Differences of Opinion and Stock Returns

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Autorise l'impression de la présente thèse.

Neuchâtel, le 24 février 2011

Le doyen

J-M Grether

Jean-Marie Grether

To the memory of my father,

ARARAT JANUNTS

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Executive Summary

This dissertation comprises of four chapters. The first chapter reviews the literature on the relationship between differences of opinion and stock returns, with special attention to the use dispersion of analysts' earnings per share forecasts in asset pricing. As reviewed, the literature is split on the relationship between forecast dispersion and stock returns both in terms of the direction of the relationship and in terms of the role of forecast dispersion. Therefore, to understand the causes of the dispersion-return relationship, I conduct detail analyses of the dispersion anomaly.

The second chapter sheds a new light on the empirical relationship between forecast dispersion and stock returns by examining whether the relationship is robust to different dispersion measures and whether the dispersion-return relationship is related to other well-known financial anomalies. My results strongly suggest that contemporaneous dispersion is negatively correlated with future stock returns. Moreover, the dispersion-return relationship is most pronounced in smallest market capitalization stocks and is robust across different measures of forecast dispersion. Notably, my results show that the dispersion anomaly is not explained by previously documented phenomena such as accruals quality, asset growth, capital investment underperformance, and equity issue anomalies.

To understand more about the dispersion-return relationship, it is necessary to understand the causes of forecast dispersion. The third chapter fills this gap by conducting a thorough analysis on the determinants of forecast dispersion such as firm risk, information asymmetries, forecasting difficulties, analyst conflicts of interest, herding. Evidence shows that forecast dispersion has several dimensions including information asymmetries and differences of opinion. On one hand, a group of analysts can have superior information. On the other hand, even when having the same information set, for example after earnings announcements, analysts revise their forecasts not necessarily in the same direction.

Regression analysis shows that forecast dispersion is a function of firm's risk, past performance, analysts' differing information set, forecasting difficulty, and analyst conflicts of interest and herding. In other words, forecast dispersion is a complex concept and different factors simultaneously explain why analysts disagree in their forecasts. Overall, my analysis importantly suggests that we should be cautious when using forecast dispersion as a measure of firm riskiness or firm information environment.

The fourth chapter investigates whether incorporating determinants of forecast dispersion as conditioning information in asset-pricing models helps capture the impact of the dispersion effect on raw and risk-adjusted returns of individual stocks (and not portfolios). I use four different specifications of the two-pass time-series regression models with time-varying betas, where betas vary with firm's market value of equity, book-to-market ratio, and the corporate spread. Regardless of the method used for risk-adjustment, there is a strong negative relation between average returns and forecast dispersion. Moreover, my results show that accounting for the determinants of forecast dispersion reduces but does not eliminate the predictive power of forecast dispersion on stock returns. Remarkably, the determinants of forecast dispersion account for half of the profitability of dispersion strategy, thus substantiating the importance of the determinants of forecast dispersion in understanding the dispersion anomaly.

Key words: differences of opinion; analyst forecast dispersion; stock returns; determinants of forecast dispersion, heterogeneous expectations; earnings per share forecasts.

“Differences of opinion is one crime that kings never forgive”

Ralph Waldo Emerson, 1803-1882

U.S. poet, essayist and transcendentalist

Introduction

For capital markets, financial analysts are important participants and play an integral part of Wall Street profit centers. Through media, analysts reach millions of individual investors. At the same time, analysts are also influential among institutional investors such as mutual fund managers that manage most of the capital under management. More importantly, banks rely on analysts to get investment-banking deals. To summarize, analysts can generate hefty trading commissions for their brokerage houses.

