers Estimate System (I/B/E/S) database produced by I/B/E/S/, Inc.

earnings forecasts are more accurate than models appears to be at odds with a large body of JDM research, which emphasizes the superiority of statistical predictions relative to human predictions. This study improves our understanding of individual analysts' earnings forecasts, providing a clearer picture of the contribution of human predictive ability relative to statistical models.

Financial analysts significantly influence the investment decisions of investors. For example, a study sponsored by the Financial Executives Research Foundation (FERF) indicates that "The advisor-dependent approach to decision making is typical of perhaps 50 percent of all individual investors..." (SRI International, 1987, p.26). Similarly, Schipper (1991) argues that

> Given their importance as intermediaries who receive and process financial information for investors, it makes sense to view analysts--sophisticated users--as representative of the group to whom financial reporting is and should be addressed (p. 105).

As the business environment changes, the needs of financial accounting information users will also evolve. Accountants have an interest in understanding these needs for two reasons. The first is so they can receive feedback regarding the usefulness of financial reporting. The second is so they can be involved in managing the accounting profession's response to such changes through financial reporting standards.[4] Studying financial analysts is important because they arguably constitute the most significant group of financial accounting information users.

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[4] This point is emphasized by Schipper (1991, p. 105) when she says that "accountants have a policy-based stake in understanding how analysts actually use financial information."

Most studies of analysts' earnings forecasts focus on summary analysts' forecasts.[5] This research has established the superiority of summary analysts' forecasts compared with time-series models (Brown & Rozeff, 1978; Collins & Hopwood, 1980; Brown, et al, 1987a; Kross, Ro & Schroeder, 1990). Although researchers have examined potential explanations for summary analysts' forecast superiority (Brown, et al, 1987a; Brown, Richardson & Schwager, 1987), their success has been limited by their use of aggregated data. By definition, aggregated or summary forecasts are composed of two or more individual forecasts. A more productive avenue to investigate explanations for the "why" questions (e.g. Why are summary analysts forecasts more accurate than model forecasts?) is at the point where the predictive judgments originate--individual analysts' forecasts.

For example, if stock prices are an aggregation of investors' expectations of future firm performance, then individuals' expectations are in a sense, the starting point of stock prices. It is therefore important to understand the nature of these individuals' expectations as well as the process by which aggregation occurs (Camerer, 1992). Analogously, individual analysts' forecasts are an important source of information for gaining further knowledge about earnings forecasts in general. Because of the scarcity of studies using individual analysts' forecasts, this study will add to existing knowledge. This potential has been noted by both accounting researchers (Givoly & Lakonishok, 1984; Schipper, 1991; L. Brown, 1993) and JDM researchers (Johnson, 1988; Camerer, 1992).

The remainder of this dissertation is structured in six chapters. Chapter II reviews

[5] Exceptions are Coggin & Hunter, (1982-1983), O'Brien (1990), Stickel (1990), Butler & Lang (1991) and Brown & Han (1992).

the relevant literature. Chapter III discusses the theory. Chapter IV describes the research design and hypotheses. Chapter V presents the results of the analyses. Chapter VI is a discussion of the results and Chapter VII discusses potential implications of the research and ideas for future research.

CHAPTER II

LITERATURE REVIEW

2.1 ANALYSTS' EARNINGS FORECASTS

In the late 1960s and early 1970s, researchers in finance started to examine financial analysts' forecasts and the relationship between financial analysts' earnings forecasts and stock prices. These studies found that analysts' forecasts are a better predictor of earnings growth than historical data (Cragg & Malkiel, 1968). Research also documented a positive association between analysts' forecasts and stock prices (Neiderhoffer & Regan, 1972).

Given the interest in the accounting literature of the early 1970s regarding the association between earnings and stock prices, analysts' forecasts of earnings was an obvious area into which accounting researchers could extend their inquiries (Givoly & Lakonishok, 1979). The major motivation for this research was that analysts' forecasts were viewed as a more desirable proxy (relative to time-series models) for the market's expectation of earnings (Gonedes, et al, 1976; Fried & Givoly, 1982; Brown, et al, 1987b). By the end of the 1980s, consistent evidence showed that analysts' forecasts are more accurate in predicting earnings than time-series models (Brown & Rozeff, 1978; Collins & Hopwood, 1980; Brown, Foster & Noreen, 1985; Brown et al. 1987a).

Further research hypothesized reasons for analysts' superior forecasting ability. Fried & Givoly (1982) suggested two reasons for the observed results. One explanation was that analysts utilize a broader information set (e.g. earnings variability, significant new contracts, labor disputes, etc.) than models and are able to use these additional data to make better earnings predictions. Another explanation is that analysts have a timing advantage over models because they can utilize data available subsequent to the announcement of data used by models. Models are limited to the most recent realizations of independent variables. Brown, et al (1987a) reports evidence supporting both explanations. Brown, Richardson & Schwager (1987) found empirical support for the information explanation using firm size as a proxy for the broadness of the information set. Additional work was done concerning timeliness (amount of time between forecast date and announcement date) of analysts' forecasts, finding that more timely forecasts tend to be more accurate (O'Brien, 1988).

In addition to efforts aimed at understanding why analysts' forecasts tend to be more accurate, researchers also sought forecast methods yielding accuracy greater than analysts. Forecast combination was studied by many researchers.[6] For example, analysts' forecasts were combined with different model forecasts to come up with a new forecast (Conroy & Harris, 1987; Guerard, 1987; Lobo & Nair, 1990; Lobo, 1992).[7] Results consistently showed that forecasts combining a model and summary analysts are more accurate than either the model or summary analysts alone.

Another finding that emerged is that analysts' forecasts tend to be systematically

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[6] Another approach was having humans adjust predictions made by models and combinations of analysts.

[7] Analysts' forecasts in this sense are actually combinations of forecasts from brokerage houses or individual analysts. For example, the I/B/E/S forecasts often used by researchers are arithmetic means of all the available forecasts for a given firm in a given period. Thus, there is actually a two stage aggregation in the research discussed in this section, one done by the forecast service and one by the researcher.

biased upward or optimistic (Brown, Foster & Noreen, 1985; Butler & Lang, 1991). This finding motivated investigations regarding the natural environment in which analysts make their decisions (Schipper, 1991). Research in this area suggests that the incentives present in financial analysts' environment may motivate them to be optimistic. For instance, analysts benefit from good relationships with the management of firms they follow because they are able to gain access to additional information.[8] In surveys, analysts report that information from management is the most important of all information types and the most frequently used source of nonquantitative information (SRI International, 1987). Thus, in order to maintain relationships that foster information transfer from firms to analysts, analysts tend toward optimism (Das, Levine & Sivaramakrishnan, 1993; Francis & Philbrick, 1993). Analysts' optimistic tendencies are likely to affect investor behavior, a related area that has recently interested researchers (Hirst, Koonce & Simko, 1995).

The research cited above has contributed much toward the understanding of financial analysts earnings forecasts. At the same time, there is consensus that much remains to be discovered, especially regarding <u>individual</u> analysts' forecasts (Givoly & Lakonishok, 1984; Schipper, 1991; L. Brown, 1993; P. Brown, 1993).

2.2 JDM RESEARCH IN FINANCIAL ACCOUNTING

While analysts' earnings forecasts have been an active area in the capital markets literature, only a limited number of JDM studies have examined this topic (Maines, 1993). One area that has been studied is the information that analysts use when making forecasts or

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[8] This was corroborated in discussions I had with practicing financial analysts. They overwhelmingly agree that management is a valued source of information and they make efforts to maintain good relationships with management.

recommendations. Analysts seek data regarding earnings, sales (Pankoff & Virgil, 1970), sales growth and profitability (Mear & Firth, 1987), and many other financial statement variables. The annual report was listed as the source of information most used by financial analysts (SRI International, 1987). The FERF study reported that after the annual report, the next three most used sources of information were SEC forms 10K and 10Q and quarterly reports. This survey corroborates experimental research by showing that quantitative, financial data are utilized most frequently by financial analysts. Other studies have found that qualitative information such as the audit opinion (Estes & Reimer, 1979) and president's letter in the annual report (Hofstedt, 1972) also affect financial analysts' decisions.[9] Analysts also view management as an important source of qualitative information (SRI International, 1987). JDM research has identified both quantitative and qualitative cues desired by analysts and the veracity of these findings is bolstered by studies using different research methodologies (e.g. survey research). Thus, one contribution of the JDM literature in financial accounting lies in an improved understanding of the types of information sought and utilized by financial analysts.

Related to the type of information used, research has shown that the amount of detail provided is important to financial analysts. Analysts polled in the FERF survey expressed a preference for more detailed information (SRI International, 1987). Results from Barrett

[9] Acland (1976) shows that a group of nonfinancial variables (taken as a whole) had a significant effect on the decisions of financial analysts. The five variables considered were organizational environment, employee morale, management achievement motivation, employee willingness to abide by institutional norms (lack of which is evidenced by turnover) and managerial satisfaction. It is not clear, however, whether one of these individual variables was more important to the analysts than any other and no analysis was done by the author to determine the effects of individual variables.

(1971) suggest that one reason financial analysts desire detailed information (supplementary to the financial statements) is to make it possible for them to recast financial results using an accounting method different from that used in the actual statements. Two groups of analysts in Barrett's study received financial statements with additional data necessary to convert between the cost and equity method of accounting for investments. The decisions of these two groups exhibited no significant differences. A third group did not receive this extra data and the decisions of the analysts in this group were significantly different from both of the other two groups. Thus, analysts seem to prefer more information to less, presumably because it allows them additional flexibility in analyzing accounting information.

Analysts process information in a variety of ways. Slovic (1969) examined two financial analysts' judgments of the growth potential of stocks. Development of the research instrument was done in collaboration with a professional broker. This same broker was also one of the participants in the study. Even though this individual helped decide which data were important to include, much of this information was not actually used by that same subject. Also, in spite of the fact that the second participant (also a broker) was chosen because he was perceived to use methods similar to the first, the results of the study showed significant variation in cue weighting between the two participants. Bouwman, Frishkoff & Frishkoff (1987) found similar between-analyst variation in a study using protocol analysis of financial analysts' investment screening decisions.

