DISPERSION IN ANALYSTS' FORECASTS

DOES IT MAKE A DIFFERENCE?

A Dissertation

by

DAVIT ADUT

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2003

Major Subject: Accounting

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ABSTRACT

Dispersion in Analysts' Forecasts: Does it Make a Difference?

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Financial analysts are an important group of information intermediaries in the capital markets. Their reports, including both earnings forecasts and stock recommendations, are widely transmitted and have a significant impact on stock prices (Womack 1996; Lys and Sohn 1990, among others). Empirical accounting research frequently relies on analysts' forecasts to construct proxies for variables of interest. For example, the error in mean forecast is used as a proxy for earnings surprise (e.g., Brown et al.1987; Wiedman 1996; Bamber et al.1997). More recent papers provide evidence that the mean consensus forecast is used as a benchmark for evaluating firm performance. (Degeorge et al. 1999; Kasznik and McNichols 2002; Lopez and Rees 2002).

Another stream of research uses the forecast dispersion as a proxy for the uncertainty or the degree of consensus among analysts and focuses on the information properties of analysts (e.g., Daley et al. 1988; Ziebart 1990; Imhoff and Lobo 1992; Lang and Lundholm 1996; Barron and Stuerke 1998; Barron et al. 1998). In this paper I combine the two streams of research, and investigate how lack of consensus changes the information environment of analysts and whether the markets perceive this change. More specifically, I investigate the amount of private information in a divergent earnings

estimate (i.e. one that is above or below the consensus), whether the markets react to it at either the time of the forecast release, at the realization of actual earnings, and whether Regulation Fair Disclosure has changed the information environment differently for high and low dispersion firms.

DEDICATION

I dedicate this dissertation to my family, Regina, Gigabriel and Sila Adut. My parents Regina and Gigabriel gave me the breath of life. In dedicating themselves to their children, they have provided emotional support which has allowed me to venture farther than I would have dared alone. Over the years their dedication to their children, has taught me the most valuable lesson in my life and that is to persevere. My sister Sila, has always impressed me with her ability to overcome difficulties and has always constituted a role model.

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I also would like to thank Dr. Thomas Lopez, Dr. Suzanne Cory and all the accounting faculty and Ph.D. students at Texas A&M University. Almost every one of them made Texas A&M University an enjoyable place to pursue a doctorate. Specially, I would like to thank my office mate Andrew Mclelland and my class mate Gia Chevis for their friendships which I will treasure for ever.

Finally, I would like to thank my extended family Lucy and Gene Goldman for all their help and support during this long journey.

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CHAPTER I

INTRODUCTION

Financial analysts are an important group of information intermediaries in the capital markets. Their reports, including both earnings forecasts and stock recommendations, are widely transmitted and have a significant impact on stock prices (Womack 1996; Lys and Sohn 1990, among others). Empirical accounting research frequently relies on analysts' forecasts to construct proxies for variables of interest. For example, the error in mean forecast is used as a proxy for earnings surprise (e.g., Brown et al.1987; Wiedman 1996; Bamber et al.1997). More recent papers provide evidence that the mean consensus forecast is used as a benchmark for evaluating firm performance. (Degeorge et al. 1999; Kasznik and McNichols 2002; Lopez and Rees 2002).

Another stream of research uses the forecast dispersion as a proxy for the uncertainty or the degree of consensus among analysts and focuses on the information properties of analysts (e.g., Daley et al. 1988; Ziebart 1990; Imhoff and Lobo 1992; Lang and Lundholm 1996; Barron and Stuerke 1998; Barron et al. 1998).[1]

This dissertation follows the style of *Accounting Review.*

[1] These papers specifically deal with the information environment as it is related to private information.

In this paper, I combine the two streams of research and investigate how lack of consensus changes the information environment of analysts and whether the markets perceive this change. [2]More specifically, I investigate the amount of private information in a divergent earnings estimate (i.e. one that is above or below the consensus), whether the markets react to it at either the time of the forecast release, at the realization of actual earnings, and whether Regulation Fair Disclosure has changed the information environment differently for high and low dispersion firms.[3]

As information intermediaries, financial analysts' careers depend crucially on their reputation. Analyst reputation, defined as perceived ability to accurately forecast earnings, affects the impact of their research on investors' investment decisions (Stickel 1992). [4] Related studies provide evidence that analyst reputation decreases with past forecast boldness, which is defined as the deviation from the consensus forecast. In an equilibrium setting, analysts should receive some benefit from these divergent estimates; otherwise they would not issue them. Fischer and Verrecchia (1998) formulate a model which predicts that an analyst receives benefits by issuing non-redundant information and these benefits increase to the extent that the information is unique to that analyst. In a sense, these conditions increase the rents associated with information asymmetry. One alternative explanation for divergence is that the analyst is simply wrong.

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[2] Prior studies provide evidence that divergent forecasts occur but these studies have not tested the market reaction associated with divergent forecasts.

[3] One of the main goals of Regulation Fair Disclosure is to level the playing field for investors by limiting the amount of private communication between firms and influential investors. Research to date has focused on the effects of Regulation Fair Disclosure and investigated the dispersion, and the amount of private information. This study differentiates itself by examining the effects of dispersion, and the effects of Reg FD.

[4] Stickel (1992) finds that forecast revisions of analysts with better reputations have a greater impact on stock prices than those of other analysts.

To control for this effect, I will partition my sample based on analysts' skill level. [5] The underlying assumption is that skilled analysts will be more inclined to protect their reputation and will not risk incurring the costs associated with providing an inaccurate and a divergent forecast unless they have private information from which they can draw rents. Based on these arguments, I hypothesize that as the divergence from the consensus estimate increases, the amount of private information conveyed by divergent forecasts issued by skilled analysts will also increase.

Whether private information can be inferred from a divergent forecast is an empirical question that I test. However, this test can provide insight only with respect to the analysts' information environment. A more interesting question is whether or not the markets actually perceive this private information and if so, do they price it accordingly? As a natural extension, I investigate whether or not the markets perceive more information in divergent forecasts issued by skilled analysts. If the hypothesis holds and the divergent forecasts issued by skilled analysts contain more private information, I expect to find a more pronounced market reaction at the announcement date of these types of forecasts.

Degeorge et al. (1999) provide evidence that analysts' expectations are used as a benchmark for managing earnings. In a related study, Lopez and Rees (2002) provide evidence that the market gives a premium to positive forecast errors by assigning a higher multiple to the level of positive unexpected earnings. Additionally, the market assesses an additional penalty for missing forecasts that is unrelated to the magnitude of

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[5] Skill can be defined in many different ways. One measure is to investigate the past accuracy. An alternative way is to rely on lists that are provided by business media.

those forecast errors. Both of these studies, as well as many other studies, assume the veracity of the I\B\E\S consensus forecast as a benchmark, but do not consider the degree of consensus that this benchmark represents. In this paper, I argue that the degree of consensus is an important consideration in measuring the premium and the penalty associated with forecast errors.

Research to date has focused on the benchmarks identified by the mean consensus estimate. This paper provides evidence that lack of consensus should also be considered when specifying a benchmark and when evaluating the performance against that benchmark. If there is a market response to divergent forecasts by skilled analysts due to additional private information, it may be that skilled analysts can provide a better benchmark for high dispersion firms. Kim et al. (2001) show analytically that mean analysts' forecasts inefficiently aggregate information by assigning too much weight to analysts' common information relative to their private information when used as a summary forecast measure of forthcoming earnings. To empirically examine this question, this paper tests whether or not for high dispersion firms, the market response associated with forecast errors will be conditional upon dispersion and skill level of the analysts.

The U.S. Securities and Exchange Commission's (SEC) official release entitled "Selective Disclosure and Insider Trading" ,commonly known as Regulation Fair Disclosure (or Reg FD), was adopted on August 10, 2000, and became effective on October 23, 2000. A primary objective of Reg FD is to eliminate the selective disclosure of all material information regarding companies' past and future operating performance and thereby, to level the playing field between analysts, institutional investors, and individual investors. Shane et al. (2002) provide evidence that Reg FD has reduced the amount of private information available to analysts at the beginning of an earnings period; however, analysts are able to compensate by gathering more information throughout the period. Mohanram and Sunder (2001) find that absolute forecast errors and dispersion increase after the implementation. They also find that the importance of both idiosyncratic discovery and of analysis increases. Research to date on this area assumes that Reg FD affects all companies and these studies use all companies to test the effects. However, Holthausen and Verrecchia (1989) provides evidence that private information becomes more valuable as the uncertainty increases. Therefore Regulation Fair Disclosure can have varying implications conditional upon dispersion associated with the firm. This paper differentiates itself by investigating the ratio of private to public information conditional upon dispersion.

As I discuss in detail throughout the paper, an understanding of the effects of lack of consensus among the analysts is important for three reasons. First, it is important to realize that divergent forecasts convey more private information that could be useful to investors. Second, lack of consensus is important for firm valuations because it affects the benchmarks upon which companies are valued. Finally, this paper emphasizes that lack of consensus can have varying implications with regards to new regulations implemented by the Securities and Exchange Commission.[6]

[6] For example, the amount of private information can be higher for high dispersion firms but can stay constant for low dispersion firms.

The remainder of the paper is organized in six chapters. The next chapter provides the literature review and the hypothesis development. Chapter III explains the research design. Chapter IV describes the sample selection procedures and provides some descriptive statistics. Chapter V presents the main empirical findings and Chapter VI provides a brief summary and presents conclusions, limitations and ideas for future research.

CHAPTER II

LITERATURE REVIEW

Dispersion Literature

Several papers have investigated the dispersion in analysts' forecasts. Chen et al. (1990) investigated the effects of the statement of financial accounting standards No.52. The authors use forecast dispersion as a relevant measure of firm risk and conclude that a reduction in dispersion associated with the adoption of SFAS No 52 provides evidence with regards to an economic consequence associated with the adoption of the accounting standard.