While analysts perform many tasks, among the most important is generating earnings forecasts. One reason is because investors care about whether the firm will meet its earnings forecasts. Another is that analysts can more finely signal their views on stocks with earnings forecasts than with stock recommendations; see Nocera and Kover (1997). Based on survey analysis, Block (1999) presents evidence that investors regard earnings forecasts rather than recommendations as a highly important input into their valuation models. Analysts process a substantial amount of information, so their forecasts are superior to those derived from simple time-series models; see Brown and Rozeff (1978) and Brown, Griffin, Hagerman, and Zmijewski (1987). When firms report earnings that exceed analyst forecasts, their stock prices increase. By contrast, when firms report earnings that fall short of analyst forecasts, their stock prices decrease. The simple fact is that news creates surprises, and surprises create volatility and trading opportunity.

The relation between the dispersion of analysts' earnings per share (EPS) forecasts and stock returns is one of the long-standing and fundamental issues in finance. Because earnings forecasts of sell-side analysts are public, in my thesis analyst by default refers to sell-side analyst and, unless otherwise stated, forecast is the EPS forecast. Throughout the thesis, I also interchangeably use "forecast dispersion" and "dispersion" to refer to the dispersion of analysts' EPS forecasts. According to Barron, Stanford, and Yu (2009), from 1990 to 2004 this dispersion measure has been used in more than ten finance papers and more than forty accounting papers in top journals; see Appendix 1 in their paper for more details.

A Google Scholar search in November 2010 for "analyst forecast dispersion and stock returns" produced about 17,000 hits. While, many papers document that forecast dispersion should be priced in the cross-section of stock returns, the sign of the relation is not clear. A growing number of studies suggest that tests of forecast dispersion that employ stock returns face challenges. On the one hand, several studies show that firms with higher forecast dispersion have lower future returns. In these studies, dispersion is not a priced risk factor but affects returns through its combination with short sale constraints; see Diether, Malloy, and Scherbina (2002), or its effect on idiosyncratic risk in levered firms; see Johnson (2004). On the other, Anderson, Ghysels, and Juergens (2005) and Qu, Starks, and Yan (2004), among others, suggest that high forecast dispersion implies high expected returns. In particular, they show that the dispersion factor (portfolio long in high-dispersion stocks and short in low-dispersion stocks) is positively related to stock returns. Anderson, Ghysels, and Juergens (2009) also study the relationship between stock returns and forecast dispersion, but using corporate profit forecasts as opposed to earnings forecasts of individual firms. They show that forecast dispersion is a risk factor that is positively priced in the cross-section of stock returns and further argue that forecast dispersion is an important determinant of stock returns.

How to explain the evidence that investors can earn excess returns by trading on the dispersion of earnings forecasts? What are the causes of analyst disagreement that induces forecast dispersion? How analyst disagreement affects stock prices. In my thesis, I take a further step to answer these questions and conduct a detailed examination of the determinants of forecast dispersion and the implication of forecast dispersion on stock prices.

This dissertation consists of four chapters. Chapter 1 presents a thorough review of the literature where investors' differences of opinion is measured by forecast dispersion. Next, I examine whether the method of measuring forecast dispersion is important in predicting stock returns. I further examine whether the relationship between average returns and forecast dispersion is due to the direct influence of dispersion, or whether dispersion is merely a proxy for other driving factors of expected stock returns.

Chapter 2 starts by shedding new light on the empirical relation between forecast dispersion and stock returns. It presents evidence that contemporaneous forecast dispersion negatively correlates with future stock returns by extending the analysis of previous studies to a longer sample period. The dispersion-return relationship is most pronounced in smallest market capitalization stocks and is robust across different measures of dispersion. This effect is not explained by previously documented phenomena such as accruals quality, asset growth, capital investment underperformance, and equity issue anomalies.

Most of the studies in the literature concentrate on interpreting the dispersion-return relationship without questioning the causes of the forecast dispersion. To understand more about the dispersion-return relationship, it is necessary to understand the causes of forecast dispersion. Chapter 3 analyses the determinants of forecast dispersion. Regression analysis shows that forecast dispersion is a function of firm's risk, past performance, analysts' differing information set, forecasting difficulty, and analyst conflicts of interest and herding. In other words, forecast dispersion is a complex concept and many factors simultaneously explain why analysts disagree in their forecasts. Overall, my results suggest that we should be cautious when using forecast dispersion as a measure of firm riskiness or firm information environment. These results are important for further understanding the observed negative relationship between forecast dispersion and stock returns.