Another issue upon which JDM research has provided some evidence is how financial analysts search for information. In studies using verbal protocol analysis, Biggs (1984) and Bouwman, Frishkoff & Frishkoff (1987) found that experienced analysts sought information in a nonsequential pattern (relative to presentation sequence), as if they were using a "mental checklist" of important items. Those with no experience searched the information sequentially. A study by Jacoby, Kuss, Mazursky & Troutman (1985), using a security selection task, found that the high performers (analysts who chose stocks earning the highest returns over a period of four quarters) acquired similar types and amounts of information across periods whereas low performers acquired significantly less information in later periods. Biggs (1984) and Bouwman, et al (1987) also noted that analysts seek information that may confirm or disconfirm expectations while inexperienced individuals tend to seek only information that confirms expectations.

JDM research in financial accounting has added important insights to our understanding of financial analysts' earnings forecasts. However, there are still many unresolved issues and unanswered questions.

2.3 OF MODELS AND MEN

Forty years ago, Meehl (1954) published a series of studies that began a long debate about human predictive ability. The context of the study was clinical psychologists diagnosing and predicting the presence of psychosis versus neurosis. The study showed that the clinicians were clearly inferior to relatively simple statistical models for clinical diagnosis and prediction. The debate that ensued continued for many years. While there were a small number of studies showing that some people perform as well as statistical models, generally, results confirmed and extended Meehl's original finding (Sawyer, 1966; Ebert & Kruse, 1978; Dawes, 1979; Kleinmuntz, 1990).

As research continued, new approaches to prediction emerged in attempts to both understand and improve predictive judgments made by humans. Einhorn (1972) studied how different methods of information combination affected resulting predictions. Physicians in his study made judgments of individual cues as well as overall judgments based on all the available cues. The individual cues were combined mechanically and compared to the overall judgments. Like many other studies, the overall judgments derived from the mechanical combination of the individual cues accounted for a significantly larger portion of the variance than did the physicians' overall judgments. Libby & Libby (1991) applied Einhorn's methodology in studying the internal control judgments of auditors. The results were similar to Einhorn's. The judgments derived using the participants' cue codings and a mechanical cue combination were more like the judgments of a panel of experts than were the global judgments.

Another attempt to improve human prediction was bootstrapping (Bowman, 1963; Goldberg, 1970). The basic idea of bootstrapping is to identify, as closely as possible, the model used by the expert to mentally combine cues. This is done by regressing the expert's judgment on the cues used in making the judgment. The resulting regression coefficients represent cue weights. Thus, bootstrapping attempts to discern the cue weights implied by the expert's judgments. Once extracted, those weights are used as a form of statistical model to generate predictions. Theoretically, the benefit of bootstrapping results from the combination of cues identified and evaluated by the expert. Bootstrapping models typically make better predictions than humans, but results have rarely shown a bootstrapping model to outperform an optimal statistical model (see Camerer, 1981 for a review).

A recent study by Blattberg & Hoch (1990) reexamined some of the issues studied in this earlier literature. They examine two different predictive domains. One is the prediction of catalog orders and the other is the prediction of coupon redemption rates. Data were gathered from two firms involved in catalog sales and three firms involved in coupon redemptions. Statistical models were developed individually for each firm (five altogether) to assist in improving predictions. Employees experienced in the respective tasks assisted the authors in identifying independent variables to include as regressors. The models were then used to generate predictions for actual catalog orders and coupon redemption rates. The experts made predictions of the same events. A combination of predictions from these two sources resulted in a significant improvement in total variance explained. After assessing the explanatory power of the combined predictions, the authors used partial correlation analysis to isolate the incremental predictive ability of the experts. The contribution of the experts was significant, explaining, on average, an additional 24 percent of the variance relative to the statistical models.

As shown by Blattberg and Hoch (1990), many of the issues brought to the forefront of JDM research by Meehl (1954) are still relevant today. For example, given human cognitive limitations, what is the appropriate role for human judges in predictive judgment? Should predictive tasks in which humans perform poorly be performed by other methods? Are there predictive tasks that humans perform well and if so, how do they differ from tasks in which humans perform poorly? Are there any aspects of predictive judgment that humans do well? How can computer-based decision aids best be developed to minimize the negative impact of human failings in predictive judgment? Given the significant progress in computer technology, questions relating to decision-aid development are of increasing interest today.

CHAPTER III

THEORY

3.1 HUMAN INFORMATION PROCESSING AND PREDICTIVE JUDGMENT

Hypothesized causes of the inferiority of human judgment are discussed frequently in the literature. Probably the most oft-cited cause is limited information processing capacity (Simon, 1955). Because of the nature of the human information processing system, people simply cannot perform a large number of computational operations in a short time. When decisions must be made in an environment characterized by the need for fast, accurate computations, people do not perform well. Even when sufficient time is available to perform optimally, people may still fail to do so. This could be because of unwillingness to expend the required mental effort (cognitive costs) or because of computational errors made during the process (Payne, Bettman & Johnson, 1993). Other causes of poor human performance suggested in the literature are fatigue, emotion, perceptual biases, overconfidence, organizational politics and reputation enhancement (Fischhoff, Slovic & Lichtenstein, 1977).

Notwithstanding these limitations, humans do possess abilities that are helpful in making accurate predictions. Cue identification is one example. The ability to recognize variables useful in predicting future events most likely results from humans' ability to learn and understand causal relationships. Humans are clearly superior to models at learning and building causal connections that relate occurrences of one event to the likelihood of occurrence of another. This ability is especially useful in cases where rare but highly diagnostic cues are present (Meehl, 1954).

Meehl (1954) referred to such cues as "broken-leg cues." For example, if one was building a model to predict outcomes for individuals in a women's Olympic figure skating championship, variables such as past performance in the technical program and long program would probably be included. However, if one of the contestants was whacked on the knee with a club in Detroit a month before the competition, this would probably prevent that contestant from winning. A computer model would not be likely to contain such a variable because of its infrequency of occurrence, but a person could effectively utilize this cue in predicting the outcome of the competition for this individual. Johnson (1988) provides evidence that humans rely heavily upon this type of cue in making judgments. He suggests that so-called experts over-emphasize information unique to the case at hand (broken-leg cues) and ignore information common to all cases. The data typically ignored by people are the data typically utilized by models. While people will examine different data for each case (depending on the case's unique features), models examine the same variables for every case (Hoch & Schkade, 1996). Case-specific data are typically not available for all cases to be judged. Because these data are not available, the judges cannot fully utilize their comparative strength. As a result, human performance, on average, is generally inferior to models since models use data that <u>are</u> available for every case. In essence, people tend to rely upon their inherent comparative strength of utilizing unique data and tend to ignore common data when making predictive judgments. The rationale for this behavior is people's perception that their desired accuracy can be achieved with much less effort using unique instead of common data. This is consistent with the idea that people make trade-offs between effort and accuracy when faced with tasks requiring mental effort (Payne, Bettman & Johnson, 1993).

Identifying complex configural relationships is another skill people sometimes manifest when making judgments. Variables are configurally related when the effect of one independent variable on the dependent variable is conditional on the level of one of the other independent variables. Brown & Solomon (1991) demonstrate that experienced auditors utilize non-linear relationships in their judgments of the risk of material misstatement of accounts receivable.

Humans also possess the ability to rapidly and effectively adapt to changes in decision environments. Because people can recognize changes in causal relationships, they can adapt their knowledge of a particular predictive domain to incorporate environmental changes. Obviously, models do not have this ability. Changes cannot be incorporated until the model builders make the needed adjustments. Thus, if predictions are needed in a domain characterized by a rapidly changing environment, the adaptability of humans will help them predict more accurately than relatively inflexible, statistical models.

Finally, humans have the ability to evaluate qualitative factors.[10] Subjective variables are of little use to statistical models because they are typically not stated in quantitative terms. Only when such variables are translated by humans can they be utilized by models. In summary, humans can contribute important skills to improving predictions, namely cue

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[10] Examples include the evaluation of the strength of a component of an internal control system (Libby & Libby, 1991) and the evaluation of the stage of development of cancer (Einhorn, 1972). In the first example, the judgments were based upon written descriptions and in the second example, the judgment were based upon pictures of tissue from various patients.

identification, rapid adaptability to dynamic predictive environments and subjective variable assessment.

Whether or not they are explicitly aware of these abilities, financial analysts exhibit behavior that is consistent with attempts to capitalize upon them. For example, financial analysts list firm management as the most important information source (SRI International, 1987). One explanation for this preference is that analysts seek to utilize their ability to integrate "broken-leg" cues into their judgments. Assuming "broken-leg" cues are most likely to be qualitative, it seems sensible for analysts to earnestly seek for qualitative information from management. Similarly, analysts have a strong preference for timely information. This preference may result from the analysts' desire to capitalize on their ability to quickly adapt to new information. The sooner new data are received, the sooner they can be integrated into mental models and forecasts. Because more timely forecasts have been shown to be more accurate (O'Brien, 1988), analysts are likely to have a strong preference for timely information. Thus, analyst behavior seems consistent with the idea that people tend to rely upon their strengths when making judgments such as earnings forecasts.

One attribute that theoretically distinguishes humans from models in making forecasts is domain specific knowledge. Forecasts utilizing domain specific knowledge could be gathered from individual analysts or from commercially available services. Gathering forecasts from individual analysts presents significant problems. For example, response rates for mailed instruments are low. Personally administered instruments are problematic because of access to subjects and cost. Also, analysts are likely to be reluctant to give out their forecasts since they represent one of the "products" analysts generate to gain their livelihoods. Forecasts gathered in such a manner are likely to be less reliable because analysts will be less motivated to do their best in making such forecasts.

Commercially available forecast services, like I/B/E/S, overcome the difficulties noted with data collection via research instruments. The I/B/E/S forecasts represent judgments made in a context wherein analysts possess and are motivated to use their domain specific knowledge as effectively as possible. The information set is not restricted and thus, if analysts possess incremental predictive ability, this context provides the best opportunity to demonstrate their abilities. Analysts are motivated to make their best efforts in providing their forecasts to commercial services because such forecasts affect their track records and reputations. One other significant benefit is that a large quantity of data is available.