Ajinkya et al. (1991) provide empirical evidence that trading volume is positively related to the degree of differing beliefs. The extent of disagreement or dispersion in financial analysts' forecast of annual earnings per share for a firm is employed as the proxy for agents' differing beliefs about the firm's prospects. The revision in analysts' mean earnings per share forecasts is used to control for the volume effects of the net information signals emanating during the period. The results indicate a significant positive association between the dispersion in analysts' forecasts of earnings per share and the volume of trading. A relatively stable and positive association is found even after controlling for the volume effects of the magnitude of monthly revisions in the mean analysts' forecasts. The evidence corroborates the theoretical result that the degree of heterogeneity in beliefs is a determinant of the intensity of trading.

Imhoff and Lobo (1992) examine the effect of uncertainty in analysts' earnings forecasts in terms of the relation between unexpected returns and unexpected earnings. The variance in analysts' earnings forecasts just prior to a firm's annual earnings announcement is employed as a firm-specific proxy for *ex ante* uncertainty. The results of the study indicate a systematic relation between ex *ante* uncertainty and the information content of the earnings. A given unit of earnings news has a greater effect on unexpected stock price change as the amount of pre-earnings announcement uncertainty decreases. Firms with relatively high *ex ante* uncertainty exhibit little or no systematic price change at the time earnings are announced.

Goss and Waegelein (1993) examine the association between executive compensation and security analysts' forecast dispersion in an agency setting. The authors hypothesize that firms that compensate managers with long-term performance plans and high percentages of managerial stock will be less likely to engage in manipulation of financial statements and their financial performance will be easier to predict, thus resulting in less dispersed forecasts. The results of the study provide evidence that firms that compensate their managers with long-term performance plans and higher levels of the company stock have less dispersion associated with their security analysts' forecasts and greater dispersion of their long-term growth in earnings.

Lang and Lundholm (1996) examine the relations between the disclosure practices of firms, the number of analysts following each firm and properties of the analysts' earnings forecasts. The authors provide evidence that firms with more informative disclosure policies have larger analyst following, more accurate analyst earnings forecast, less dispersion among individual analyst forecasts and less volatility in forecast revisions.

Lobo and Tung (1998) investigate the relationship between the dispersion of analysts' earnings forecasts and stock price variability around quarterly earnings announcements. Consistent with the theoretical predictions, the empirical analysis shows that stock price variability at the time of earnings announcement is positively related to the degree of analysts' earnings forecast dispersion.

Information Environment

Several papers have investigated the information environment of the analysts. Brown et al. (1987) present a model that provides determinants of *ex ante* forecast accuracy and examines conditions under which a particular forecasting approach would yield superior measure of earnings surprise. The authors find that the superior forecasting ability of analysts over time-series models is related to characteristics of a firm's information environment, namely firm size and the dispersion in analysts' forecasts.

Stickel (1989) provides evidence on the demand for and supply of analyst forecasts of the annual earnings per share. Evidence is provided on the timing of forecasts around interim earnings announcements and on the effect of incentives on revision activity. The results indicate that annual earnings forecasts are relatively stale or out of date in the two weeks prior to interim announcements. In the two weeks after interim announcements, revision activity increases. This increase is greater if absolute unexpected interim earnings are larger, if there are more competing analysts, if unexpected interim earnings are negative and if it is late in the fiscal year.

Holthausen and Verrecchia (1989) present a partially revealing rational expectations model of competitive trading to identify two effects of information releases; an informedness effect and a consensus effect. The informedness effect measures the extent to which agents become more knowledgeable, and the consensus effect measures the extent of agreement among agents at the time of an information release. The authors demonstrate that informedness and consensus generally occur jointly when information is disseminated, and that unexpected price changes and trading volume are each influenced by both informedness and consensus. The paper provides an economic rationale for examining both price and volume effects at the time of information releases.

Lys and Sohn (1990) investigate the information content of analyst earnings forecast revisions in a setting where numerous analysts follow a given company. The results indicate that individual analyst earnings forecast revisions reflect “some, but not all” of the information. The authors also investigate whether forecasts for a given company occurring in close succession are a mere copy of each other. Forecast revisions occurring in close succession are likely to be correlated, because the information received by analysts is not likely to be independent. However, if analysts act independently, individual forecasts will contain some idiosyncratic information and consecutive forecast revisions will be informative. The results provide evidence that analyst earnings forecasts are informative independent of the time elapsed since the preceding forecast, indicating that investors perceive analysts to act independently. The authors also examine the relative importance of the innovative and the confirmatory components of consecutive forecast revisions. As the accuracy of individual analysts forecasts decreases, investors will reduce their response to individual forecasts that deviate from the consensus because these forecasts are likely to be in accurate. Thus, when analyst earnings forecasts are sufficiently noisy, individual forecast revisions will be informative not only because they provide “new information” but also because they confirm information provided by the preceding forecasts. The evidence indicates that confirmatory and innovative components of forecast revisions are equally important for security evaluation.

Wiedman (1996) extends Brown et al. (1987) by testing whether the characteristics of firms’ information environment, namely, firm size and dispersion in analysts’ forecasts are also related to superiority as a proxy for the market’s expectations for earnings. The paper provides evidence that analysts forecast errors have a higher association with excess returns than random walk forecast errors for the overall sample and that this higher association is positively related to firm size and negatively related to dispersion in analysts’ forecasts.

Barron et al. (1998) presents a model that relates properties of the analysts’ information environment to the properties of their forecasts. First, the authors express forecast dispersion and error in the mean forecast in terms of analyst uncertainty and consensus (that is, the degree to which analysts share a common belief). Second, the authors show that the quality of common and private information available to analysts can be measured by using the overall uncertainty and the average pair wise covariance among analysts' beliefs.[7] The authors base their analysis on a model of expectations in which each analyst observes two signals about future earnings. One public (common across all analysts) and one private. The findings of the paper provide guidance on how to construct valid measures of uncertainty and consensus from widely available earnings forecast and realization data.

Kim et al. (2001) show analytically that mean analysts forecasts inefficiently aggregate information by assigning too much weight to analysts' common information relative to their private information when used as a summary forecast measure of forthcoming earnings. The authors show that inadequate information weighing can constitute a large portion of expected forecast errors. Unlike the effects of individual analysts' biases, the overweighing of common information, and the resulting inefficiency of the mean forecast, are exacerbated as the number of analyst forecasting increases. A more precise summary forecast of earnings than the current mean forecast is the current mean forecast plus a positive multiple of the change in the mean forecast.

Barron et al. (2002) examine the information analysts' forecasts convey, how the characteristics of this information change after earnings announcements, and how this information relates to the number of analysts producing new forecasts after earnings announcements. The authors focus on changes in the degree to which forecasts of different analysts convey redundant information after earnings announcements.

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[7] A more detailed explanation can be found in the paper on pages 424-426.

The authors provide evidence that precision and the amount of analysts' common and private information both increase around earnings announcements. The authors also provide evidence that analyst's incorporate most private information in their forecast revisions following earnings announcements and, as a result the mean forecast becomes more informative because it reflects a richer set of information.

Regulation Fair Disclosure

Several recent academic studies investigate the effect of Reg FD on the information environment. Heflin, Subramanyam and Zhang (2003) report that after Reg FD's effective date, return volatility surrounding earnings announcement was lower, post-announcement price convergence was faster, analyst forecast bias, accuracy and dispersion remained relatively unchanged, and the quantity of the voluntary forward-looking disclosures by companies increased. Over all, the authors conclude that Reg FD has not resulted in a deterioration of the information environment.

Shane, Soderstrom, and Yoon (2002) study a longer post-Reg FD period and find that long-term absolute forecast errors are larger in the post-Reg FD periods relative to errors documented in 1999. However, after controlling for the long term uncertainty and the sign of the short-term absolute forecast error, they find that short-term absolute forecast errors are significantly lower in the post-Reg FD period compared to the preceding year. In addition, the authors find a smaller absolute price response to earnings announcements in the post –Reg FD period compared to the preceding year. Taken together, the results suggest that Reg FD has reduced the amount of private information available to analysts at the beginning of the earnings period, however, analysts are able to compensate by gathering more information throughout the period until ultimately, the level of publicly available information prior to the earnings announcement is as high or higher than the pre-Reg FD periods.

Mohanram and Sunder (2001) analyze the impact of Reg FD on analysts' forecasting ability. The authors find that both absolute forecast errors and forecast dispersion increase after the implementation of Reg FD. The authors also find that the importance of idiosyncratic discovery and analysis increases in the post Reg FD period. Overall, the results of the study support the SEC's stated objective for Reg FD first by showing that superior analysts are more likely to differentiate themselves in the post Reg FD world and second by demonstrating that analysts' incentives to gather private information and perform independent analysis are enhanced after Reg FD.

Zitzewitz (2002) investigate the issue of private and public information by investigating the day that the forecast is issued. He posits that when several analysts' forecasts occur on the same day, it is usually due to value-relevant information about the firm being disclosed to the general public. In contrast, the occurrence of a single forecast suggests that the analyst is private information to update their expectations. The author finds that consistent with the intended affects of Reg FD, the percentage of analysts' forecasts that occurred on days when no other analyst issued a forecast changed from 70 percent in the pre-Reg FD period to 50 percent in the post-Reg FD period.

Meeting and Beating Expectations

Degeorge et al. (1999) examine earnings management as a response to implicit and explicit rewards for attaining specific levels of earnings, such as positive earnings, an improvement over last year, or the market's consensus forecast. The authors posit that managers manage their earnings to exceed three thresholds. The first is to report profits as opposed to losses, which arises from the psychologically important distinction between positive and negative numbers. The second and the third benchmarks are performance relative to prior comparable period and performance relative to analysts' earnings projections. The results indicate that the positive EPS threshold is the most important; it prevails regardless of whether or not the other two thresholds are met. The threshold of previous period earnings is the second in importance: it asserts itself only if the positive EPS threshold is met, but it is present regardless of whether earnings make the analysts' forecast. The threshold of analysts' forecast is the weakest; mattering if both the other thresholds are met.