Chapter 4 investigates whether forecast dispersion is priced in the cross-section of individual stock returns (and not portfolios). I use two-pass time-series regression models with time-varying betas, where betas vary with firm's market value of equity, book-to-market ratio, and the corporate spread; see Brennan, Chordia, and Subrahmanyam (1998) and Avramov and Chordia (2006). Results show that forecast dispersion stays negatively correlated with future stock return. Accounting for the determinants of forecast dispersion reduces but does not eliminate the predictive power of forecast dispersion on stock returns.

Chapter 1: Differences of Opinion and Stock Returns: A Literature Review

1.1 Introduction

The capital asset pricing model, (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) states that the expected return of a stock is linearly related to its non-diversifiable risk. One key assumption of CAPM is that everyone shares homogeneous expectations. Lintner (1969) relaxes the assumption of homogeneous expectations and shows that the major implications of the CAPM are unaffected. For example, Lintner concludes that the same combination of stocks is optimal for every investor, and that the amounts invested in each stock is equivalent to the ratio of that stock's market value to the total value of all stocks. Assuming that investors have difference degrees of risk aversion, Lintner also shows that a single scalar measure of risk aversion still determines stock prices. In other words, stock prices are determined assuming a representative investor has a coefficient of risk aversion equal to the weighted average of all risk aversions. Although there are many other studies discussing how to aggregate heterogeneous expectations, what causes investors' heterogeneity is still an open question. Is it the economic uncertainty, information asymmetries, or differences in interpreting public information?

Harris and Raviv (1993), Kandel and Pearson (1995), and Bamber, Barron, and Stober (1999) document a positive relationship between price changes and trading volume. They show even higher volume around earnings announcements than during other periods with similar price changes and no earnings news. Thus, the price change is not the only determinant of trading volume. The assumption of different interpretation of information also helps explaining the relationship between price changes and trading volume. In order to rationalize trade among investors, we have to modify the assumption that investors hold the same expectations and same interpretation; see also Karpoff (1986) and Varian (1985a).

Investor expectations are intrinsically unobservable, thus measuring their heterogeneity poses challenging methodological problems. Because investors use financial analyst expectations in forming their own expectations, we can use analyst expectations to proxy for investor expectations. Unfortunately, financial analysts normally issue only their point forecasts. Aggregating these individual forecasts offers some indication of the degree of consensus among analysts, but it does not provide information regarding the confidence that each analyst attaches to his/her point forecast. Three widely used sources of analyst forecasts are the Institutional Brokers' Estimate System (I/B/E/S), the Livingston survey, and the Survey of Professional Forecasters (SPF).[1] While I/B/E/S collects earnings forecasts for individual firms, Livingston survey and the SPF provide forecasts for macroeconomic variables. In addition, I/B/E/S and Livingston survey distribute only point forecasts but the SPF provides both point forecasts and the histogram of forecasts for GDP, unemployment, inflation, and other major macroeconomic variables. Thus, the SPF is useful in addressing the question of whether heterogeneous expectations represent uncertainty, measured by analyst's confidence in her forecast.