3.2 STATISTICAL MODEL PREDICTION

Even though statistical model predictions are generally more accurate than human predictions, statistical models are not a panacea for universally improving predictions. Models also have weaknesses. For example, models cannot perform any of the judgmental tasks required in building models. Such tasks could include determining the appropriate independent variables, determining the appropriate functional form, specifying the appropriate autocorrelation structure, etc. Models are also not able to utilize rare but diagnostic cues when they are available. Furthermore, models cannot easily judge subjective, but nevertheless, predictive variables. Finally, models are not well-suited to adapt to changing environments. This could be a significant challenge in predicting earnings. Thomas (1993) discusses evidence suggesting that the process generating earnings has slowly changed over the last 30 years. There is also evidence suggesting that the earnings generation process differs from firm to firm and that these processes are nonstationary rather than stationary (Ziebart, 1987). Assuming the earnings generation process is ever-changing, the ideas discussed earlier predict that human forecasts will outperform statistical model forecasts.

Research in AI/expert systems seeks to develop models that exhibit adaptability and that automate some judgmental tasks traditionally performed by humans. The capabilities of such systems have increased dramatically since this research commenced (Messier, 1993). Nevertheless, such systems are not in widespread use, indicating that the objectives of this research area have not yet been attained.

3.3 COMPLEMENTARITY OF HUMANS AND MODELS

The relative strengths and weaknesses of humans and models in making predictions are complementary. The weaknesses of humans are the strengths of models and the strengths of humans are the weaknesses of models. For example, while humans have limited computational capacity, models are relatively unlimited in their ability to quickly perform complex computations. Similarly, the flexibility of humans to adapt to changes in prediction environments is an important ability that models lack. Because of the complementarity of humans and statistical models strengths and weaknesses, researchers have sought improvement in predictive accuracy by combining these two prediction methods.

Combining predictions to improve overall accuracy has been effective in many contexts (Clemen, 1989). Combinations studied in the literature include model and model (Granger & Ramanathan, 1984), expert and expert (Ashton & Ashton, 1985), model and consensus forecasts of experts (Guerard, 1987; Conroy & Harris, 1987), and model and individual experts (Blattberg & Hoch, 1990). The first three combination methods mentioned above have been studied relatively more than the latter one. Thus, an additional contribution of this dissertation is providing evidence concerning the combination of models with the judgments of individual experts in the area of earnings forecasts.

Most of the existing forecast combination literature attempts to show that improved predictions result from combining forecasts generated by different methods. The emphasis has been on the outcome produced by the combination method (Guerard, 1987; Conroy & Harris, 1987; Wolfe & Flores, 1990). As a result of this emphasis, little has been learned regarding the specific contribution made by individuals to the improvement of predictions. One notable exception is the study by Blattberg and Hoch (1990) mentioned above. Like other studies in the area of forecasting, it demonstrates a significant improvement in predictive accuracy from the combination of different prediction methods. In addition, the study quantifies the contribution of the individual expert in terms of incremental predictive ability.

Scientific skepticism prevents us from assuming the results of the Blattberg and Hoch (1990) tasks will replicate in the earnings forecast domain. On the other hand, the results of the forecast combination studies cited above suggest that individual analysts contribute significantly to earnings forecast quality. In addition, earnings prediction models have undergone a great deal more scrutiny than the models used by Blattberg and Hoch (1990). It is plausible that state-of-the-art, univariate time-series models of earnings are capturing close to the maximal information available to this type of statistical method, given current data sources.[11] Because summary analysts' forecasts consistently outperform thoroughly tested models, it may be that the strong performance of analysts' forecasts is due to the strength of individual analysts' forecasting ability.

The foregoing discussion suggests reasons why analysts are likely to make a significant contribution to the improvement of earnings forecasts. Existing research does not satisfactorily address the issue of <u>individual</u> analysts' contribution to forecast quality. Thus, this dissertation seeks to provide insights regarding individual analysts' contribution to the improvement of earnings forecasts.

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[11] Advances in technology may enhance the quality and quantity of information in existing databases. In addition, advances in modeling technology (e.g. new statistical techniques) may eventually improve performance.

CHAPTER IV

RESEARCH METHOD

The accomplishment of this study's objectives required the gathering and preparation of archival data from various sources and the analysis of the resulting data. The analysis consists of two components. The first component was accomplished in two steps. The first step assessed the relative accuracy of different methods of generating one quarter-ahead earnings forecasts. Forecast errors derived from the forecasts were analyzed using multivariate analysis of variance (MANOVA). The second step of the first component also used MANOVA to examine the relationship between analysts' forecast bias and model forecast bias.

The second component is an analysis of the incremental predictive ability of individual analysts and statistical models to forecast accuracy. This was examined using regression analysis. Additionally, a related analysis examines whether or not analysts or models demonstrate differing incremental predictive ability between industries.

4.1 SAMPLE

4.1.1 Firms The selection of firms used in this study was constrained by two factors. The first was the number of analysts forecasting EPS for a given firm. Firms with less than five analysts providing forecasts were eliminated. Of the 595 firms that were included in both the I/B/E/S and Compustat databases, 256 had five or more analysts with a sufficient number of forecasts.[12] Another constraint was data availability for the generation of statistical model forecasts. For the accuracy and bias analyses, 43 firms had insufficient historical data, thus reducing the final sample to 213. For the incremental predictive ability analysis, 42 firms had insufficient historical data resulting in a final sample of 214. Firms were grouped according to SIC codes to facilitate analysis of the interaction between forecast generation method and firm type. Two groupings were used. One categorization contained 17 groups and the other categorization contained 12 groups. The details regarding these groupings are shown in Tables 1A and 1B.

4.1.2 Time Period Quarterly data from the years 1990-1993 were used for all analyses. The purpose of examining four years of data was to reduce the size of the data set to a manageable level. Limiting firms rather than time periods was also considered as a constraint. However, limiting firms would have reduced the total number of analysts included in the study since analysts tend to follow firms across time. Since one major objective of this study was to understand how individual analysts' forecasts relate to forecasts generated by other methods, it was more important to maximize the number of analysts rather than the number of time periods included in the study. Balancing the size of the data set with the objective of maximizing the number of analysts was most effectively accomplished by imposing the time period constraint noted above.

The final data set consisted of the twelve quarters starting with the second quarter of 1990 and ending with the first quarter of 1993. All 16 quarters between 1990 and 1993

[12] The number of forecasts considered sufficient for including an analyst was 12 forecasts out of the 16 quarterly forecasts starting in the first quarter of 1990 and ending in the last quarter of 1993.

TABLE 1A
Details of Firm Group Category - 17 Groups

Firm Group	Number of Firms	SIC Code	Industry Description
1	6	1000-1999	Mining, Construction
2	20[a]	2000-2599	Food, Tobacco, Textiles, Apparel, Wood Products, Furniture & Fixtures
3	13	2600-2699	Paper
4	9	2700-2799	Publishing & Printing
5	28	2800-2899	Chemicals
6	12	2900-2999	Petroleum & Coal Products
7	8	3000-3499	Rubber & Plastics, Leather, Stone, Clay & Glass, Primary Metals, Fabricated Metals
8	16	3500-3599	Industrial Equipment
9	11	3600-3699	Electronic & Electric Equipment
10	12	3700-3799	Transportation Equipment
11	15	3800-3999	Instruments, Misc. Manufacturing
12	11	4000-4599	Transportation
13	11	4600-4999	Communications, Utilities
14	10	5000-5999	Wholesale & Retail
15	17	6000-6099	Banking
16	6	6100-6999	Securities Brokerages, Insurance, Real Estate
17	8	7000-7999	Personal, Business & Repair Services, Recreation.
Total	213[b]		

[a] This represent firms for the accuracy and bias analysis. For the incremental predictive ability analysis, the number of firms is 21.

[b] For the incremental predictive ability analysis, the total number of firms is 214.

TABLE 1B
Details of Firm Group Category - 12 Groups

Firm Group	Number of Firms	SIC Code	Industry Description
1	6	1000-1999	Mining, Construction
2	20[a]	2000-2599	Food, Tobacco, Textiles, Apparel, Wood Products, Furniture & Fixtures
3	22	2600-2799	Paper, Publishing & Printing
4	28	2800-2899	Chemicals
5	12	2900-2999	Petroleum & Coal Products
6	8	3000-3499	Rubber & Plastics, Leather, Stone, Clay & Glass, Primary Metals, Fabricated Metals
7	27	3500-3699	Industrial Equipment, Electronic Equipment
8	27	3700-3999	Transportation Equipment, Instruments, Misc. Manufacturing
9	22	4000-4999	Transportation, Communications, Utilities
10	10	5000-5999	Wholesale & Retail
11	23	6000-6999	Banking, Securities Brokerages, Insurance, Real Estate
12	8	7000-7999	Personal, Business & Repair Services, Recreation.
Total	213[b]		

[a] This represent firms for the accuracy and bias analysis. For the incremental predictive ability analysis, the number of firms is 21.
[b] For the incremental predictive ability analysis, the total number of firms is 214.

could not be used because of missing data points for many individual analysts. The quarters not included in the analysis (1st quarter of 1990 & 2nd, 3rd & 4th quarter of 1993) were eliminated because they had the highest occurrence of missing data points among the individual analysts. The rates of missing data for the eliminated quarters were 14%, 19%, 16% and 19%, respectively. Missing data rates for all quarters are shown in Table 2.

Some analysts had missing data in quarters other than those that were eliminated. When this was the case, these missing data points were filled in. The method used sought to shift the fewest number of forecasts possible to fill in the missing forecast. If the missing forecast was in the first two years of the test period (1990-1991), any preceding forecasts were shifted forward to fill in the gap. If the missing forecast was in the last two years of the test period (1992-1993), any subsequent forecasts were shifted backward to fill in the gap. For example, if an analyst was missing the forecast for the third quarter of 1990, the first and second quarter forecasts of 1990 were shifted forward to fill this gap. In cases like this, the 1990 first quarter forecast was not eliminated, but was used to fill in the missing data point. Thus, the 1990 first quarter forecast became the second quarter forecast and the second quarter forecast became the third quarter forecast.