Kasznik and McNichols (2002) examine whether firms achieve greater share value, all else equal, by meeting analysts' expectations. The authors hypothesize that firms meeting expectations receive either of two kinds of market rewards, higher analysts' earnings forecast that lead to higher valuations or a market reward controlling for earnings forecasts. The authors find that analysts' forecasts are not higher for firms that meet expectations relative to those that do not, controlling for the level of current year's earnings information. The authors also find that one or two years ahead earnings are higher for firms that meet expectations relative to those that do not. Earnings three years ahead, however, are not generally greater for firms that consistently meet expectations, controlling for analysts' post-announcement earnings forecasts. These findings indicate firms meeting expectations are not"rewarded" by analysts with higher earnings forecasts than are warranted.

Lopez and Rees (2002) examine the difference in stock price sensitivity between positive and negative forecast errors to investigate whether the market rewards (penalizes) firms for (not) beating analysts' forecasts. The authors also assess whether the sensitivity of stock prices to current forecast errors differs for firms with a historical tendency to consistently report positive earnings surprises. The evidence suggests that the increasing frequency of positive forecast errors is a rational response by managers to three market-related incentives. First, the market yields a premium to positive forecast errors by assigning a higher multiple to the level of unexpected earnings. Second, the market assesses an additional penalty, unrelated to the magnitude of the forecast error, to firms that do not meet forecasts. Third, though the market recognizes historical patterns of forecast errors and adjusts for the systematic component of unexpected earnings, it rewards firms that consistently beat earnings forecasts by attaching a higher multiple to the unsystematic portion of unexpected earnings.

Bartov et al. (2002) examine the manner by which earnings expectations are met, measure the rewards to meeting or beating earnings expectations (MBE) formed just prior to the release of quarterly earnings, and test alternative explanations for this reward. The evidence supports the claims that MBE phenomenon has become more widespread in recent years and that the pattern by which MBE is obtained is consistent with both earnings management and expectation management. More importantly, the evidence shows that after controlling for overall earnings performance in the quarter, firms that manage to meet or beat their earnings expectations enjoy an average quarterly return that is almost 3% higher than firms who fail to do so. While investors appear to discount MBE cases that are likely to result from expectation or earnings management, the premium in the cases is still significant. These results indicate that the market places a premium on meeting or beating analysts' forecasts.

Chevis et al. (2001) study the characteristics of firms that consistently meet or exceed analysts' expectations over a long time period spanning multiple quarters. The authors find that firms that meet the expectations are more likely to be firms with higher growth, a pattern of increasing earnings, a larger analyst following, lower forecast dispersion among analyst, and greater earnings stability. The authors also find that price-earnings multiple is on average higher for profit firms that meet the expectations conditional on growth, leverage and a pattern of increasing earnings.

The present study differs from the previously cited studies in some important ways. First, this study extends past studies in dispersion and previous "meet or beat" literature by investigating the effects of dispersion on the premium associated with "meeting or beating". Prior literature has investigated the price and the volume reaction to analysts' forecast dispersion, but these studies have not investigated the effects of dispersion on the premium. This issue is important to investigate because of the emphasis placed on meeting or beating the estimates. Anecdotal and academic literatures both provide evidence that firms can lose market value by not meeting analysts' estimates.[8] This paper will provide additional evidence regarding how this premium will change with regards to dispersion, and answer the question: will the markets react to dispersion in analysts' forecasts or will they be fixated on meeting or beating without any other conditions?

Second, this paper will propose a different benchmark for markets' expectations. This paper posits that the most recent forecast will be a better proxy for firms with high dispersion. Research to date has focused on the use of mean forecasts as a proxy. Kim et al. (2001) analytically provide evidence that when analysts possess both the common and private information, the mean forecast over weights the information common to all analysts, thereby failing to fully exploit their private information. However, in the case of high dispersion, analysts will have incentives to provide more private information therefore the market reaction to the most recent forecast should be higher than the mean forecast for high dispersion firms.[9] One other possible explanation is that the different market reaction could be just due to the elapsed time. To control for this effect, I will also investigate the market reaction to firms with low dispersion. My expectation is that the market reaction for high-dispersion firms will be higher than the market reaction for the firms with low dispersion.

Third, Barron et al. (2002) provides evidence those amounts of analysts' common and private information both increase around earnings announcements.

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[8] Lopez and Rees (2001).

[9] Using Barron et al. (1998). This can be tested.

This finding suggests that earnings announcements typically cause more new common information to be conveyed in individual analysts' forecasts than private information. The authors posit that *relative* increases in analysts' private information after earnings announcements are larger, in large part because analysts start out with little or no private information about earnings. This paper differentiates itself by positing that in the case of high dispersion, the analysts will communicate more private information before the announcements; therefore the mean of the most recent forecasts will be more valuable. In addition, this paper will provide evidence by testing the market reaction controlling for the dispersion.

Finally, research to date provides conflicting results with regards to dispersion. Heflin et al. provide evidence that dispersion has not changed after the Reg FD. Mohanram and Sunder (2001) provide evidence that dispersion has changed and they provide additional information on how Reg FD has caused a shift between private and public information. This paper will provide a contribution by comparing how dispersion affects the shift between the private and the public information after and before the implementation of the Regulation Fair Disclosure. My study differentiates itself by investigating the effectiveness of Reg FD for high dispersion firms.

CHAPTER III

HYPOTHESIS DEVELOPMENT

Accounting research frequently relies on analysts' forecasts to construct proxies for variables of interest. For example, the error in the mean forecast is used as a proxy for earnings surprise (e.g., Brown et al.1987; Wiedman; 1996; Bamber et al.1997). In addition, forecast dispersion and the error in the mean forecast is used as a proxy for the uncertainty or the degree of consensus among analysts or market participants (e.g., Daley et al.1988; Ziebart 1990; Imhoff and Lobo 1992; Lang and Lundholm 1996; Barron and Stuerke 1998). Although the effects of dispersion have been investigated in previous literature, it is still not clear why certain analysts choose to deviate from the consensus estimates, and what information is revealed by their actions. This paper investigates forecasts that diverge from the consensus. I posit that these forecasts will contain private information, conditional on the reputation of the individual analyst and on the dispersion in analysts' forecasts.

The intuition underlying my hypothesis stems from an equilibrium argument where the benefits of issuing a divergent forecast (i.e., one that is above or below the consensus estimate) should outweigh the reputation costs of issuing an incorrect forecast. Prior papers provide evidence that an analyst's reputation is of great importance to that analysts' career and reputation decreases with past forecast error boldness, which is defined as a deviation from the consensus. The fact that we observe divergent forecasts suggests that there should be benefits associated with them. Fischer and Verrecchia (1998) formulate a model which predicts that each analysts' dominant concern is to increase the net benefits to those trading on the analysts' own non-redundant information. These benefits decrease to the degree that other informed investors act on the same information. Under these circumstances, an analyst might risk his reputation only if he or she has private information that can be used to generate rents from information asymmetry. My first hypothesis posits that the amount of private information increases as the distance from the existing consensus increases. One alternative explanation for the distance from the consensus to be high is that a specific analyst can provide an estimate that is wrong. I will control for this by investigating the accuracy of the forecast. These reasons provide the basis for my first hypothesis.

H1: *As the distance from the existing consensus estimate increases, so does the amount of private information contained in skilled analysts' estimates.*

To further my investigation, I examine the markets' reaction to a divergent forecast. The model presented above does not speak to markets' perceptions[10]. In other words, if markets perceive divergent forecast by skilled analysts to have more information, then there will be a more pronounced market reaction at the announcement date of the divergent forecast. These reasons provide the basis for my second hypothesis.

H2: *As the distance from the existing consensus estimate increases, the market reaction will be more pronounced to the divergent estimate issued by the skilled analysts.*

[10] This model deals with analysts' information environment.

Degeorge et al. (1999) provide evidence that meeting analysts' expectations is used as a benchmark for managing earnings. In a related study, Lopez and Rees (2002) provide evidence that market yields a premium to positive forecast errors by assigning a higher multiple to the level of positive unexpected earnings. Additionally, the market assesses an additional penalty for missing forecasts that is unrelated to the magnitude of the forecast errors. Both of these studies take as given the veracity of the I\B\E\S consensus forecast as a benchmark and do not consider the degree of consensus that this benchmark represents. In this paper, I argue that the degree of consensus is an important consideration in measuring the premium associated with positive forecast errors.

Intuitively, a large dispersion in analysts' forecasts indicates that there is little consensus among analysts with respect to the future earnings performance. In this case, using a point estimate as a benchmark for evaluating firm performance ignores the degree of uncertainty associated with the estimate. Because the degree of dispersion in analysts' forecasts is publicly available information, it is reasonable to hypothesize that the market will impound the degree of uncertainty surrounding the consensus forecast. In particular, I hypothesize that the investor confidence in a positive forecast error will be greater when the forecast error is derived from a forecast that reflects a greater degree of consensus among analysts. That is, the probability that observed positive errors are actually positive would be greater when there is a greater degree of consensus among analysts. Accordingly, my third hypothesis is stated as follows:

H3: *The market response associated with forecast errors will be significantly different for high dispersion firms (low consensus) as compared to low dispersion firms (high consensus).*

Hypothesis three provides evidence that lack of consensus is associated with a differential market response. Prior research also provides evidence that there is a premium associated with meeting or beating the mean consensus estimate, which suggests that it is perceived as a benchmark. To further investigate the effects of dispersion, I partition the estimates into high dispersion and low dispersion sub-samples and test whether there is a difference in the premium associated with meeting or beating the estimates between skilled and unskilled analysts. More specifically, I change the benchmark from the mean consensus estimate to a mean estimate from skilled analysts and compare the effect of dispersion among these categories. A difference in the premiums provides evidence that the premium or the penalty associated with meeting or beating the estimates varies according to the benchmark used. My fourth hypothesis is stated as follows:

H4: *The premium (penalty) associated with positive (negative) errors will be conditional upon dispersion and the skill level of analysts that issues the estimates.*

Shane et al. (2002) provide evidence that Reg FD has reduced the amount of private information available to analysts at the beginning of the earnings period. However, analysts are able to compensate by gathering more information throughout the period until, ultimately, the level of publicly available information prior to earnings announcements is as high as or higher than pre-Reg FD periods. Mohanram and Sunder (2001) find that absolute forecast errors and dispersion increase after the implementation of Reg FD. The authors also find that the importance of idiosyncratic discovery and analysis increases in the post- Reg FD. Research to date assumes that Reg FD will have the same effect on all companies. However, Fischer and Verrecchia (1998) provide evidence that private information is more valuable as uncertainty increases; as the distance from the consensus increases. In cases where the lack of consensus is high, the markets' expectations are not clear and the price discovery process is not finished; therefore, private information is more valuable. On the other hand, for low dispersion firms the price discovery process is completed and the value of private information is relatively low. I predict that if Reg FD has curtailed the information environment with regards to getting private information from managers, then the ratio of public to private information between the high and low dispersion firms should be larger in the post- Reg FD period. On the other hand, if Reg FD has enhanced the information environment then the ratio of private information to private information between the high dispersion and low dispersion firms should be lower in the post -Reg FD period. This reasoning provides the basis for my two-sided fifth hypothesis.