The use of forecast dispersion to proxy for uncertainty is controversial. As Bomberger and Frazer (1981) emphasize "the standard deviation among individual forecasts of inflation is, strictly speaking, a measure of the dispersion of opinion rather than a measure of the confidence in which those opinions are held". Consensus among analysts need not imply a high degree of confidence in their point forecasts. Assuming that uncertainty is related to forecast error, Bomberger and Frazer (1981) find high correlation (0.77) between forecast dispersion and uncertainty. They use inflation forecasts from Livingston survey. Lambros and Zarnowitz (1987) also point to the important distinction between forecast dispersion and uncertainty, but argue that Bomberger and Frazer's result is inconclusive because past forecast errors represent only past uncertainty, thus ignoring future uncertainty that includes

[1] Federal Reserve Bank of Philadelphia provides both the Livingston survey and the SPF.

latest news, prospective shifts in economic policies, and changes in external factors that affect business and finance. Using the SPF, Lambros and Zarnowitz (1987) show a positive correlation between forecast dispersion and uncertainty, where uncertainty is proxied by the spread of the probability distribution of point forecasts. Although they support the use of forecast dispersion as a measure for uncertainty, Lambros and Zarnowitz (1987) show that forecast dispersion understates uncertainty; see also Engle (1983), D'Amico and Orphanides (2008).

There may be periods where analysts agree on future high uncertainty, and hence forecast dispersion will be low even though uncertainty is high. The opposite relation arises when analysts strongly disagree on their point forecasts but are confident about their individual predictions. This situation arises when analysts disagree on their models and scenarios. Thus, lacking any theoretical basis, the strength and the stability of the relationship between forecast dispersion and uncertainty becomes an empirical issue. Lahiri and Sheng (2010) find that the relationship depends on both the sample period and the length of the forecasting horizon. Decomposing forecast errors into common and idiosyncratic components, they show that uncertainty equals forecast dispersion plus the variance of future aggregate shocks that accumulate over horizons. This finding has important implications. It suggests that the robustness of the proxy depends on the variance of aggregate shocks over time and across horizons. Forecast dispersion is a reliable measure for uncertainty in stable periods. In periods with large volatility of aggregate shocks, however, dispersion becomes a less reliable proxy. As for the horizon effect, they find the longer the forecast horizon, the larger is the difference between dispersion and uncertainty.

Using the I/B/E/S earnings forecasts data, many researchers parallel studied whether forecast dispersion is a proxy for risk or uncertainty. Theory suggests that forecast dispersion reflects both risk and uncertainty; see Abarbanell, Lanen, and Verrecchia (1995), Barron, Kim, Lim, and Stevens (1998), among others. Anderson et al. (2009) note that risk and uncertainty are different concept, and describe “an event risky if its outcome is unknown but the distribution of its outcomes is known, and an event is uncertain if its outcome is unknown and the distribution of its outcomes is also unknown”. Barry and Brown (1985) demonstrate that, as the amount of public information increases, analysts’ forecasts converge. Thus, they suggest forecast dispersion as a proxy for parameter uncertainty. By uncertainty, they mean the estimation risk of the parameters of an asset-pricing model. However, a few years later, Barry and Jennings (1992) suggest that the adequacy of forecast dispersion as a proxy for parameter uncertainty depends on the relative amount of public versus private information. When there is more public than private information, additional private information can lead toward high forecast dispersion.

Barron and Stuerke (1998) bring two further evidence supporting forecast dispersion as a proxy for future uncertainty. First, soon after earnings announcements, they show positive association between forecast dispersion and the proportion of analysts who revise their forecasts at least twice during the same quarter. This confirms Abarbanell et al. (1995) hypothesis that as forecast dispersion increases after earnings announcements, investors are less informed, thus demand for more information. Second, forecast dispersion is positively associated with stock price changes around the next quarterly earnings announcements. This suggests that forecast dispersion reflects uncertainty that affects stock prices.