The main benefit to this procedure was the facilitation of the analysis. The sample size would have been significantly reduced had this not been done because any series of analyst's forecasts with a missing forecast would be ignored by the software used for the analysis. The cost of this procedure is that no inferences can be drawn about specific periods. The benefit outweighed the cost because the focus of this study is on analysts, not time periods and making these data substitutions allowed for the most analysts to be included

TABLE 2
Missing Analysts' Forecasts By Period

Period	Mean Missing Forecasts	Percent Missing Forecasts
90-1	30.4	14%
90-2	19.8	9%
90-3	8.4	4%
90-4	6.2	3%
91-1	11.4	5%
91-2	6.8	3%
91-3	5.8	3%
91-4	5.8	3%
92-1	5.4	3%
92-2	3.2	2%
92-3	4	2%
92-4	4.6	2%
93-1	11.8	6%
93-2	41.4	19%
93-3	34	16%
93-4	40.2	19%

in the analysis.

4.2 DATA SOURCES

4.2.1 Analysts' Forecasts Individual analysts' and summary analysts' forecasts of quarterly EPS were gathered from the I/B/E/S database for the years 1990-1993.[13]

4.2.2 Model Forecasts Statistical model forecasts were generated using historical data. The capital markets literature offers a myriad of models for forecasting quarterly EPS. ARIMA-type models are identified in accounting literature as reliable for forecasting quarterly earnings (Brown et al, 1987a). The ARIMA model developed by Brown and Rozeff (1979) is one such model. Research has shown this model to be the most accurate of those commonly used in the accounting literature (Bathke & Lorek, 1984). In addition to this model, a hybrid model that utilizes both times series data and macroeconomic data was estimated and used to generate forecasts. The purpose of using an additional model was to prevent any potential results from being model specific and to identify other variables that are useful in forecasting earnings. This was done by modifying the Brown-Rozeff model. Specifically, a constant term and one of four additional variables (gross domestic product, individual firm revenues, prior period stock prices and total corporate profits) were added and the moving average term was removed.[14] Thus, for each firm, five model forecasts

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[13] The Institutional Brokers Estimate System (I/B/E/S) is a service of I/B/E/S Inc. and has been provided as part of a broad academic program to encourage earnings expectations research.

[14] A constant was added to stabilize the estimations. Estimations were done without a constant and numerous problems emerged. For example, the Durbin-Watson statistics for numerous firms indicated that the residuals still exhibited autocorrelation, in spite of using both differenced independent variables and an estimation procedure specifically intended to eliminate autocorrelation. Additionally, models were estimated for about 40 firms using models with and

were estimated: a time series model and four hybrid models. Quarterly data from 1980 to 1989 were used to estimate the models. Statistical model forecasts were generated for each quarter of the years 1990 to 1993. The forecasts from each model for a given firm were compared to the actual values for the same firm to determine the most accurate model forecast.[15] Only the most accurate model forecast was used in the analysis. The number of times each model was used in the analyses and the equation for each model is shown in Table 3.

4.2.3 Actual Quarterly EPS Actual EPS (excluding extraordinary items) data were taken from Compustat. Although I/B/E/S provides actual EPS values, researchers have found Compustat to be a more reliable source of quarterly EPS data (Philbrick & Ricks, 1991).

4.3 ANALYSES

Two types of analyses were performed. The first examines forecast accuracy and bias of analysts and models. The purpose of the second is to examine the incremental predictive ability of individual financial analysts.

4.3.1 Accuracy Analysis This analysis assesses the relative accuracy of the different forecast generation methods. This is important because it will positively establish the differential performance of the forecast generation methods.

Five analysts were used for each firm and period to be included in the analysis. For firms with more than five analysts' forecasts, the five analysts with the most complete data

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without a constant. The forecasts produced by the model with a constant were more accurate 73 percent of the time. Thus, the model with the constant was chosen.

[15] The mean square error (MSE) metric was used to make this evaluation.

TABLE 3

Number of Times Different Statistical Models Used in Analysis

Model Type	Times Used	Percent
Times Series[a]	104	48.8%
Hybrid - GDP[b] (Gross Domestic Product)	25[c]	11.7%
Hybrid - REV[b] (Firm Revenues)	31	14.6%
Hybrid - STP[b] (Firm Stock Price)	41	19.3%
Hybrid - PRF[b] (Total Corporate Profits)	12	5.6%
Total	213[d]	100%

[a] The equation for the Brown-Rozeff model is

$$EPS_{jt} = EPS_{j,t-4} + a_1(EPS_{j,t-1} - EPS_{j,t-5}) + a_2e_{j,t-4}$$

[b] The equations for the hybrid models are

$$EPS_{jt} = a_0 + EPS_{j,t-4} + a_1(EPS_{j,t-1} - EPS_{j,t-5}) + a_2(GDP_t - GDP_{t-4}) + e_{jt}$$
$$EPS_{jt} = a_0 + EPS_{j,t-4} + a_1(EPS_{j,t-1} - EPS_{j,t-5}) + a_2(REV_{j,t-1} - REV_{j,t-5}) + e_{jt}$$
$$EPS_{jt} = a_0 + EPS_{j,t-4} + a_1(EPS_{j,t-1} - EPS_{j,t-5}) + a_2STP_{jt} + e_{jt}$$
$$EPS_{jt} = a_0 + EPS_{j,t-4} + a_1(EPS_{j,t-1} - EPS_{j,t-5}) + a_2(PRF_t - PRF_{t-4}) + e_{jt}$$

EPS_{j*} = Quarterly EPS for firm j and the period noted (* = t, t-1, t-4 or t-5).
e_{j*} = Residual for firm j and the period noted (*= t or t-4).
GDP_* = Forecasted Gross Domestic Product for the period noted (*= t or t-4).
REV_{j*} = Net Revenue for firm j and the period noted (*= t-1 or t-5).
STP_{jt} = Stock Price for firm j, period t.
PRF_* = Forecasted Total Corporate Profit for the period noted (*= t or t-4)

[c] For the incremental predictive ability analysis, the number of firms is 26.

[d] Total firms for the incremental predictive ability analysis is 214.

series were chosen. Next, forecast errors were computed for each of the analysts. Forecast errors were computed using the absolute percentage error (APE) and percentage error (PE) metric. APE was chosen because it does not alter the magnitude of error (as does a squared error metric) and because of its frequent use in the literature. PE was chosen to facilitate bias analysis since it preserves the positive/negative characteristic of the forecast errors.[16] The formula for the APE metric is as follows:

$$\mathbf{APE_{ijt}} = |\mathbf{F_{ijt}} - \mathbf{A_{jt}}|/\mathbf{SP_{jt}} \tag{1}$$

where

APE_{ijt} = absolute percentage error for analyst i, firm j, period t,
F_{ijt} = analysts i's forecast for firm j, period t,
A_{jt} = actual EPS for firm j, period t,
SP_{jt} = stock price for firm j, period t.

Forecast errors were also computed using this metric for the other three forecast generation methods. The three other forecast generation methods are statistical model, summary analysts and combined forecasts. The combined forecast was generated by computing the arithmetic mean of each of the five individual analysts' forecasts with the model forecast. Thus, five combined forecasts resulted for each firm in every quarter. The resulting data set consisted of four elements for a given firm in a given period. For example, for firm 1,

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[16] The choice of metrics may lead some to infer I have assumed an incentive structure that penalizes overestimation and underestimation equally. In reality, the incentives faced by analysts are varied and complex. They may include, but are not limited to a desire to maintain a positive working relationship with forecastee management (the incentive most frequently noted in the existing literature), an asymmetric loss function, and a desire to be one of the top analysts in a respective industry (See footnote 1). Because these institutional incentives influence analysts in opposite ways, it is not clear which metric best represents existing incentives. The choice of metric is not based on assumed incentive structure. Rather, it is based upon the desire to objectively measure the forecast errors made by analysts.

quarter 1, the first element consisted of five individual analysts' forecasts. The second element consisted of the model forecast, the third element consisted of the summary analysts' forecast and the last element consisted of five combined forecasts. Multivariate analysis of variance (MANOVA) was used to analyze the data described above. The three factors (independent variables) used in the analysis are firm group, time period and forecast generation method. The alternative hypothesis is that the summary analysts' forecasts will be the most accurate, combined forecasts will be the second-most accurate, individual analysts will be the third most accurate and models will be the least accurate. There are no specific expectations regarding the firm and time period factors other than the result from O'Brien (1990) that some periods and some firms are easier to predict than others.

4.3.2 Bias Analysis Optimism (systematic upward bias) in individual analysts' forecasts is a recently noted phenomenon (Butler & Lang, 1991). Evidence suggests that analysts' forecasts are consistently higher than actual EPS and research has sought to identify and examine possible explanations for these results (Francis & Philbrick, 1993). The purpose of the bias analysis in this study is to document the relationship between individual analysts' forecast bias and the forecast bias of the statistical models used in this study. The analysis of forecast bias seeks to establish the presence of the bias for the sample of analysts (both individual and summary) and model forecasts used in this study. Any bias resulting from these forecast generation methods will be compared for significant differences. The alternative hypothesis is that the bias of analysts' forecasts (individual and summary) will be optimistic and will be significantly different from the bias of the model forecasts.

One motivation for this analysis is to explicitly document part of the process producing the empirical result from prior research that combinations of analysts' forecasts and model forecasts are more accurate than either forecast alone. Specifically, assuming that model forecasts exhibit either an absence of or pessimistic forecast bias and that individual analysts exhibit optimistic forecast bias, a combination of the two will, on average, be less biased (more accurate). This is at least partly because the errors will offset each other in the combination process.

Like the accuracy analysis, this analysis uses forecast error as the dependent variable. However, unlike the accuracy analysis, the forecast errors were computed using the PE metric. The formula for the PE error metric is as follows:

$$\mathbf{PE_{ijt} \quad = \quad [F_{ijt} \; - \; A_{jt}]/SP_{jt}} \quad (2)$$

where

PE_{ijt} =percentage error for analyst i, firm j, period t,
F_{ijt} =analysts i's forecast for firm j, period t,
A_{jt} =actual EPS for firm j, period t,
SP_{jt} =stock price for firm j, period t.