$H5_0$: *Regulation Fair Disclosure has had no effect on the ratio of public to private information between high and low dispersion firms.*

$H5_1$: *Regulation Fair Disclosure has changed the ratio of public to private information between high and low dispersion firms.*

CHAPTER IV

RESEARCH DESIGN

4.1 Private Information

My first hypothesis posits that for high dispersion firms, as the distance from the consensus estimate increases, the estimates issued by skilled analysts will contain more private information. To test this hypothesis, one needs to have a measure of overall uncertainty and the amount of private information contained in analysts' estimates. Barron et al. (1998) develop a model that allows for the inference of fundamental properties of analysts' information from observed individual forecasts. In their model, the authors analytically show that expected forecast dispersion is a function of the total variability and the amount of consensus among analysts. Total variability is measured as the average of the total variance that exists in the analysts' forecasts, and consensus is measured as the covariance among analysts' forecast errors.[11]

$$D = V - C \qquad (1)$$

where;

D= expected forecast dispersion,

V= is the measure of overall uncertainty, and

C= is the measure of consensus.

[11] For a more detailed explanation, refer to Barron et al. (1998) page 426.

For a firm to be classified as high dispersion, it should have a high value for V and a low value for C. In other words, the variance among analysts should be high and there should be a lack of consensus among the analysts. In this paper, I posit that as the distance from the consensus estimate increases, the amount of private information will also increase. When the distance increases, the covariance will decrease only if the new information is private. Alternatively, if the increase in the distance is due to public information, then the covariance will increase as will the ratio of the common information (covariance between the estimates) to the total variability. Following this logic, I employ a model that focuses on the analyst properties of uncertainty (U) and consensus (ρ), to infer the amount of private information contained in analysts' published forecasts. Uncertainty (U) and consensus (ρ) are expressed as follows:

$$U = \left(1 - \frac{1}{N}\right)D + SE \qquad (2)$$

$$\rho = \frac{SE - \frac{D}{N}}{\left(1 - \frac{1}{N}\right)D + SE} \quad , \qquad (3)$$

where

$$D = \frac{1}{N-1}\sum_{a=1}^{N}(F_a - \overline{F})^2 \qquad (4)$$

$$SE = (E - \overline{F})^2 , \qquad (5)$$

and F_a is the forecast by analyst a,

$\overline{F}$ is the mean forecast, and

E is the actual earnings.

Barron et al. (1998) demonstrate that errors in common versus private information influence forecast dispersion and errors differently, and yield insights into how certain theoretical properties of the analysts' information environment are reflected in empirical forecast measures. The intuition behind this approach can be explained by referring to two theoretical constructs: uncertainty and consensus. "Uncertainty"refers to the expected squared error in individual forecasts aggregated across the total number of analysts. "Consensus" refers to the degree to which analysts share a common belief.[12] It is measured by the covariance among analysts.

Based on Barron's theoretical constructs, I create a proxy for the private information of a specific analyst. I use a revolving approach and update ρ every time a new estimate is added to the information set. This procedure provides an incrementalρ, which is the measure that should be used to test the amount of private information in a specific forecast. Due to the design of the measure, ρ is not meaningful when the number of forecasts issued for a specific firm is low. Therefore, I delete those observations that have a low analyst following[13]. The distance from the consensus estimate is the absolute difference calculated by subtracting the estimate from the consensus estimate at the time of the specific forecast.

[12] This consensus construct is also used by Holthausen and Verrecchia (1990)
[13] The cut-off point is disclosed in the appropriate table.

4.2 Regression Models

My first hypothesis predicts that as the distance from the consensus estimate increases, the amount of private information contained in skilled analysts' estimates increase. This hypothesis is tested by estimating the following least squares regression:

$$Dist_{it} = \alpha_o + \beta_1 \rho_{it} + \beta_2 Skill_k + \beta_3 (Skill_k * \rho_{it}) + \varepsilon_{it} \qquad (6)$$

where:

$Dist_{it}$ = is the absolute difference between the mean forecast and the analysts' forecasts at the time the forecasts are issued,

ρ_{it} = the forecast specific ratio of private information to total variability,

$Skill_{it}$ = 1 if the skill level is above the mean and is calculated based on ranks obtained from mean forecast errors over years by specific analysts.

A significant coefficient in the ratio of common to total information provides evidence that the distance from the consensus estimate is associated with the amount of private information disclosed in the forecasts. To further investigate this issue, I partition the sample into high and low dispersion categories and estimate the equation again.[14]

4.3 Market Response

I investigate whether the market reacts to divergent forecasts issued by skilled analysts. Numerous studies have investigated the information content of earnings by regressing abnormal returns, cumulated over a short window surrounding the earnings announcement date, on unexpected earnings. I use a similar approach and test

[14] In this study, I choose to classify a high dispersion firm by calculating the standard deviation for all the firm specific estimates in the period. If the standard deviation is above the 75th percentile of the sample then the firm is classified as a high dispersion firm.

cumulative abnormal returns over a 3-day period around the forecast release date. The basic regression model takes the following form:

$$CAR_{it} = \alpha_0 + \beta_1 \, Dist_{it} + \beta_2 \, Skill_k + \beta_3 \, (Dist_{it} * Skill_k) + \beta_4 \sum_{j=1}^{16} YR_t + \beta_5 \sum_{j=1}^{2} \lambda_j X_{it} + \varepsilon_{it} \quad (7)$$

where:

CAR_{it} = a 3-day market adjusted return for firm *i* over the interval extending from one trading day prior to the forecast announcement date through one trading day after the forecast announcement,

$Dist_{it}$ = is the absolute difference between the consensus forecast and the analysts' forecast at the time the forecast is issued, and

$Skill_{it}$ = is 1 if the skill level of the historic errors is above the mean, which is calculated based on ranks obtained from mean forecast errors over the years 1983-2000 by specific analysts, 0 otherwise.

YR_t = year specific dummy.

X_{it} = Log of assets and leverage used as control variables.

Equation seven measures market response at the release time of the forecast. In the next test, I focus on abnormal returns cumulated over the estimate date and the earnings announcement date. I hypothesize that lack of consensus reduces the probability that a positive forecast error will really be positive. To test the effect of consensus at the earnings realization, I will estimate the regression model below.

$$CAR_{it} = \alpha_0 + \beta_1 Dis_{it} + \beta_2 Skill_k + \beta_3 SUE_{it} + \beta_4 (Dis_{it} * SUE_{it})$$

$$+ \beta_5 (Skill_k * SUE_{it}) + \beta_6 (Dis_{it} * SUE_{it} * Skill_k)$$

$$+ \beta_7 \sum_{j=1}^{16} YR_t + \beta_8 \sum_{j=1}^{2} \lambda_j X_{it} + \epsilon_{it} \quad (8)$$

where:

CAR_{it} = Abnormal returns cumulated over the estimate date of the specific forecast and earnings announcement date for the firm

Dis_{it} = 1 if the average distance is above the mean, 0 otherwise

$Skill_{it}$ = 1 if the skill level is above the mean , calculated based on ranks obtained from mean forecast errors over years by specific analysts, and

SUE_{itj} = analyst specific forecast errors calculated by taking the difference between the actual earnings and the estimate provided by the specific analyst.

YR_t = year specific dummy.

X_{it} = Log of assets and leverage used as control variables.

The coefficients tested in the regression model will provide evidence regarding hypothesized relations. For example, a significant and positive coefficient indicates a positive relation between the distance and the cumulative abnormal returns. I expect the coefficient of the distance to be significant and negative, but when distance interacts with the skill I expect to find a significant positive coefficient. To further investigate this issue, I will partition the sample into high and low dispersion and estimate the equation again. A significant difference between coefficients will provide further evidence that dispersion makes a difference.

Next, I turn my attention to the effects of dispersion on the premium (penalty) associated with meeting (not meeting) expectations. In this model, I test whether dispersion and skill of analysts make a difference in the premium associated with meeting or beating expectations. I create new consensus numbers based on the skill levels of the analysts, and estimate the following regression models.

$$CAR_{it} = \alpha_0 + \beta_1 Short_{it} + \beta_2 Beat_{it} + \beta_3 UE_{it} + \beta_4 Disp_{it} + \beta_5 (UE^* Disp_{it})$$

$$+\beta_6(UE_{it} * Beat_{it}) + \beta_7(UE^* Disp_{it} * Beat_{it}) + \sum_{j=1}^{5} \lambda_j X_{jit} + \varepsilon_{it} \qquad (9)$$

$$CAR_{it} = \alpha_0 + \alpha_1 \text{ SA Short}_{it} + \alpha_2 \text{ SA Beat}_{it} + \alpha_3 UE_{it} + \alpha_4 Disp_{it}$$

$$+ \alpha_5 (UE^* Disp_{it}) + \alpha_6 (UE_{it} * \text{SA Beat}_{it}) + \alpha_7(UE^* Disp_{it} * \text{SABeat}_{it})$$

$$+ \sum_{j=1}^{5} \lambda_j X_{jit} + \varepsilon_{it} \qquad (10)$$

where:

CAR_{it} = a 3-day market adjusted return for firm *i* over the interval extending from one trading day prior to the earnings announcement date through one trading day after the earnings announcement.