The literature on how to proxy investor heterogeneity is vast and still growing. Bid-ask spread is a widely used proxy for differences of opinion. The idea that investors have different opinions that creates a spread, motivates the use of bid-ask spread; see Handa, Schwartz, and Tiwari (2003), Houge, Loughran, Suchanek, and Yan (2001). Another closely related measure is the probability of information-based trading (PIN) advanced by Easley, Hvidkjaer, and O'Hara (2002). Given a history of trades, they develop a microstructure model to estimate the probability that the next trade is from an informed trader. When information about the payoff of a stock is private rather than public and uninformed investors cannot perfectly infer such private information from prices, they require a greater expected excess return. Easley et al. (2002) interpret PIN as a measure of information risk and show evidence that is does predict stock prices. Numerous papers treat high trading volume as an indicator of inventors' differences of opinion. Bamber (1987) and Bamber, Barron, and Stober (1997) find that total trading volume is higher around earnings announcements and suggest that it is investors' differences of opinion driving trading volume. Trading volume may in addition proxy for differences of interpretation; see Kandel and Pearson (1995). Garfinkel and Sokobin (2006) compute the abnormal trading volume (by previous volume) around earnings announcement and show that it is positively associated with future stock returns. Because trading volume is measured on the basis of executed trades, a recent paper of Garfinkel (2009) argues that it is not an appropriate proxy for investors' differences of opinion. If an investor's order is not executed, it is because he was unwilling to accept the market price. Thus, execution prices do not accurately reflect investors' private valuations. Garfinkel proposes a new proxy of differences of opinion from order data, and shows that it positively correlates with other extensively used proxies such as bid-ask spread and analyst forecast dispersion.

Despite the numerous studies discussing whether heterogeneous expectations represent economic uncertainty or information risk, the impact of heterogeneity on equilibrium stock prices is yet to be fully understood. This article reviews the literature on the relationship between differences of opinion and stock returns, with special attention to the use forecast dispersion in empirical asset pricing tests. An important distinction between forecast dispersion and the above-mentioned proxies of differences of opinion is that forecast dispersion is a forward-looking measure. There is at least one reason why analyst disagreement is important for asset pricing - to know if we can achieve abnormal returns based on public information. Many authors have incorporated differences of opinion into asset pricing models. Although I will not be able to review all papers in this literature, I try to cover the largest possible range of studies.

I review the theoretical literature in Section 1.2, and present the empirical literature in Section 1.3. Section 1.4 discusses potential driving forces behind the currently known stylized facts. Section 1.5 concludes.

1.2 Theory

1.2.1 Positive differences of opinion-return relationship

One strand in differences of opinion literature suggests that high differences of opinion stocks should have lower current prices than low differences of opinion stocks. Williams (1977) examines the differences of opinion-return relationship within a CAPM framework. When investors disagree on stock returns, they demand higher rates of return. Varian (1985b) and Mayshar (1983) extend CAPM assuming 1) no restrictions on short selling, and 2) that investors have identical preferences except for differing opinions about expected stock returns. If risk aversion does not decline too rapidly, then differences of opinion decreases current prices and increases expected returns. Cho (1992), Abel (1989), and Kazemi (1991) draw similar conclusion that risk-averse investors decrease current stock prices because high differences of opinion makes stock's future payoffs riskier.

Fama and French (2007) show that when some investors do not hold the tangency portfolio from the minimum-variance frontier (for reasons of information asymmetry, transaction costs, asset tastes, or the like), other investors will also deviate from the tangency portfolio, in order to clear the market. This makes the market portfolio different from the tangency portfolio, thus moving stock prices away from the CAPM pricing. Uppal and Wang (2003) also show that the ambiguity joint distribution of stock returns results in undiversified portfolios. In the same spirit, Levy (1978) and Merton (1987) assume that it is costly for investors to keep track of all stocks in the market - thus investors only hold stocks with which they are familiar. Söderlind (2009) also contends that differences of opinion affects stock prices through little diversification. However, if investors are risk-averse, they diversify so the effect of differences of opinion vanishes.