MANOVA was used to analyze this set of data. The three factors used in the accuracy analysis (firm group, time period and forecast generation method) are also used in the bias analysis. In addition to the MANOVA analysis, the sign test, a non-parametric method was used in analyzing this data. This test provides evidence regarding the direction of any bias, but not regarding the magnitude of bias. This additional test will be employed to triangulate results from the first test.

4.3.3 Incremental Predictive Ability Analysis The incremental predictive ability of analysts and models was examined using regression analysis. The first test performed was to determine the existence of incremental predictive ability for both individual analysts and models. The first step in performing this test was to run a full effects regression model. The regression equation used for this step was as follows:

$$\mathbf{EPS_{jt}} = \mathbf{b_o} + \mathbf{b_1 MF_{jt}} + \mathbf{b_2 AF_{1jt}} + \mathbf{b_3 AF_{2jt}} + \mathbf{b_4 AF_{3jt}} + \mathbf{b_5 AF_{4jt}} + \mathbf{b_6 AF_{5jt}} + \mathbf{e_{ijt}}, \quad (3)$$

where

EPS_{jt}	=	Quarterly EPS for firm j, period t,
AF_{ijt}	=	Analyst's Forecast for analyst i, firm j, period t,
MF_{jt}	=	Model Forecast for firm j, period t,
e_{ijt}	=	Error term for analyst i, firm j, period t.

Two reduced model regressions were then run. First, the model forecast was removed from equation (3) leaving only the analysts' forecasts. Then all the analysts' forecasts were removed from equation (3), leaving only the model forecast. An F statistic was constructed using the sum of squared errors for each of the three regressions to test whether or not the increment in variance explained was significantly different from zero (Neter, Wasserman & Kutner, 1985, p. 290-291). The hypothesis regarding incremental predictive ability is that both model forecasts and the analysts' forecasts will add a significant amount of explanatory power. This is consistent with research in other domains wherein the idea of incremental predictive ability has been examined (Blattberg & Hoch, 1990). It is also consistent with research suggesting that people do not fully integrate time series properties of earnings into their forecasts (Hand & Maines, 1994).

An interesting finding from O'Brien (1990) is that some firms' earnings are easier to predict than others. This finding is extended by examining whether or not there is a differential incremental contribution made by analysts based on industry. For example, some industries may exhibit relatively stable earnings (e.g. public utilities) whereas others are likely to be volatile (e.g. biotechnology). Analysts may contribute relatively less to forecast accuracy in stable industries as opposed to volatile industries. Regression was used to examine the issue of differing incremental predictive ability between industries. The first step of this analysis was to regress the individual analysts' forecasts on the model forecast for a given firm and quarter. The purpose of this regression was to identify the portion of the model forecast that is not shared with the analysts' forecasts. The regression equation used is as follows:

$$MF_{jt} = c_0 + c_1 AF_{ijt} + e_{ijt}, \qquad (4)$$

where

AF_{ijt} = Analyst's Forecast for analyst i, firm j, period t,
MF_{jt} = Model Forecast for firm j, period t,
e_{ijt} = Error term for analyst i, firm j, period t.

This regression was run with each of the five sets of individual analysts' forecasts. The residuals from these five regressions were then used as independent variables in another regression to test for differential incremental predictive ability between industries. In addition to the five sets of residuals from equation (4), eleven dummy variables were crossed with the five residual variables and added to this regression equation. The regression equation is as follows:

$$EPS_{jt} = d_0 + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + d_6(DUM_1{*}e_{1jt}) + \ldots +$$

$$d_{60}(DUM_{11}{*}e_{5jt}) + u_{jt}, \qquad (5)$$

where

EPS_{jt}	=	Quarterly EPS for firm j, period t,
DUM_i	=	Dummy variable for firm group i,
e_{ijt}	=	Residual term from equation (4) for analyst i, firm j, period t,
u_{jt}	=	Error term for firm j, period t.

After this model was run, a reduced model was run. The reduced model is as follows:

$$EPS_{jt} = d_0 + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + u_{jt} \qquad (6)$$

The first step of this analysis was to compute an F statistic to determine if there was a significant amount of incremental explained variance between the full model and the reduced model. After this determination was made, the coefficients on the interaction terms (e.g. $DUM_1{*}e_{1jt}$) were examined for statistical significance. The alternative hypothesis for this test is that the relatively volatile industries will have significant regression coefficients on the interaction terms, indicating greater differential incremental predictive ability for analysts making forecasts for firms in these industries. After this was completed, a similar analysis was performed. The only change was that the analysts' and model forecasts were interchanged in equation 4, thus focusing on the differential incremental predictive ability of the models. The alternative hypothesis for this test is that the relatively stable industries will have significant regression coefficients on the interaction terms, indicating greater differential incremental predictive ability for model forecasts for firms in these industries.

CHAPTER V

RESULTS

5.1 ACCURACY ANALYSIS

This analysis uses forecast errors measured using absolute percentage error (APE)[17]. The data were transformed using a log transformation because the untransformed data contained outliers. In some cases, the forecast error was zero because the analyst's prediction was exactly correct. These values could not be transformed using a log transformation because the natural log of zero is undefined. This problem was dealt with using a truncation procedure. The first step was to assess the minimum transformed forecast error for all forecast methods. Then, a value less than this was inserted for all cases where the transformed forecast error was undefined. This maintained the ordering of analysts' transformed forecast errors. None of the transformed forecast errors were less than -15. This value (-15) was used as the transformed forecast error for cases in which an analyst's forecast was exactly correct. Histograms of the transformed data showed normally distributed data except for a small group of data points at -15.

The first analysis used MANOVA to determine whether or not there are significant differences for the between-subject (firm group) and within-subject (forecast generation method) effects. The results for the between-subjects variable are significant ($F(16,196)=3.648$, $p=.000$) for both 17 firm groups and for 12 firm groups

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[17] The formula is |Forecast-Actual|/Stock Price.

(F(11,201)=2.085, p=.023). The results for the within-subject variable are highly significant for both 17 (F(11,186) = 6.286, p = .000; Wilks' Lambda=.729) and 12 firm groups (F(11,191)=5.336, p=.000; Wilks' Lambda=.765). The interaction between forecast generation method and firm group is not significant for 17 firm groups (F(176,1719)=1.123, p=.139; Wilks' Lambda=.371) and is marginally significant for 12 firm groups (F(121,1516)=1.221; p=.058; Wilks' Lambda=.482). The overall results of the accuracy analysis suggest that forecasts produced using different methods vary significantly in accuracy. While there may be some be interaction between the method used to generate forecasts and the type of firm whose EPS is being forecasted, it appears to be marginal.

The next step is to examine all possible combinations of forecast generation method (within-subject) in order to understand the sources of the overall difference. The results of these contrasts showed significant differences among all contrasts except the contrast between the individual analysts' forecasts and the I/B/E/S summary forecasts. The statistics relating to these contrasts are shown in Tables 4A and 4B. Means and standard deviations for the untransformed data are shown in Tables 5 and means and standard deviations for the transformed data are shown in Table 6.

As predicted, these results indicate significant accuracy differences between forecast generation methods except for individual analysts and the I/B/E/S summary. As hypothesized, the results suggest that the model forecasts are the least accurate. Analyst generated forecasts (individual analyst's forecasts and the I/B/E/S summary forecasts) are the most accurate. This result is consistent with the hypothesis for the I/B/E/S summary

TABLE 4A
MANOVA Contrast results - APE (log transformation)
Firm groups = 17

Contrast	F statistic	p Value
A vs. M	51.709	0.000
A vs. S	1.890	0.171
A vs. C	66.031	0.000
M vs. S	39.138	0.000
M vs. C	10.537	0.001
S vs. C	37.568	0.000

A=Ind analysts, M=Model, S=I/B/E/S Summary, C=Combined

TABLE 4B
MANOVA Contrast results - APE (log transformation)
Firm groups = 12

Contrast	F statistic	p Value
A vs. M	38.541	0.000
A vs. S	1.383	0.241
A vs. C	54.884	0.000
M vs. S	28.806	0.000
M vs. C	4.707	0.031
S vs. C	31.528	0.000

A=Ind analysts, M=Model, S=I/B/E/S Summary, C=Combined

TABLE 5
Means and standard deviations for APE

Forecast Type	Mean Forecast Error	Std Dev
Individual Analysts (A)	0.0099	0.0303
Model (M)	0.0134	0.0342
I/B/E/S Summary (S)	0.0101	0.0295
Combined (C)	0.0107	0.0292

TABLE 6
Means and standard deviations for transformed APE

Forecast Type	Mean Forecast Error	Std Dev
Individual Analysts (A)	-6.222	2.622
Model (M)	-5.513	1.606
I/B/E/S Summary (S)	-6.124	2.524
Combined (C)	-5.664	1.518

forecasts, but not for the individual analysts' forecasts. The combined forecasts fall between the analyst generated forecasts and the models. This result was hypothesized in relation to the I/B/E/S summary forecasts, but not in relation to the individual analysts' forecasts. This accuracy ordering is both similar to and different from prior research findings. Consistent with other studies in the accounting literature, the model forecasts are found to be the least accurate (Fried & Givoly, 1982). However, unlike other studies dealing with forecast combination, the combined forecasts are less accurate than the analyst generated forecasts (Conroy & Harris, 1987; Guerard, 1987; Lobo, 1992). One potential reason for this difference is that most prior forecast combination studies combined summary and model forecasts, not individual and model forecasts as was done in this study.

5.2 BIAS ANALYSIS

The results of this analysis reflect the use of the percentage error metric (PE). Because of outliers, the data were transformed using a square-root transformation. In cases where the forecast was higher than actual EPS (thus resulting in a negative percentage error), the negative sign was temporarily removed so square roots could be computed. After the square roots were computed, the negative signs were imposed back on the data, thus allowing for the detection of any systematic bias. The statistical results reported are based on the transformed data since the transformed data were closer to being normally distributed than the actual error measures.