$Disp_{it}$ = the standard deviation of all the forecasts for time t,

UE_{it} = unexpected earnings for firm *i*, which is defined as the difference between actual quarterly earnings per share in quarter *t* and the consensus analyst forecast as obtained from I/B/E/S, deflated by the end-of quarter stock price,

$Short_{it}$ = 1 when actual earnings in the quarter falls below the consensus analyst earnings forecast; otherwise 0,

$Beat_{it}$ = 1 when actual earnings in the current quarter exceeds the consensus analyst earnings forecast; otherwise 0, SA Short $_{it}$ = 1 when actual earnings in the quarter falls below the consensus analyst earnings forecast issued by skilled analysts; otherwise 0,

SA Beat $_{it}$= 1 when actual earnings in the current quarter exceeds the consensus analyst earnings forecast issued by skilled analysts; otherwise 0, and

X $_{jt}$= UE interacted with a vector of control variables identified in the prior literature as cross-sectional determinants of earnings response coefficients.

The control variables that are contained in X $_{j}$ are growth, leverage, risk and earnings permanence. Prior research has found these variables to be important determinants of the earning response coefficients (Kormendi and Lipe, 1987; Collins and Kothari, 1989; Easton and Zmijewski, 1989). Growth is defined as the market-to-book ratio as of the end of the quarter. Leverage is calculated as long-term debt divided by the sum of long-term debt, preferred stockholder equity, and common stock holders' equity. A firm's market model beta calculated using the CRSP equally weighted market portfolio, is used as a proxy for risk.[15] Firm size is the log of total assets. I use the E_{it}/P_{it} ratio to control for earnings' persistence where E_{it} is reported earnings per share for quarter *t* and P_{it} is the end-of-quarter price.

Finally, I investigate the effects of Reg FD as an externality and test the effects that it might have on the ratio of public to private information. To test my final hypothesis, I partition the sample based on the amount of dispersion and investigate whether dispersion affects the ratio of public to private information contained in the forecasts

[15] The firm-specific beta was calculated using days –60 through –11 and +11 through +60 relative to the earnings announcement date.

4.4 Sample Selection Procedures

The initial sample consists of 1,195,134 firm-quarter observations (12,551 firms) from 1983 through 2001 for which analyst forecast data is available on the 2001 version of the I/B/E/S database. From this initial sample, I eliminate those firms that have less than two forecasts per period and missing actual earnings per share in the database. My research design requires at least two forecasts in order to calculate the amount of private information. Accordingly, those firms that do not have at least two forecasts for the period can not be used in the regression analyses, which further reduce the sample by 186,318 firm-quarter observations. [16] To increase the power of the tests, the sample is reduced so that the study can capture the effects associated with high dispersion and analysts' coverage[17]. The sample was further reduced because of insufficient CRSP and Compustat data items which are necessary in calculating the abnormal returns and control variables used in this model. Criteria to be retrained in the final sample are outlined in Panel A of Table 1. The data contained extreme values for unexpected earnings, growth and standard deviation which were eliminated if they were less than 1% or more than 99% of the distribution. Financial statement data and earnings announcement dates were obtained from *Compustat Quarterly*. Stock return data were obtained from CRSP. Analyst information and actual earnings-per-share data were obtained from I/B/E/S.

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[16] The 133,622 firm-quarter observations eliminated due to this requirement is less than 9 times the observations used in the study.

[17] To be more specific, I delete the firms are not being followed by 15 analysts for some of the tests. I also use the 75 percentile range to identify high dispersion firms.

4.5 *Descriptive Statistics*

Panel B of Table 1 provides descriptive statistics for the sample used in this study. The market value of the firms averaged $3,085 million, and the average total assets were $4,880 million. Panel B also provides descriptive statistics with regards to the dispersion that exists among financial analysts. The mean dispersion is 0.073. The 10th percentile is 0.004 and the 90th percentile is 0.110. Distance is calculated as the difference between the mean analysts' forecast and the individual forecast at the time the estimate is issued. The average absolute distance is 0.037 and ranges from 0.000 to 0.085. The private information variable has a mean of 0.122 and ranges from zero to 0.484. These statistics are similar to results documented in prior studies.[18]

[18] Rees and Adut (2002) and Rees and Lopez provide similar results in their study.

CHAPTER V

EMPERICAL RESULTS

5. Empirical Results

5.1 *The Effect of Skill and Private Information on Distance.*

Empirical Tests of H1

My initial tests investigate whether there is a correlation between the distance from the mean and the amount of private information possessed by a specific analyst. I expect to find a significantly positive association between Dis and skill level possessed by analysts. Consistent with my predictions, Panel A of Table 2 provides evidence that the amount of private information, skill and the interaction between the skill and the amount of private information are all positive and significant.[19]

In October of 2000, The Securities and Exchange Commission implemented Regulation Fair Disclosure. A primary objective of Reg FD is to eliminate selective disclosure of all material information about companies' past and future operating performance. This regulation may have an affect on the amount of private information disseminate to market participants and the analysts. To control for this, I partition the sample into two periods: before and after the regulation.

[19] To further investigate the issue I check to see whether the coefficients are significantly different from each other. These tests are provided in Panel B of Table 2. The findings provide evidence that the coefficients are significantly different from each other at the one percent level and better.

Consistent with my predictions, skill, amount of private information and the interaction variables are still significant and the adjusted –R^2 increases to 7.11%, more than double, as compared to pre-periods. The results indicate that the coefficient associated with the private information increases after Reg FD.[20] However, the coefficient associated with the interaction between the skill and the amount of private information decreases after the implementation of the new regulation. To further investigate the issue, Panel B of Table 2 presents the results of the tests that compare the coefficients of the variables before and after the implementation. The results indicate that there are significant differences between the coefficients. All of my findings are consistent with the notion that there is relationship between the distance from the mean and the amount of private information that the analysts have. This relationship holds after controlling for the skill of the analysts.

The amount of private information as identified in Barron et al (1998) depends on the covariance between the analysts. Covariance and dispersion become more meaningful when a firm is being followed by a larger number of analysts. To increase the robustness of the results, I estimate the model again and only include the firms that are being followed by eight or more analysts. The results presented in Panel C provide evidence that the amount of private information is still significant and positively correlated with the distance.

[20] Mohanrem and Sunder (2002) report similar results.

The coefficient is even higher for firms that are being followed by eight or more analysts. Skill variable is also significant and the coefficient is higher for widely followed firms. One interesting result is that the coefficient on private information decreases in Post-Reg FD period for high coverage firms but increases for the full-sample. Another interesting point is that the coefficient on interaction between the skill and private information is higher for widely followed firms. These results provide evidence that the skill of the analyst becomes more important for widely followed firms. The association between the distance and the amount of private information is significantly positive and is consistent throughout the analysis.

5.2 *Abnormal Returns Based on Skill, Private Information at Analysts' Estimate Date. Empirical Tests of H2*

The second hypothesis investigates whether there is a market reaction associated with the divergent forecasts at the time these forecasts are issued. To test this, I investigate the abnormal returns around three days surrounding the estimate date. The design involves year dummies to control for time effects. Since my data extends from 1983 to 2001, it was necessary to control for time effects.[21]

[21] Shane et al. (2002) uses a similar design to test the effects of Regulation Fair Disclosure.

The abnormal returns were calculated using the CRSP value- weighted market portfolio.[22] Panel A of Table 3 provides evidence that distance is significantly and negatively associated with cumulative abnormal returns when there is a five day difference between the estimate date and the earnings announcement date. This finding is consistent with the notion that the markets react negatively to forecasts that are away from the mean estimate. One possible explanation for this finding could be that the markets do not believe the validity of the estimate because it is different from the mean of the other estimates. Consistent with this idea, the results indicate that when the distance is interacted with the perceived skill (measured as the historical accuracy of the analysts) of the analysts, there is a significant and positive market reaction. Although the overall effect is still negative, the fact that the divergent forecast is issued by a skilled analysts lowers the negative association

In this test, I focus on firms that have high analyst coverage and I restrict the sample where there is a five day difference between the estimate date and the earnings announcement date. There are a couple of reasons for these restrictions. First, the markets will be more likely to react to divergent estimates of widely covered firms just due to information dissemination. If a firm is widely followed by analysts, this new piece of information will be readily available for investors to use. Second, I restrict the sample to include only divergent forecasts that stay divergent as the time gets closer to earnings announcement date. Investors will most likely over look a divergent forecast at

[22] I also estimated the regression models using the equally- weighted market portfolio and the results were qualitatively similar.

the beginning of the period thinking that these divergent forecasts will get revised down or upwards depending on the consensus estimate.

Next, I investigate the effects of dispersion on abnormal returns. Panel B of Table 3 provides evidence about dispersion, calculated as the standard deviation of all the estimates by firm and period. The results provide evidence that, consistent with the prior findings, distance is significant and negative. The interaction between the distance and skill is still positive and significant. The coefficients provide evidence that the negative association implied by distance is lowered when the divergent estimates are issued by skilled analysts. Although, the interaction between distance, skill and dispersion is not significant, the coefficient is significantly different when compared with the coefficient on the interaction between distance and skill.

5.3 *Abnormal Returns Based on Distance and Skill at Earnings Announcement Date. Empirical Tests of H3*

The results presented in Table 3 provide evidence that distance and skill variables are associated with cumulative abnormal returns at the announcement date of the estimate. I further investigate this issue by incorporating the forecast errors and measure cumulative abnormal returns through the period starting from the estimate date and extend through the earnings announcement date. Panel A of Table 4 provides evidence that the distance and errors are negatively correlated with the abnormal returns at the earnings announcement date but it turns positive and significant when interacted with skill. All of these findings are consistent with my hypothesis. These findings provide evidence that divergent forecasts and the errors associated with divergent forecasts that were issued by skilled analysts are positively associated with cumulative abnormal returns. To control for year to year cross sectional dependence, I also estimate the annual regressions, the findings are consistent with the pooled regression results. Panel B of Table 4 focuses on the coefficient differences. The tests indicate that the coefficient on the interaction between distance and the errors is significantly different from the coefficient on the interaction between distance, errors and the skill. The tests also indicate that the coefficient on the interaction between skill and the errors is significantly different from the interaction of distance, errors and skill. These results justify the inclusion of these specific variables into the models. Overall the results are consistent with the notion that distance and skill are important variables as they relate to cumulative abnormal returns calculated around the estimate date for divergent forecasts and earnings announcement dates.