Detemple and Murthy (1994) find that stock prices in the differences of opinion economy are equal to the weighted average of prices that would prevail in the corresponding economies with homogeneous beliefs. The proportion of the total wealth held determines the weights. Decomposing stock returns into risk and uncertainty components, Kogan and Wang (2003) and Anderson et al. (2009) show that both risk and uncertainty carry risk premium. In particular, they show theoretically that expected excess return of a stock depends on a measure of risk aversion times the amount of risk plus a measure of uncertainty aversion times the amount of uncertainty. Anderson et al. (2009) define risk as the market volatility and measure uncertainty by the dispersion of corporate profit forecasts from the SPF (rather than earning forecasts of individual firms). They observe that the uncertainty-return relationship is stronger than the risk-return relationship. The correlation between market excess return and uncertainty is 0.28 whereas the correlation with risk is only 0.15.

1.2.2 Negative differences of opinion-return relationship

Theory changes when short-sale costs are introduced. As set forth by Miller (1977), high short-sale costs prevent pessimistic views to reflect in stock prices. The intuition behind this result is simple. With high short-sale costs, pessimistic investors are forced to sit on the side lines while optimistic investors buy the stocks. Thus, the marginal investor who sets the price is the optimistic one. Basak (2005) shows that risk transfers from pessimists to optimists. Pessimists simply do not trade as opposed to selling short, which is what they do in an unconstrained setting. The greater the differences of opinion between optimists and pessimists, the higher the current stock price, hence the lower the expected returns. Jarrow (1980), however, demonstrates that short-sale costs are not enough to generate subsequent low returns. In principle, the price of high differences of opinion stocks could rise or fall depending on how investors disagree about the covariance matrix of the next period's prices. If they agree upon the covariance matrix, relative stock prices will rise. Jarrow appears to be at odds with Miller but this is not the case: Miller examines the effects of relaxing only one stock's short-sale cost, while Jarrow models the impact of simultaneously eliminating all short-sale costs.

Differences of opinion and short-sale costs are not enough to rationalize overpricing. High short-sale costs explain why arbitrageurs fail to short overpriced stocks, but not why some investors (presumably the optimists) are willing to hold these stocks. Overpricing only occurs if there is reason to hold the overpriced stocks. Harrison and Kreps (1978) develop a dynamic model where investors choose to hold overpriced stocks because of the possibility of reselling to more optimistic investors in the future. Since an investor knows that in the future other investors may value the asset more than he does, he is rationally willing to pay more for the stock than he would pay if he is forced to hold it forever; see also Morris (1996), Duffie, Gârleanu, and Pedersen (2002), and Scheinkman and Xiong (2003).

1.2.3 No differences of opinion-return relationship

Difference of opinion does not necessary lead to overpricing. Diamond and Verrecchia (1987) assume that investors glean information from trading activity and that short-selling is costly. They differentiate between informed investors who posses private information and uninformed investors who observe only public information (e.g., all trades that take place). Because high short-sale costs may prevent informed investors from trading, uninformed investors infer that "no trade is bad news". Therefore, uninformed investors do not trade either. As a result, despite the short-sale costs and differences of opinion, stocks do not become overpriced. Hong and Stein (2003) also achieve unbiased prices by introducing competitive, risk-neutral, and perfectly rational arbitrageurs who do not face short-sale costs. The arbitrageurs recognize that the true value of a stock is lower than the optimistic investors' value, short-sell the stock and push its price back to true value. In summary, some papers predict no relation between differences of opinion and subsequent returns, but rely on perfectly rational arbitrageurs that can eliminate mispricing. However, as Shleifer and Vishny (1997) note, arbitrageurs may be unable to close arbitrage opportunities when facing the risk that mispricing gets worse before it vanishes.

1.3 Evidence

The empirical literature also produces contradictory results. I start with the discussion of the choice of forecast dispersion as a proxy of differences of opinion. Then I review the empirical literature on the opinion-return relationship. Table 1.1 lists the selected papers along with their methods and brief conclusions.