The results of the MANOVA show significant differences between firm groups (between-subject) for both the 17 ($F(16,196)=2.161$, $p=.008$) and 12 ($F(11,201)=1.811$, $p=.054$) firm groupings. The results also show significant differences between the different forecast generation methods (within-subject) for both the 17 firm grouping ($F(11,186)=5.116$, $p=.000$; Wilks' Lambda=.768) and the 12 firm grouping ($F(11,191)=5.041$, $p=.000$; Wilks' Lambda=.775). The interaction between forecast generation method and firm group is significant for the 17 firm grouping ($F(176,1719)=1.217$, $p=.033$; Wilks' Lambda=.343) but is not significant for the 12 firm grouping ($F(121,1516)=1.142$, $p=.147$; Wilks' Lambda=.504). These results suggest that there are significant differences between the mean percentage errors for different forecast generation methods. However, they do not indicate the direction of any bias. The next step involves examining mean percentage error for the different forecast generation methods as well as examining contrasts between the means, including a test of whether or not the means are significantly different from zero. Results for contrasts between all pairs of forecast generation methods are shown in Tables 7A and 7B. Contrast results that test for differences from zero for mean percentage error are shown in Tables 8A and 8B. Mean percentage errors for the different forecast generation methods are shown in Table 9 and the means for the transformed data are shown in Table 10. The combination of the contrast results and mean percentage errors reveal a pattern of bias different than hypothesized. While all possible combinations of forecast generation method pairings are statistically different from each other, neither the individual nor the I/B/E/S summary analyst forecasts are significantly different from zero. Both individual and the summary analysts show no significant bias, neither optimistic nor pessimistic. Mean percentage error for the model forecasts is significantly different from zero and shows an optimism bias. The results for the combined forecasts is the same as for the model forecasts.

TABLE 7A
MANOVA Contrast results - PE (sqrt transformation)
Firm groups = 17

Contrast	F (1,196)	p Value
A vs. M	36.267	0.000
A vs. S	7.220	0.008
A vs. C	24.329	0.000
M vs. S	25.670	0.000
M vs. C	44.705	0.000
S vs. C	9.390	0.002

A=Ind analysts, M=Model, S=I/B/E/S Summary, C=Combined

TABLE 7B
MANOVA Contrast results - PE (sqrt transformation)
Firm groups = 12

Contrast	F (1,201)	p Value
A vs. M	36.090	0.000
A vs. S	7.047	0.009
A vs. C	24.395	0.000
M vs. S	25.464	0.000
M vs. C	44.812	0.000
S vs. C	9.236	0.003

A=Ind analysts, M=Model, S=I/B/E/S Summary, C=Combined

TABLE 8A
MANOVA contrasts results - Test for Difference from Zero
Firm groups = 17

Forecast Type	F (1,196)	p Value
Individual Analysts (A)	2.581	0.110
Model (M)	32.764	0.000
I/B/E/S Summary (S)	0.270	0.604
Combined (C)	3.351	0.069

TABLE 8B
MANOVA contrasts results - Test for Difference from Zero
Firm groups = 12

Forecast Type	F(1,201)	p Value
Individual Analysts (A)	1.895	0.170
Model (M)	32.793	0.000
I/B/E/S Summary (S)	0.101	0.750
Combined (C)	4.016	0.046

TABLE 9
Means and standard deviations for PE

Forecast Type	Mean Forecast Error	Std Dev
Individual Analysts (A)	0.00165	0.0319
Model (M)	0.00424	0.0365
I/B/E/S Summary (S)	0.00216	0.0311
Combined (C)	0.00285	0.0310

TABLE 10
Means and standard deviations for transformed PE

Forecast Type	Mean Forecast Error	Std Dev
Individual Analysts (A)	-0.00545	0.0998
Model (M)	0.0194	0.114
I/B/E/S Summary (S)	-0.00203	0.100
Combined (C)	0.00573	0.103

This unexpected result regarding analysts' bias motivated further analysis using the sign test. Because of the error metric used, the magnitude of the forecasts errors could be masking the actual bias displayed by analysts. It is possible that the positive percentage errors were systematically larger than the negative percentage errors and such a pattern would mask the actual frequency of positive and negative forecast errors. The sign test considers only the sign of the forecast errors and thus gives a clearer picture of the frequency of positive and negative forecast errors. The number of positive and negative forecasts errors was counted for all forecast generation methods in all twelve periods used and then Z-values for the sign test were computed.[18] The results are shown in Table 11. Contrary to the hypothesis, the results show a consistent pessimistic bias for the individual analysts' forecasts. The model forecasts are significantly different from the individual analysts' forecasts, as expected and exhibit a consistent optimism bias. Summary analysts' forecast bias is not as consistent, but leans toward pessimism. Given the results for the analysts and the model, the bias results for the combined analysts, by construction, fall at a point between the individual analysts' and the model forecast results.

5.3 INCREMENTAL PREDICTIVE ABILITY ANALYSIS

The results of this analysis indicate that both individual analysts' forecasts and model forecasts exhibit incremental predictive ability. The results of this statistical test are reported in Table 12A. The results in which the reduced model includes only the model forecasts

[18] If forecast error was zero (i.e. forecasted EPS was exactly equal to actual EPS), the observation was eliminated from the sample. On average there were approximately 7 percent of the analysts' forecasts that were not included in the sample for the sign test because forecast error was zero.

TABLE 11
Forecast Bias Analysis
Sign Test Results
(Values reported are Z-values)

Approximate Quarter	A	+/-	M	+/-	S	+/-	C	+/-
90-2	3.909[a]	-	0.274	+	2.375[a]	-	2.275[b]	-
90-3	3.688[a]	-	1.644[b]	+	2.857[a]	-	1.973[b]	-
90-4	1.081	-	2.055[b]	+	0.070	+	1.069	-
91-1	2.289[b]	-	3.289[a]	+	0.763	-	0.329	-
91-2	3.592[a]	-	0.274	+	2.257[a]	-	0.850	-
91-3	2.555[a]	-	1.644[b]	+	1.055	-	1.288	-
91-4	1.087	-	1.096	+	0.140	-	0.219	-
92-1	2.416[a]	-	3.289[a]	+	1.750[b]	-	0.301	+
92-2	0.542	-	2.604[a]	+	0.425	+	1.617	+
92-3	0.369	+	2.878[a]	+	1.066	+	1.644[b]	+
92-4	0.114	+	0.411	+	0.497	-	0.164	-
93-1	2.336[a]	-	0.822	+	0.144	+	0.356	-

A=Ind analysts, M=Model, S=I/B/E/S Summary, C=Combined

[a] Significant at .01 level
[b] Significant at .05 level

+ indicates positive bias
- indicates negative bias

indicates that adding the five individual analysts' as independent variables significantly increases the amount of variance explained ($F(5,2566)=71.157$, $p<.001$). Likewise, when the reduced model includes only the individual analysts' forecasts, adding the model forecasts results in a significant increase in the amount of variance explained ($F(1,2562)=390.22$, $p<.001$). A related analysis was done in which each of the five sets of analysts forecasts was added individually as an independent variable to form the full model. The results of these tests are reported in Table 12B. These additional tests indicate that the presence of incremental predictive ability is consistent across all five sets of the individual analysts' forecasts. As hypothesized, both individual analysts' forecasts and model forecasts possess significant incremental predictive ability.

Another part of the incremental predictive ability analysis examined whether or not analysts and models exhibit differential incremental predictive ability between industries. This analysis also utilizes the strategy of estimating a full model and a reduced model and then examining the increment in explained variance. When the analysts' unique predictive contributions (residual from regression of individual analysts' forecasts on model forecasts) were used as independent variables (as well as being crossed with dummy variables for industry groups), there was a significant increment in explained variance. Similarly, when the models' unique predictive contributions (residual from regression of model forecasts on individual analysts' forecasts) were used as independent variables (as well as being crossed with dummy variables for industry groups), there was a significant increment in explained variance. These results are shown in Tables 13A and 13B. However, these overall results did not reveal which specific industries were more or less easily predicted. In order to

TABLE 12A
F Statistic Computations for Incremental Predictive Ability Analysis
Using Data for All Individual Analysts

Full Model	Red. Model	SSE(F)	SSE(R)	df(F)	df(R)	F Stat	p Value
M + 5ANL	M	2693.1	3067.3	5	2566	71.157	<.001
M + 5ANL	5ANL	2693.1	3103.5	1	2562	390.23	<.001

TABLE 12B
F Statistic Computations for Incremental Predictive Ability Analysis
Using Data for Individual Analysts One at a Time

Full Model	Red. Model	SSE(F)	SSE(R)	df(F)	df(R)	F Stat	p Value
M + A1	M	2943.6	3067.3	1	2566	107.81	<.001
M + A2	M	2762.3	3067.3	1	2566	283.20	<.001
M + A3	M	2744.1	3067.3	1	2566	302.09	<.001
M + A4	M	2792.5	3067.3	1	2566	252.48	<.001
M + A5	M	2784.3	3067.3	1	2566	260.73	<.001
Mean F						241.26	
M + A1	A1	2943.6	3719.0	1	2566	675.70	<.001
M + A2	A2	2762.3	3233.1	1	2566	437.12	<.001
M + A3	A3	2744.1	3199.7	1	2566	425.83	<.001
M + A4	A4	2792.5	3393.7	1	2566	552.24	<.001
M + A5	A5	2784.3	3245.0	1	2566	424.40	<.001
Mean F						503.06	

TABLE 13A
Overall Test for Differential Incremental Predictive Ability Using Analysts' Unique Predictive Contribution

SSE(F)	SSE(R)	df(F)	df(R)	F Stat	p Value
3370.8	3805.3	55	2562	5.875	<.001

<u>Full Model</u>
$EPS_{jt} = d_o + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + d_6(DUM_1{*}e_{1jt}) + \ldots + d_{60}(DUM_{11}{*}e_{5jt}) + u_{jt}.$

<u>Reduced Model</u>
$EPS_{jt} = d_o + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + u_{jt}$

EPS_{jt} = Quarterly EPS for firm j, period t.
DUM_i = Dummy variable for firm group i.
e_{ijt} = Residual term with A_i as dep var. and M as indep var. for analyst i, firm j, period t.
u_{jt} = Error term for firm j, period t.