Table 4 establishes a link between cumulative abnormal returns and the skill and distance. Table 5 differentiates between high and low dispersion firms. If the dispersion level is high then the consensus variable is coded 0 and 1 otherwise. The results indicate that consensus and distance variables retain their significance both in the pooled regression and annual regressions. The coefficient on the interaction between distance, skill, errors and consensus is negative and significant. The results provide evidence that the coefficient on the interaction between errors, skill and distance is positive but when consensus is introduced, the incremental contribution is negative. Additionally, the test of the coefficients also provides evidence that the coefficients are significantly different from each other.

5.4 *The Effect of Dispersion on the Premium Associated with Meeting and Beating Analysts' Estimates.*

Empirical Tests of H4

Lopez and Rees (2002) provide evidence that there is a premium associated with meeting or beating analysts' consensus estimates. The authors report that the interaction variable between unexpected earnings and the beat variable is positive and significant. Table 6 presents similar results. After establishing consistent results, I introduce the dispersion variable to the model. The results are still consistent, but I find that the interaction variable between unexpected earnings, dispersion, and beating the consensus estimates is negative and significant in both the pooled and annual regressions. Although the coefficient is negative, in absolute value it is less that the coefficient on the interaction variable (UE*Beat).[23] These results suggest that the premium is lower for firms that beat with high dispersion. To further investigate the issue, Panel B of Table 6 presents the results of the coefficient differences. The results indicate that the coefficient associated with unexpected earnings and the beat variable is significantly different from the interaction variable that includes unexpected earnings, dispersion, and beat.[24]

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[23] In the annual regressions, the coefficient on the interaction (UE*Beat*Disp) is slightly higher than the coefficient on the UE*Beat.

[24] The robustness of the results was checked by using the mean forecasts as well. The results are qualitatively similar.

These results provide evidence that dispersion is an important factor in determining the premium associated with meeting or beating analysts' estimates.

The second issue that I investigate is whether there is a premium associated with meeting or beating skilled analysts' mean estimates. To test this hypothesis, I combine equation 9 and 10 and estimate the model. The results are presented in Table 7. The results are consistent with my earlier findings in the sense that unexpected earnings and the beat variables are significant and positive in both the pooled regressions and the annual regressions. The interaction variable between unexpected earnings and dispersion is also negative and significant. The beat variable for the skilled analysts is not significant in the pooled regression but it is significant in the annual regressions. The short variable for the skilled analysts is not significant in both regressions. The results of Panel B of Table 7 present evidence that the coefficients of beat and the SAbeat (the mean for skilled analysts) are significantly different. The results also indicate that the coefficients of SAbeat and SAshort are significantly different.

5.5 *The Differential Effect of Regulation Fair Disclosure on High and Low Dispersion Firms.*

Empirical Tests of H5

Research to date has not differentiated between high dispersion and low dispersion firms when investigating the effects of Regulation Fair Disclosure. Table 8 presents the results of the empirical tests which consider this difference. The results indicate that there is a significant difference in the amount of public information between low and high dispersion firms. [25] The results indicate that the amount of public information is significantly higher for low dispersion firms as compared to high dispersion firms before the new regulation as well as after the implementation of Reg FD. Significant differences on the amount of public information between high and low dispersion firms provide evidence that dispersion does make a difference on the amount of public information inherent in analysts' forecasts. In this paper, I provide preliminary evidence and this area should be further investigated.

[25] Table 8 presents the ratio of the public information as identified in Barron et al. (1998). The measure used in this table applies to all of the firms as opposed to specific estimates.

CHAPTER VI

CONCLUSIONS

Research to date has provided empirical evidence that analysts' reports, including both earnings forecasts and stock recommendations, are widely transmitted and have a significant impact on stock prices (Womack 1996; Lys and Sohn 1990, among others). Although this area has been researched quite extensively, the majority of the papers focuses on or uses the mean expectations. In this paper, I take a different approach and investigate dispersion among analysts' estimates as well as the divergent forecasts issued by analysts. [26] I posit that divergent forecasts provide additional information to investors and that dispersion makes a difference in the abnormal returns surrounding estimate days as well as in the period between the estimate date and earnings announcement date. In addition, I investigate whether Regulation Fair Disclosure has changed the information environment with regards to dispersion.[27] In this paper, I provide empirical evidence on five issues related to dispersion and divergent forecasts: 1) Is the distance from the consensus estimate associated with the amount of private information and the skill of the analyst? ; 2) Do the markets react to divergent estimates issued by skilled analysts at the estimate announcement date? ;

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[26] Some other papers that deal with dispersion are Daley et al. 1988; Ziebart 1990; Imhoff and Lobo 1992; Lang and Lundholm 1996; Barron and Stuerke 1997; Barron et al. 1998

[27] I measure the amount of private information using Barron et al. (1998) methodology, this, measure includes both the private communications that an analyst might have as well as the specific expertise of a specific analyst. Reg FD might actually decrease the amount of private information communicated by the management but at the same time increase the expertise of the analyst as evidenced in Shane et al. (2002).

3) Does the market response associated with forecast errors at the earnings announcement date differ based on distance and skill? ; 4) Is the premium (penalty) associated with positive (negative) errors conditional upon the dispersion and the skill level of the analysts that issue the estimates? ; 5) Has Regulation Fair Disclosure had an effect on the ratio of public information to private information between high dispersion and low dispersion firms?

The results indicate that the amount of private information is positively associated with the distance and this relation holds when private information variable is interacted with the skill. These results provide evidence that when analysts issue a divergent forecast, this forecast is associated with private information. One interesting finding is that the explanatory power of the model doubled after the implementation of the regulation Fair Disclosure. The coefficient on the private information has increased as well, this finding is consistent with the notion that the association between divergent forecasts and the amount of private information has increased as a result of the new regulation. Significant and positive differences provide evidence that there is a temporal difference among the variables.

The second issue that I examine is whether the markets react to this increased amount of private information in a three-day window surrounding the estimate date. My evidence indicates that there is a negative association between distance and the cumulative abnormal returns surrounding the estimate date. These results are consistent with the notion that the markets will perceive the existence of a divergent forecast as a bad news scenario unless the estimate is issued by a skilled analyst[28]. The positive reaction to divergent forecasts issued by skilled analysts is smaller for high dispersion firms. This finding is consistent with the notion that the markets value dispersion as bad news and assign a lower multiple to divergent forecasts issued by skilled analysts.

Next, I investigate the market response to divergent forecasts around a longer window. This will provide insights with regards to the valuation of the errors for divergent forecasts. The abnormal returns are calculated over the period starting from the day the divergent forecast is issued and extends till earnings announcement date. My results are consistent with prior findings in the sense that cumulative abnormal returns (long window) are associated with divergent forecasts that are issued by skilled analysts.

In a high dispersion setting, the results provide evidence that consensus decreases the magnitude of the market response associated with divergent forecasts issued by skilled analysts. Over all, the results are consistent with the notion that dispersion does make a difference in the market responses associated with divergent forecasts.

Lopez and Rees (2002) provide evidence that there is a premium associated with meeting and beating analysts' expectations. Consistent with their study, I find a positive reaction to unexpected earnings and to beating expectations. In this paper, I provide evidence that dispersion is also associated with the premium associated with meeting and beating analysts' forecasts.

[28] This finding is consistent with prior studies in the sense that a divergent forecast will increase the dispersion about the future cash flows of the company and this will be perceived as bad news. However, if this forecast is issued by a skilled analyst then there is a positive reaction which increases the credibility of the forecast and investors pay more attention and this is perceived to be a positive scenario.

I document a smaller and a negative coefficient on the interaction variable (UE*Disp*Beat*). These results are consistent with the prior findings in the sense that dispersion is perceived as bad news and lowers the premium associated with meeting or beating the forecasts.

Prior tests provide evidence that the distance from the mean is associated with cumulative abnormal returns and if these divergent estimates are issued by skilled analysts then the markets react positively. I take the next step and test whether mean expectations formed by skilled analysts would constitute a better benchmark with regards to market reaction surrounding the earnings announcement date. Although this variable is not significant in the pooled models, it is significant in the annual regressions, and coefficient tests indicate that it is significantly different from the beat variable. The results provide partial support for my hypothesis.

Finally, I investigate whether regulation Fair Disclosure had a different effect on high dispersion firms. My results are consistent with the notion that low dispersion firms have more public information when compared to low dispersion firms. This finding is supported after the implementation of Reg FD as well. These findings support that there are significant differences between low and high dispersion firms.

Overall, my findings provide evidence that dispersion does make a significant difference in the information environment of analysts. More specifically, I provide evidence that divergent forecasts are associated with the amount of private information and the markets respond to these estimates differently conditioned upon the skill level of the analysts. These conclusions are also supported when I investigate the abnormal returns over a long window period which starts the day the divergent forecast is estimated and ends on the day the earnings are announced. This paper extends the prior research by introducing dispersion when calculating the premium associated with meeting or beating the analysts' estimates. My findings suggest that the premium associated with beating the consensus forecast is lower when the model is estimated for high dispersion firm. The results indicate that there is a negative association between cumulative abnormal returns and the interaction variable between dispersion, unexpected earnings and beating the consensus estimate.

My study has several limitations. First, I examine the information environment of analysts within the context of forecasts, my conclusions can not be generalized to analysts' reports and other services provided by them.[29] Second, as a theoretical construct this paper relies on a model presented in Barron et al. (1998) study, therefore my conclusions are constrained by the limitations of the model. Finally, my sample includes firms and forecasts that are covered in I/B/E/S, the inferences about the amount of private information can be different if other forecasts (for example, Whisper forecasts can be an alternative source for private information) are considered.[30]

In this paper, I provide evidence with regards to divergent forecasts and dispersion as it relates to private information and market response associated with these estimates.