1.3.1 Forecast dispersion as a measure of differences of opinion

As a proxy for the differences of opinion, I employ the earnings forecast dispersion. I/B/E/S provides analyst point forecasts of annual earnings. The use of forecast dispersion as a measure of differences of opinion explicitly assumes that analyst estimates are surrogates for investor estimates. Several papers emphasize that the use of analyst forecast dispersion as a proxy for investor differences of opinion has some flaws. For example, Abarbanell et al. (1995) show analytically that forecast dispersion does not fully capture investor differences of opinion, because other forecast attributes also affect forecast precision. Specifically, the precision of information common to all analysts and the number of analysts forecasting earnings also affect forecast dispersion. Thus, forecast dispersion alone is not a sufficient statistics to measure investor differences of opinion. Barron (1995) shows empirically that even with no change in forecast dispersion, trading may occur when analysts change their relative positions from one forecast period to the next, referred to as “belief jumbling”.

Although some papers criticize the use of analyst forecast dispersion as a proxy for investor differences of opinion, much evidence shows that analyst forecasts is a key variable in the price formation process. Elton, Gruber, and Gultekin (1981) ask whether investors can earn excess returns based on analyst growth forecasts. They find no such evidence. This suggests that stock prices incorporate the information contained in analyst forecasts. Another strain of literature finds a positive relationship between forecast dispersion and trading volume; see Comiskey, Walkling, and Weeks (1987), Ajinkya, Atiase, and Gift (1991), among others. In addition, Ajinkya and Gift (1985) find a positive correlation between forecast dispersion and the implied standard deviation of stock returns from option prices. In summary, analyst forecast dispersion has incremental information in price formation process.

Analysts spend considerable time and effort in forecasting future earnings of firms and make their forecasts public. Since investors consult analysts in forming their own expectations, investor expectations may be influenced by - and so reflect - analyst expectations. Analyst expectations are not however limited to public information. Analysts also visit firms they follow and discuss prospects with executives. To prevent selective disclosure, on August 10, 2000 the U.S. Securities and Exchange Commission introduced a set of “fair disclosure regulations”, generally referred to as “Reg FD”. Although the rules require a firm to reveal any material information to analysts and investors simultaneously, analysts still obtain useful information during conference calls. Bowen, Davis, and Matsumoto (2002) show that prior to Reg FD, conference calls increase analyst forecast accuracy. After the Reg FD, forecast dispersion has decreased suggesting that information asymmetries has decreased after Reg FD; see also Agrawal, Chadha, and Chen (2006), Kwag and Small (2007), and Irani and Karamanou (2003). However, as argued by Byard and Shaw (2003), firms with a reputation of higher quality disclosures reflect greater precision in analysts' both common and private information. This suggests that analysts rely more heavily on public information rather than communications with firms' executives. Overall, it is reasonable to assume that analyst forecasts are acceptable proxies for investor expectations.

In the absence of direct measures of future uncertainty, researchers have widely used the dispersion of point estimates of earnings to refer to future uncertainty. When we employ forecast dispersion to indicate uncertainty, the assumption is that this measure is a proxy for the diffuseness of the corresponding forecasts' probability distributions. While there is no theoretical relationship between forecast dispersion and future uncertainty, there is some empirical support for viewing forecast dispersion as a proxy for future uncertainty. Using the SPF gross national product forecasts, Lambros and Zarnowitz (1987) find a significant positive relationship between the average of standard deviation of probability distributions and the standard deviation of point estimates. Bomberger (1996) shows that the variance of subsequent forecast errors is proportional to the variance of forecasts. These findings suggest that the assumption of using forecast dispersion as a measure of uncertainty is on solid grounds; see also Rich and Butler (1998) and Bomberger (1999). Using longer period, a recent paper by Giordani and Söderlind (2003) confirms the use of forecast dispersion a measure of uncertainty.