TABLE 13B
Overall Test for Differential Incremental Predictive Ability Using Model's Unique Predictive Contribution

SSE(F)	SSE(R)	df(F)	df(R)	F Stat	p Value
2854.6	3257.1	55	2562	6.428	<.001

<u>Full Model</u>
$EPS_{jt} = d_o + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + d_6(DUM_1{*}e_{1jt}) + \ldots + d_{60}(DUM_{11}{*}e_{5jt}) + u_{jt}.$

<u>Reduced Model</u>
$EPS_{jt} = d_o + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + u_{jt}$

EPS_{jt} = Quarterly EPS for firm j, period t.
DUM_i = Dummy variable for firm group i.
e_{ijt} = Residual term with M as dep var. and A_i as indep var. for analyst i, firm j, period t.
u_{jt} = Error term for firm j, period t.

disentangle this relationship, two additional analyses were done.

First, full and reduced models (based on equation 3) were estimated for each of the 12 firm groups. The differences in adjusted R^2 between the full and reduced models for each group were computed and are reported in Tables 14A and 14B. Mean forecast errors and standard deviations for the 12 industry groups are reported in Tables 15A and 15B. Results for the groups with fewer than 20 analysts are considered unreliable due to small sample size and are not reported. The second analysis used both sets of residuals (model regressed on analysts and vice versa) computed in equation 4. Both sets of residuals were then regressed on actual EPS for the firm groups with more than 20 firms. The adjusted R^2 from these two regressions were used to form a ratio for each firm group. These ratios are reported in the sixth column of Tables 14A and 14B. The results of these analyses suggest some support for the hypothesized differences in incremental predictive ability. The rankings in Tables 14A and 14B are in decreasing order of incremental predictive ability. The analysts displayed the greatest incremental predictive ability in the Banking, Securities Brokerages, Insurance and Real Estate industry (group 11) while the models displayed the least incremental predictive ability for this industry. The industry in which models showed the greatest incremental predictive ability, Transportation, Communication and Utilities (group 9), was also the one in which the analysts showed the second least incremental predictive ability. The ratios shown in the last column of Tables 14A and 14B bolster this result.

TABLE 14A
Differential Incremental Predictive Ability Analysis For Analysts

Firm Group[a]	Number of Firms	Full Model Adj R^2	Reduced Model Adj R^2	Analysts' Contribution to Full Model Adj R^2	Ratio of Adj R^2 (Analyst/Model)[b]
11	23	.406	.055	.351	6.254
8	27	.217	.078	.139	0.814
4	28	.260	.156	.104	0.297
3	22	.818	.717	.101	0.806
7	27	.409	.342	.067	0.317
9	22	.404	.349	.055	0.128
2	21	.339	.297	.042	0.470

[a] The industry descriptions of the firm groups included in this table are as follows:

11 - Banking, Securities Brokerages, Insurance, Real Estate,
8 - Transportation Equipment, Instruments, Misc. Manufacturing,
4 - Chemicals,
3 - Paper, Publishing & Printing
7 - Industrial Equipment, Electronic Equipment
9 - Transportation, Communications, Utilities
2 - Food, Tobacco, Textiles, Apparel, Wood Products, Furniture & Fixtures

[b] The Adjusted R^2 figures used to form the ratios in this column are from different regressions than the other columns in the table. The ratios are based on equation 6 which is repeated here for convenience:

$$EPS_{jt} = d_o + d_1e_{1jt} + d_2e_{2jt} + d_3e_{3jt} + d_4e_{4jt} + d_5e_{5jt} + u_{jt}$$

This regression was run with the analysts' unique predictive contribution (e_{ajt} from $AF_{ajt} = c_0 + c_1MF_{jt} + e_{ajt}$) as the independent variable and then with the model's unique predictive contribution (e_{mjt} from $MF_{jt} = c_0 + c_1AF_{ajt} + e_{mjt}$) as the independent variable. The Adjusted R^2 from these two regressions were then used to form the ratios reported in this column. For this table, the Adjusted R^2 from the regression with the analysts' unique predictive contribution as independent variable was the numerator of the ratio reported.

TABLE 14B
Differential Incremental Predictive Ability Analysis For Models

Firm Group[a]	Number of Firms	Full Model Adj R^2	Reduced Model Adj R^2	Models' Contribution to Full Model Adj R^2	Ratio of Adj R^2 (Model/Analyst)[b]
9	22	.404	.179	.225	7.805
7	27	.409	.263	.146	3.158
3	22	.818	.724	.094	1.240
2	21	.339	.247	.092	2.129
4	28	.260	.172	.088	3.368
8	27	.217	.212	.005	1.229
11	23	.406	.403	.003	0.160

[a] The industry descriptions of the firm groups included in this table are as follows:

9 - Transportation, Communications, Utilities.
7 - Industrial Equipment, Electronic Equipment.
3 - Paper, Publishing & Printing.
2 - Food, Tobacco, Textiles, Apparel, Wood Products, Furniture & Fixtures,
4 - Chemicals,
8 - Transportation Equipment, Instruments, Misc. Manufacturing,
11 - Banking, Securities Brokerages, Insurance, Real Estate.

[b] The Adjusted R^2 figures used to form the ratios in this column are from different regressions than the other columns in the table. The ratios are based on equation 6 which is repeated here for convenience:

$$EPS_{it} = d_{o} + d_1e_{1it} + d_2e_{2it} + d_3e_{3it} + d_4e_{4it} + d_5e_{5it} + u_{it}$$

This regression was run with the analysts' unique predictive contribution (e_{ait} from $AF_{ijt} = c_o + c_1MF_{it} + e_{ijt}$) as the independent variable and then with the model's unique predictive contribution (e_{mit} from $MF_{it} = c_o + c_1AF_{ijt} + e_{ijt}$) as the independent variable. The Adjusted R^2 from these two regressions were then used to form the ratios reported in this column. For this table, the Adjusted R^2 from the regression with the model's unique predictive contribution as independent variable was the numerator of the ratio reported.

TABLE 15A
Mean Forecast Error by Firm Group - APE

Firm Group	Industry Description	Number of Firms	Mean Forecast Error	Std Dev
1	Mining, Construction	6	0.0137	0.0461
2	Food, Tobacco, Textiles, Apparel, Wood Products, Furniture & Fixtures	20	0.00566	0.0112
3	Paper, Publishing & Printing	22	0.00601	0.00867
4	Chemicals	28	0.00604	0.0113
5	Petroleum & Coal Products	12	0.00834	0.0150
6	Rubber & Plastics, Leather, Stone, Clay & Glass, Primary Metals, Fabricated Metals	8	0.00427	0.00809
7	Industrial Equipment, Electronic Equipment	27	0.0176	0.0489
8	Transportation Equipment, Instruments, Misc. Manufacturing	27	0.0131	0.0359
9	Transportation, Communications, Utilities	22	0.0148	0.0318
10	Wholesale & Retail	10	0.00629	0.0127
11	Banking, Securities Brokerages, Insurance, Real Estate	23	0.0157	0.0426
12	Personal, Business & Repair Services, Recreation	8	0.00530	0.00523

TABLE 15B
Mean Forecast Error by Firm Group - Transformed APE

Firm Group	Industry Description	Number of Firms	Mean Forecast Error	Std Dev
1	Mining, Construction	6	-5.734	1.956
2	Food, Tobacco, Textiles, Apparel, Wood Products, Furniture & Fixtures	20	-6.258	2.126
3	Paper, Publishing & Printing	22	-6.143	2.007
4	Chemicals	28	-6.372	2.287
5	Petroleum & Coal Products	12	-5.636	1.522
6	Rubber & Plastics, Leather, Stone, Clay & Glass, Primary Metals, Fabricated Metals	8	-6.496	2.149
7	Industrial Equipment, Electronic Equipment	27	-5.576	2.186
8	Transportation Equipment, Instruments, Misc. Manufacturing	27	-5.787	2.140
9	Transportation, Communications, Utilities	22	-5.413	1.973
10	Wholesale & Retail	10	-6.381	2.487
11	Banking, Securities Brokerages, Insurance, Real Estate	23	-5.690	2.260
12	Personal, Business & Repair Services, Recreation	8	-6.025	2.090

CHAPTER VI

DISCUSSION

6.1 ACCURACY ANALYSIS

The results of this analysis indicate that for the time period studied, individual financial analysts' forecasts are the most accurate of the forecast generation methods examined. Summary analysts forecasts were second most accurate, but the difference between individual and summary analysts was not significant. Forecasts derived from combining analysts and model forecasts were the third most accurate and model forecasts were the least accurate. These results bolster findings of previous studies by documenting the superior accuracy of analysts' forecasts in a more recent time period. It is interesting that the individual analysts' forecast were more accurate than the summary analysts' forecasts. The summary forecast is the average of all analysts contributing a forecast for a given quarter and firm. Aggregations of multiple forecasts tend to be more accurate than the individual forecasts alone, but the results of this study are not consistent with this tendency. The lack of statistical significance for this difference does not warrant making inferences about accuracy differences between individual analysts' forecasts and summary analysts' forecasts. One potential explanation for this result is that the sample of analysts forecasts was not random. The analysts forecasts used in this study focused on analysts who have a minimum of three years experience forecasting specific firms. This constraint may have resulted in a sample of more experienced and generally more accurate analysts. This possibility may be fertile ground further investigation.

Another interesting result is that the combined forecasts were less accurate than the analyst generated forecasts. One likely reason combined forecasts' accuracy was different than hypothesized may have been the relative weightings used in computing the combinations. Other possible weights could be investigated to find the weighting that minimizes APE for the combined forecasts. Theoretically, there should be some combination of the individual analysts and models that is more accurate than either one individually. The results from the incremental predictive ability analysis provide additional reason to believe that a weighting combination other than 50-50 will result in the combined forecasts being more accurate then the analysts generated forecasts. Since the incremental predictive ability analysis showed that model forecasts explained some variance not explained by analysts' forecasts, some combination other than 50-50 will utilize the model's contribution to improve the accuracy of the combined forecast.