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[29] For example, Dugar A. and S. Nathan investigate analysts' recommendations.
[30] Bagnoli et al (1999). and Rees et al. (2003) investigate whisper forecasts as alternative sources of information.

Because of the differences between the accounting systems, it would be interesting to investigate the role of divergent forecasts and private information in an international setting. The differences between code law and common law based accounting systems might be a good foundation to justify the need for future studies as they relate to private information.

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APPENDIX

Table 1
Sample Selection and Descriptive Statistics

Panel A: Sample Selection Process

	No. of Firms	No. of Observations
Firms found on I/B/E/S[31]	12,551	1,195,134
Less: Insufficient forecast data[32]	(3,625)	(186.318)
Insufficient Compustat, CRSP Data[33]	(1,707)	(107,523)
Final Sample	7,219	901,293

Panel B: Descriptive Statistics[34]

	Mean	Std. Dev.	Median	10^{th} Perc.	90^{th} Perc.
Dis	0.037	0.104	0.010	0.000	0.085
ρ	0.122	0.281	0.000	0.000	0.484
Disp	0.073	1.415	0.02	0.004	0.110
TA	$4,880	21,910	$576	$61	$9,078
MVE	$3,085	147,39	$40	$73	$5,380

[31] The 2001 version of the I/B/E/S database was employed to gather the initial sample. Years of coverage extend from 1983 to 2001.

[32] Firms that have less than 2 forecasts were deleted since the private information proxy can not be calculated. Firms that did not have their actual earnings per share in the database were also deleted.

[33] Compustat data is necessary to calculate growth, leverage, and size. CRSP data is necessary to calculate the abnormal returns. The outliers are also deleted in this screen.

[34] Descriptive statistics are provided for the following variables:

Dis = absolute difference between the mean forecast and analysts' forecast at the time the forecast is issued;
ρ = forecast specific ratio of private information to total variability;
Disp = standard deviation of all the forecasts for time t.
TA = book value of total assets (in millions); and
MVE = end of quarter market value of equity (in millions).

Table 2

Regression Results Based on Private Information and Skill

Panel A: Distance Model[35]

$$Dis_{it} = \alpha_o + \beta_1 \rho_{it} + \beta_2 \, Skill_k + \beta_3 (Skill * \rho_{it}) + \varepsilon_{it} \text{ (full sample)}$$

$$Dis_{it} = \alpha_o + \phi_1 \rho_{it} + \phi_2 \, Skill_k + \phi_3 (Skill * \rho_{it}) + \varepsilon_{it} \text{ (pre-Reg FD)}$$

$$Dis_{it} = \alpha_o + \lambda_1 \rho_{it} + \lambda_2 \, Skill_k + \lambda_3 (Skill * \rho_{it}) + \varepsilon_{it} \text{ (post-Reg FD)}$$

	Int.	ρ	Skill	Skill* ρ	Adj-R^2
Coef. from pooled regression	0.018**	0.023**	0.027**	0.028**	
(t-statistics)	(119.40)	(45.87)	(125.24)	(39.60)	3.22 %
Pre- Reg FD Period (n=942,921)	0.018**	0.022**	0.026**	0.028**	
	(113.17)	(40.97)	(115.96)	(37.84)	3.17 %
Post-Reg FD Period (n=65,895)	0.020**	0.026**	0.020**	0.016**	7.11 %
	(56.65)	(33.03)	(36.76)	(11.90)	

[35] *, ** significant at 0.05 and 0.01 respectively.

Dis = is the absolute difference between the mean forecast and specific analysts' forecast at the time the forecast is issued.

ρ = forecast specific ratio of private information to total variability.

Skill = calculated based on ranks obtained from mean forecast errors over the time period by specific analysts;

Table 2 (continued)

Panel B: Tests of Panel A Coefficient Differences

Coefficient Difference	F-value
ϕ_1-λ_1=0	91.62**
ϕ_2-λ_2=0	45.10**
ϕ_3-λ_3=0	77.97**

Panel C: Regression Results Based on Private Information and Skill For firms that are Being Followed by Eight or more Analysts

$$Dis_{it} = \alpha_o + \beta_1 \rho_{it} + \beta_2 Skill_k + \beta_3 (Skill * \rho_{it}) + \varepsilon_{it} \quad \text{(full Sample)}$$

$$Dis_{it} = \alpha_o + \phi_1 \rho_{it} + \phi_2 Skill_k + \phi_3 (Skill * \rho_{it}) + \varepsilon_{it} \quad \text{(pre-Reg FD)}$$

$$Dis_{it} = \alpha_o + \lambda_1 \rho_{it} + \lambda_2 Skill_k + \lambda_3 (S kill * \rho_{it}) + \varepsilon_{it} \quad \text{(post-Reg FD)}$$

	Int.	ρ	Skill	Skill* ρ	Adj-R^2
Coef. from pooled regression	0.029***	0.030***	0.054***	0.039***	4.50%
(t-statistics)	(169.60)	(63.14)	(120.21)	(29.68)	
Pre- Reg FD Period (n=550,093)	0.029***	0.030***	0.051***	0.037***	4.31%
	(160.18)	(59.62)	(110.68)	(27.20)	
Post-Reg FD Period (n=65,947)	0.028***	0.026***	0.029***	0.027***	5.05%
	(82.49)	(33.69)	(22.88)	(8.74)	

Table 3
Regression Results Based on Skill, Private Information and
Cumulative Abnormal Returns at the Estimate Announcement Date

Panel A: Abnormal returns surrounding analyst's estimate date.[36] For high following analysts and 5 days difference between the estimate date and the earnings announcement date.

$$CAR_{it} = \alpha_0 + \beta_1 \ Dist_{it} + \beta_2 \ Skill_k + \beta_3 \ (Dis_{it} * Skill_k) + \beta_4 \sum_{j=1}^{16} YR_t + \beta_5 \sum_{l=1}^{2} \gamma \ X + \epsilon_{it}$$

	Int	Dis	Skill	Dis*Skill	Adj-R^2
Coefficients from Regressions	0.056***	-0.187***	-0.011***	0.158***	3.84%
(t-statistics)	(10.27)	(-6.57)	(-5.22)	(4.38)	
Annual Mean Coefficients	0.045	-0.084	-0.012	0.092	

36 *, **,*** significant at 0.05 , 0.01 and higher than 0.001 respectively
CAR = the 3-day market-adjusted abnormal return using the CRSP value-weighted market portfolio return cumulated from one trading day before to one trading day after the estimate announcement date
Dis = is the absolute difference between the mean forecast and specific analysts' forecast at the time the forecast is issued.
Disp = 1 if he standard deviation is higher than the 75 percentile
Skill =calculated based on ranks obtained from mean forecast errors over the time period by specific analysts.
La = log of assets included as a control for size. Used as control variables
Lev = a firms' leverage and is calculated as long-term debt divided by the sum of long-term debt, preferred stock holders' equity and common stock holders' equity; used as control variables
YR = Year specific dummy.

Panel B: Model Including Dispersion For High Following Analysts and 5 Days Difference between the Estimate Date and the Earnings Announcement Date. [37]

$$CAR_{it} = \alpha_0 + \beta_1\ Dist_{it} + \beta_2\ Skill_k + \beta_3\ Disp_{it} + \beta_4\ (Dis_{it} * Skill_k) + \beta_5\ (Dist_{it} * Skill_k * Disp_{it}) + \beta_4 \sum_{j=1}^{16} YR_t + \beta_5 \sum_{l=1}^{2} \gamma\ X + \epsilon_{it}$$

	Int	Dis	Skill	Disp	Dis* Skill	Dis* Skill * Disp	
Coefficients from Pooled regressions	0.056***	-0.201***	-0.011***	0.002	0.181***	-0.043	3.82%
T-Statistics	(10.21)	(-7.01)	(-5.31)	(0.47)	(4.28)	(-0.97)	
$\beta_4 - \beta_5 = 0$						8.79***	

[37] *, **,*** significant at 0.05 , 0.01 and higher than 0.001 respectively.
The interaction variable between distance and dispersion was removed from the model because of severe multicollinearity issues.
Control variables that are used in the model are log of assets and leverage. These factors have been found to be significant in prior studies.

Table 4
Regression Results Based on Skill, Private Information and
Cumulative Abnormal Returns Around the Estimate Date and Earnings
Announcement Date.

Panel A: Abnormal returns surrounding estimate date and earnings announcement date.[38]

$$CAR_{it} = \alpha_0 + \beta_1 \text{ Dis} + \beta_2 \text{ Skill} + \beta_3 \text{ SUE}_{it} + \beta_4 (\text{Dis} * \text{Skill}) + \beta_5 (\text{Dis} * \text{SUE}_{it})$$

$$+ \beta_6 (\text{Skill}_{it} * \text{SUE}_{it}) + \beta_7 (\text{Dis} * \text{SUE}_{it} * \text{Skill}) + \epsilon_{it}$$

	Int.	Dis	Skill	SUE	Dis* SUE	Skill* SUE	Dis* SUE* Skill	Adj-R^2
Coef. from pooled regression	0.005***	-0.246***	-0.002***	-0.068***	-0.090***	0.055***	0.094***	1.67%
(t-statistics)	(20.20)	(61.95)	(-5.82)	(-24.57)	(-23.43)	(19.34)	(24.43)	
Mean coef. from annual regressions	0.007***	-0.020***	-0.004***	-0.069***	-0.07***	0.047*	0.070	
(t-statistic)	(3.24)	(5.45)	(-2.73)	(-3.53)	(-3.22)	(2.55)	(3.29)***	
[No of Coef.>0]	[17/19]	[1/19]	[4/19]	[1/19]	[7/19]	[18/19]	[14/19]	

[38] *, **,*** significant at 0.05 , 0.01 and higher than 0.001 respectively.
CAR_{it} = abnormal returns cumulated over the estimate date for a specific forecast and the earnings announcement date for the firm.
Dis = 1 if the distance is above the mean 0 otherwise
Skill = 1 if an analyst is considered skilled (past mean forecast errors) 0 otherwise.
Sue = Analyst specific forecast errors calculated by taking the difference between the actual earnings and the estimate provided by the specific analyst.

Table 4 (continued)

Panel B :Test of Panel A Coefficient differences

Coefficient Difference	F-value
$\beta_5 - \beta_7 = 0$	582.14***
$\beta_6 - \beta_7 = 0$	40.55***

Table 5
Regression Results Based on Skill, Private Information, Cumulative Abnormal Returns and Consensus

Panel A: For firms that are being followed by 16 or more analysts.[39]

$$CAR_{it} = \alpha_0 + \beta_1 Dis_{it} + \beta_2 Skill + \beta_3 Sue_{it} + \beta_4 Con_{it} + \beta_5 (Sue_{it} * Skill) + \beta_6 (Dis_{it} * Sue_{it}) + \beta_7 (Sue_{it} * Con_{it}) + \beta_8 (Sue_{it} * Dis_{it} * Skill) + \beta_9 (Skill * Sue_{it} * Con_{it}) + \beta_{10} (Dis_{it} * Sue_{it} * Con_{it}) + \beta_{11} (Dis_{it} * Skill * Con_{it}) + \beta_{12} (Dis_{it} * Skill * Sue_{it} * Con_{it}) + \epsilon_{it}$$

Variable Name	Coef, from pooled regressions (t-statistic)	Mean coef. from annual regressions (t-statistic)	Number of positive Coefficients	Adj-R^2
Intercept	0.010****	0.012****		2.70 %
	(6.42)	(4.10)	[16/17]	
Dis	-0.631****	-0.019****		
	(-26.46)	(-4.33)	[2/17]	
Skill	-0.00	-0.002		
	(-0.11)	(-1.07)	[5/17]	
Sue	0.015	0.006		
	(0.96)	(0.14)	[7/17]	
Con	-0.014****	-0.014****		
	(-14.21)	(-2.89)	[3/17]	
Sue*Skill	-0.02	-0.041		
	(-1.24)	(-0.81)	[10/17]	
Dis*Sue	-0.06****	-0.058		
	(-2.71)	(-1.18)	[5/17]	
Sue*Con	-0.079****	-0.050		
	(-4.23)	(-1.34)	[6/17]	
Sue*Dis*Skill	0.143****	0.108		
	(5.62)	(1.48)	[14/17]	
Skill*Sue*Con	0.076****	0.090*		
	(3.68)	(1.85)	[11/17]	
Dis*Sue *Con	-0.031	-0.056		
	(-1.23)	(-1.24)	[8/17]	
Dis*Skill*Con	0.015****	0.007*		
	(9.35)	(1.77)	[12/17]	
Dis*Skill*Sue*Con	-0.058*	-0.032		
	(-2.05)	(-0.43)	[6/17]	

[39] *,**, ***,**** significant at 0.05 , 0.01 and higher than 0.001 respectively.
CAR = Cumulative abnormal returns calculated around the estimate date and earnings announcement date for each specific estimate.
Dis = 1 if the distance is above the mean;
Skill = calculated based on ranks obtained from mean forecast errors over the time period by specific analysts.
Sue = Analyst specific forecast errors calculated by taking the difference between the actual earnings and the estimate provided by the specific analyst.
Con = 1 if the standard deviation is above the mean, 0 otherwise

Table 5 (continued)

Panel B: Test of Panel A Coefficient differences

Coefficient Difference	F-value
$\beta_8 - \beta_{12} = 0$	14.85***
$\beta_{11} - \beta_{12} = 0$	6.54***

Table 6
Regression Results Based on Unexpected Earnings, Meeting and Dispersion

Panel A: Abnormal returns surrounding earnings' announcement date.[40]

$$CAR_{it} = \alpha_0 + \beta_1 Short_{it} + \beta_2 Beat_{it} + \beta_3 UE_{it} + \beta_4 Disp_{it} + \beta_5 (UE^* Disp_{it})$$
$$+\beta_6(UE_{it} * Beat_{it}) + \beta_7(UE^* Disp_{it} * Beat_{it}) + \sum_{j=1}^{5} \lambda_j X_{jit} + \varepsilon_{it}$$

Variable Name	Coef, from pooled regressions (t-statistic)	Mean coef. from annual regressions (t-statistic)	Adj-R^2
Intercept	-0.002 (-1.14)	-0.001 (-0.44)	4.04%
Short	-0.003 (-1.68)	-0.004 (-2.58)	
Beat	0.012*** (6.39)	0.010*** (6.30)	
UE	1.099*** (14.16)	1.132*** (5.53)	
Disp	-0.001 (-1.00)	-0.000 (-0.40)	
UE**Beat	2.00*** (12.39)	1.121*** (3.97)	
UE*Disp	-0.400*** (-5.74)	-0.446*** (-4.07)	
UE*Disp*Beat	-1.890*** (-9.36)		

[40] *, **, *** significant at 0.05, 0.01 and higher than 0.001 respectively.

CAR = the 3-day market adjusted abnormal return using the CRSP value-weighted market portfolio return cumulated from one trading day before to one trading day after the earnings announcement date.
UE = unexpected earnings: defined as the difference between the reported earnings and the consensus analyst forecast.
Short = 1 when actual earnings fall below analysts' forecasts 0 otherwise.
Beat = 1 when actual earnings exceed analysts' forecasts 0 otherwise.
Disp = 1 when the standard deviation is above the mean
X_j = UE interacted with the cross-sectional earnings response coefficient determinant. Following determinants are
Growth = market to book ratio;
Lev= a firms' leverage and is calculated as long-term debt divided by the sum of long-term debt, preferred stock holders' equity and common stock holders' equity;
Risk= Beta;
Size= the natural log of total assets;
Persist = a measure of persistence, defined as the earnings/price ratio for every quarter.

Table 6 (continued)

Panel B :Test of Panel A Coefficient differences

Coefficient Difference	F-value
$\beta_6 - \beta_7 = 0$	130.56***
$\beta_5 - \beta_7 = 0$	37.88***

Table 7
Regression Results Based on Skilled Analysts' Mean, Dispersion and Cumulative Abnormal Returns

Panel A: Abnormal returns surrounding earnings' announcement date.[41]

$$CAR_{it} = \alpha_0 + \beta_1 UE_{it} + \beta_2 Beat_{it} + \beta_3 Short_{it} + \beta_4 Disp_{it} + \beta_5 (UE^* Disp_{it})$$
$$+\beta_6(UE_{it} * Beat_{it}) + \beta_7(UE^* Disp_{it} * Beat_{it}) + \beta_8 SAbeat_{it} + \beta_9 SAshort_{it}$$
$$+\beta_{10} (UE_{it} * Disp_{it} * SAbeat_{it}) + \sum_{j=1}^{5} \lambda_j X_{jit} + \varepsilon_{it}$$

Variable Name	Coef, from pooled regressions (t-statistic)	Mean coef. from annual regressions (t-statistic)	Adj-R^2
Intercept	-0.002	-0.002	3.93%
	(-1.27)	(-0.92)	
UE	0.440**	0.585**	
	(12.64)	(6.10)	
Beat	0.012**	0.010**	
	(7.15)	(7.01)	
Short	-0.006**	-0.005**	
	(-3.48)	(-3.42)	
Disp	-0.007	0.000	
	(-1.63)	(0.14)	
UE*Disp	-0.886**	-0.866**	
	(-5.28)	(-2.19)	
UE**Beat	1.123**	0.770**	
	(12.23)	(4.48)	
UE*Disp*Beat	-5.39**	-4.966**	
	(-4.10)	(-1.90)	
SAbeat	0.002	0.003**	
	(1.86)	(2.49)	
SAshort	0.001	0.000	
	(1.13)	(0.32)	
UE*Disp* SAbeat	-0.816	-0.639	
	(-0.72)	(-0.26)	

[41] *, ** significant at 0.05 and 0.01 respectively

CAR = the 3-day market adjusted abnormal return using the CRSP value-weighted market portfolio return cumulated from one trading day before to one trading day after the earnings announcement date.
UE = unexpected earnings: defined as the difference between the reported earnings and the consensus analyst forecast deflated by the stock price at the end of the quarter.
Short = 1 when actual earnings fall below analysts' forecasts 0 otherwise.
Beat = 1 when actual earnings exceed analysts' forecasts 0 otherwise.
Disp = 1 when the standard deviation is above the 75th percentile.
SAbeat= 1 when actual earnings exceed skilled analysts' mean estimates, 0 otherwise
SAshort.=1 when actual earnings fall below skilled analysts' forecasts ,0 otherwise
X_j = UE interacted with the cross-sectional earnings response coefficient determinants.

Table 7 (continued)

Panel B: Test of Panel A Coefficient differences

Coefficient Difference	F-value
β_2 - β_3=0	110.49**
β_2 -β_8=0	19.83**
β_8 - β_9 =0	3.32
β_{10}-β_6=0	2.95
β_7-β_{10}=0	3.88*

Table 8

Tests of the Means Based on Dispersion and Regulation Fair Disclosure

Panel A: Before the implementation of Regulation Fair Disclosure[42]

	High Dispersion Firms	Low Dispersion Firms	Test of the mean difference
The ratio of public information	0.5854	0.6507	64.86**
N	202,000	872,000	

Panel B: After the implementation of Regulation Fair Disclosure

	High Dispersion Firms	Low Dispersion Firms	Test of the mean difference
The ratio of public information	0.5583	0.6018	14.07**
N	18,044	56,691	

[42] *, ** significant at 0.05 and 0.01 respectively
The implementation date of the regulation Fair disclosure is October 2000.

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Published Articles in Referred Journals

Adut, D., W. Cready, T. Lopez. 2003. Restructuring charges and CEO cash compensation: a reexamination. *The Accounting Review* 78 (January): 169-193.

Working Papers

Rees, L., D. Adut (2003) The effect of regulation fair disclosure on the relative accuracy of analysts' published forecasts versus whisper forecasts, Working Paper, Texas A&M University, College Station

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