While the accuracy results show the same pattern as prior studies in the accounting literature, these results differ from the JDM literature. Earnings forecasting is one of a small number of domains in which human forecasting is more accurate than statistical forecasting. Other domain in which humans forecast more accurately than models are catalog order forecasting and coupon redemption rate forecasting (Blattberg & Hoch, 1990). One characteristic these environments share is the opportunity for forecasters to receive consistent, timely feedback about their forecasts. While there are likely to be other important characteristics, the availability of feedback and the opportunity this provides for learning is an important environmental characteristic that likely contributes to the success of forecasters in these domains.

6.2 BIAS ANALYSIS

Unlike previous studies, the results indicate that analysts were pessimistic in making their forecasts. One possible explanation for this difference is that the macroeconomic climate during 1990-1993 was different from the climate during time periods used in prior studies. During 1990 and 1991, the US economy was in recession. Both real GDP and total corporate profits declined for three of the eight quarters starting in the first quarter of 1990 and ending with the last quarter of 1991. These macroeconomic conditions may have affected the forecasts of individual financial analysts. The casual connection between poor macroeconomic conditions and pessimistic financial analysts forecasts of EPS is certainly not well defined. Obviously, other explanations are also possible. However, this result suggests there are additional factors affecting analysts' forecast bias that have not been considered in prior studies. This also suggests that the explanation of financial analysts' optimism in the existing literature does tell the whole story.

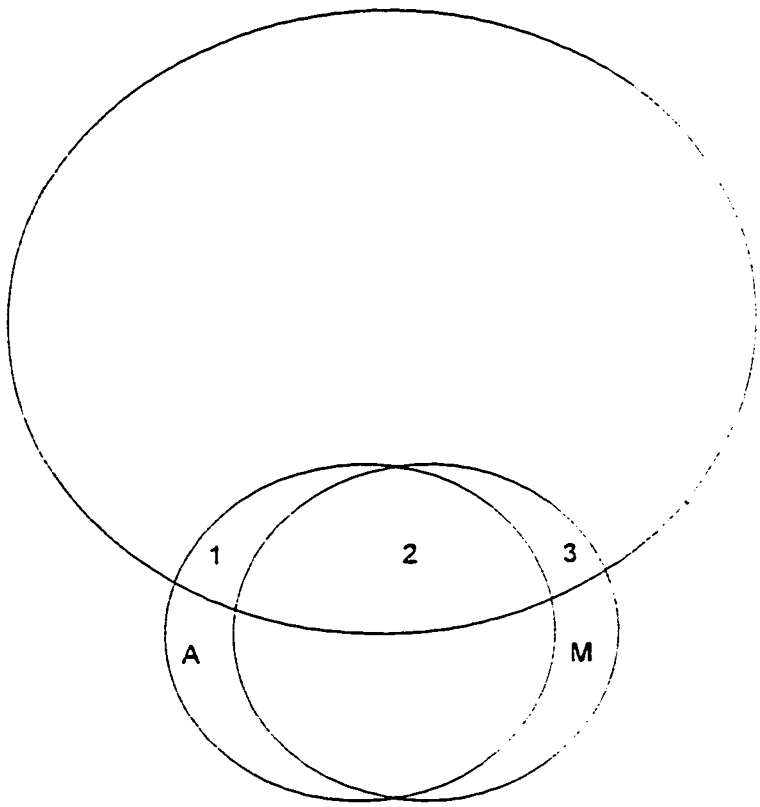
6.3 INCREMENTAL PREDICTIVE ABILITY ANALYSIS

The results from this analysis strongly support the conclusion that individual financial analysts exhibit predictive ability above that possessed by models and vice versa. Analysts and models also share a common portion of predictive ability. A simple Venn diagram illustrates this point. In Figure 1, the large circle represents the total variance to be explained in forecasting EPS. The smaller circle labeled A represents the analysts' forecasts. The smaller circle labeled M represents the model forecasts. The intersection of circles A and M that is inside the larger circle represents the portion of variance both analyst and model explain (area 2). The area of intersection between circle A and the larger circle that is not shared with circle M represents variance explained solely by the analysts' forecasts (area 1). In this study, this increment in explained variance is equal to .088 (.354 {Full model adjusted R^2} - .266 {reduced model adjusted R^2}). The intersection between circle M and the larger circle that is not shared with circle A represents variance explained solely by the model forecasts (area 3). The amount of the increment of explained variance in this case is .098 (.354 - .256). Thus, it seems that the unique elements of predictive ability possessed by the analysts and models are smaller than the portion that is common to both. There appears to be a modest but significant increase in the amount of explained variance as indicated by the analysis. This result is consistent with the idea that both analysts and model possess strengths in making forecasts that are somewhat complementary.

These results are also consistent with research from other domains (Blattberg & Hoch, 1990). The presence of incremental predictive ability for the models is particularly useful since, unlike the Blattberg and Hoch study, no individuals with knowledge of and experience in forecasting earnings were consulted to develop model forecasts. Thus, even simple models made a significant contribution to the forecasting results. More refined models may make an even greater contribution.

The differential incremental predictive ability results suggest that different forecast generation methods contribute differentially in forecasting earnings for different industries. There is some support for the hypothesis that analysts contribute more to predictive ability when used for forecasting earnings in less stable industries than in more stable industries. Likewise, there is some support for the hypothesis that models contribute more to predictive ability when used for forecasting earnings in more stable industries than in less stable industries. The rankings of industries by incremental predictive ability results show somewhat of an inverse pattern. Those industries in which analysts tend to contribute more to predictive ability are those in which models tend to contribute less and vice versa. Other tests could be devised that would likely yield more focused results. For example, a finer distinction (based on SIC code) than that used in this study could be used along with a larger number of analysts' forecasts to ensure sufficiently large sample sizes. Such a test would give more focused results than this study about specific industries. Nevertheless, the tests performed in this study provide unmistakable evidence that analysts make a greater contribution to predictive ability in some industries than in others.

FIGURE 1



CHAPTER VII

CONCLUSION

The purpose of this study was to examine whether or not individual financial analysts possess incremental predictive ability. Individual financial analysts' forecasts of quarterly EPS for the years 1990 through 1993 were obtained from I/B/E/S and a variety of statistical models were estimated using historical data. An analysis was done to explicitly establish the relative accuracy rankings of the different forecast generation methods as well as an analysis concerning forecast bias. The final analysis dealt with incremental predictive ability.

7.1 RESEARCH IMPLICATIONS

The earnings forecasts of individual financial analysts' is an important topic for accountants and accounting researchers to study for many reasons. First, studies like this suggest that because analysts are able to effectively use accounting information in developing their forecasts, they are one of the most desirable groups from whom accountants should seek feedback regarding efforts to develop more useful financial reporting. This is because of the unique perspective financial analysts have with respect to accounting information.

Second, knowledge gained from this type of research "should improve our ability to teach financial accounting courses to all students, including those planning careers that involve the preparation (as opposed to the use) of financial statements" (Schipper, 1991, p. 106). Studies such as this show that analysts serve as one important medium through which accounting information is processed in order to be used by investors. Since at least half of all investors rely upon the "advisor-dependent approach" in making their investment decisions, the estimates and recommendations produced by analysts receive significant attention. Understanding that financial analysts are the link between accounting information and investors should motivate accounting professors to focus on how accounting reporting will affect and be perceived by financial analysts. This perspective can help guide preparation of materials, assignments, etc. that will strengthen students' understanding of the relationships between accounting information, the financial community and investors.

A final reason that examining individual analysts' forecasts is important is to continue the search for ways to improve the accuracy of earnings forecasts. Improved understanding of human predictive ability is one area that can contribute to making such progress. Studies such as this suggest that people possess useful predictive skills and a better understanding of these abilities may contribute to improving such abilities.

In addition to benefitting accountants, the knowledge gained may be useful to managers of investment firms in directing training resources to areas that will be most beneficial. Understanding the role of individuals' predictive ability in forecasting earnings can help focus training effort on parts of the forecasting process in which analysts have the most potential for improvement. For instance, because of people's ability to adapt their knowledge to changing environments, training resources may be more efficiently spent developing industry specific knowledge in new analysts rather than training them in the use of general computer modeling techniques. By doing so, analysts will hopefully be better able to discriminate between important and unimportant environmental changes. Analysts should be trained in areas where they have an advantage over models so that they can maximize their contribution to the forecasting process.

7.2 FUTURE RESEARCH

One area for future research mentioned earlier is examining potential reasons for the individual analysts being more accurate than the summary analysts. This could be done at the same time as seeking to better understand the aggregation process. In this study, using an aggregation of individual forecasts did not provide a discernable benefit, but many other studies suggest that a small benefit is typically gained from aggregation. Examining forecast aggregation at a detailed level could provide insight into the unexpected results of this study and as well as into the process of forecast aggregation. One specific issue that could be addressed in selective vs. nonselective aggregation.

Another area for future research relates to forecast combination. As mentioned earlier, there should be a weighting combination that minimizes the forecast error for the combined forecasts. This weighting should also result in combined forecasts that are more accurate than the analyst-generated forecasts. Searching for this combination is one obvious area for future research. Also, existing literature suggests that creating forecasts by combining different forecasts yields benefits, but the results are mixed regarding the most effective methods for combination. Further examination of forecast combinations may provide results that will help make sense of the results of studies to date.

Given that individual analysts exhibit a significant amount of incremental predictive ability, an area of research that could also be pursued is a more in-depth study of the processes used by analysts in generating EPS forecasts. Data collection techniques such as verbal protocol analysis may be helpful in gaining further insight regarding specific characteristics of analysts' thought processes. Research of this nature may improve our understanding of relationships between data items that analysts use in developing forecasts.

Another potentially fruitful area of research is to develop more sophisticated forecasting models using the expertise one or more practicing financial analysts. Further work could also be done that seeks to understand which specific attributes of the earnings forecasting environment enable analysts to perform well, relative to other environments. Finally, work could be done that examines the effectiveness of forecast decomposition as a tool for improving individual earnings forecasts.

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