Forecast dispersion is also an appealing proxy for differences of opinion because unlike other measures, such as short-interest or breadth of ownership, it is available for a large number of firms. Nevertheless, this measure also has drawbacks. For example, the calculation of forecast dispersion requires at least two forecasts. Thus, there is an unavoidable issue of data deletion when using the I/B/E/S datasets, since I/B/E/S does not cover many listed firms. This sample bias seems to be negligible because La Porta (1996) presents evidence that portfolio performance of equal-weighted stocks in I/B/E/S is almost identical to stocks in Center for Research in Security Prices (CRSP), suggesting that I/B/E/S and CRSP stocks are similar.

Forecast dispersion is usually defined as the standard deviation of analysts' forecast normalized by the absolute value of the average forecast. The reason for normalizing the standard deviation by the absolute value of the average forecast is to exclude the size effect and that the standard deviation of forecasts increases with the average forecast. I/B/E/S provides earnings forecast data on a split-adjusted basis, rounded to the nearest cent (i.e., at two decimal places). Because not all forecasts divide precisely to a cent, adjusting for stock-splits and rounding to the nearest cent cause a loss of information. For example, if a stock has split 10-fold, EPS forecasts of 10 and 12 cents would be reported as 1 cent per share in the I/B/E/S split-adjusted datasets. In reality, they are 1 and 1.2 cents per share, respectively. I/B/E/S split-adjusted summary dataset thus records a zero standard deviation of forecasts, when in fact it is 0.14 cent and forecast dispersion is 0.14/1.1 = 0.13. The rounding procedure in I/B/E/S underestimates forecast dispersion for firms that split their stocks. Diether et al. (2002), Payne and Thomas (2003), and Baber and Kang (2002) show that this split-adjustment procedure can lead to wrong conclusions. The unadjusted summary dataset is now available for individual firms and it contains summary statistics on split-unadjusted forecasts.

1.3.2 Negative dispersion-return relationship

A number of empirical studies find that forecast dispersion is negatively associated with subsequent returns. Several explanations are suggested in the literature: 1) short-selling, 2) analyst guidance, and 3) analyst conflicts of interest.

1.3.2.1 Short-Selling

Using the I/B/E/S unadjusted summary dataset, Diether et al. (2002) find that in U.S. markets, during the period of 1983 to 2000, high-dispersion stocks underperform low-dispersion stocks by 9.48% yearly. Surprisingly, they also find a positive correlation between forecast dispersion and commonly used measures of risk such as the beta, standard deviation of returns, and the standard deviation of earnings. Thus, they argue that the relation between forecast dispersion and subsequent stock returns is hard to reconcile within a risk-based explanation. This cross-sectional dispersion-return relation is unexplained by standard asset pricing models including the Fama and French (1993) model or extension of this model augmented by Carhart (1997) momentum factor. Diether et al. (2002) suggest that forecast dispersion is a proxy for difference of opinion rather than risk. Specifically, as set forth by Miller (1977), higher dispersion introduces a larger optimistic bias into stock prices as optimistic investors bid prices up, while short-sale costs prevent pessimistic views from being reflected in stock prices, thus causing high dispersion stocks to become overpriced. Although Diether et al. (2002) do not directly consider short-sale costs, Kot (2006) does provide empirical support for a positive relationship between short-interest and forecast dispersion. Boehme, Danielsen, and Sorescu (2006) also find that when short-sale costs are high, forecast dispersion is negatively correlated with future stock returns but when short-sale costs are absent, the correlation becomes positive.

Diether et al. (2002) report that the dispersion effect is significant for all size groups during 1983-1991. However, for 1992-2000 it is significant only for the smallest size group. A reduction in obstacles to short selling may be the cause. In a contemporaneous study, Baik and Park (2003) also obtain the negative dispersion-return relationship that continues to hold up to three years.[2] They find the dispersion effect to be concentrated among highly illiquid stocks, so they contend that high arbitrage costs deter investors from exploiting the dispersion effect. By contrast, Johnson (2004) argues that forecast dispersion is a proxy for information risk rather than differences of opinion. Assuming that dispersion increases firm's total risk,

[2] Diether et al. (2002) and Baik and Park (2003) differ in two aspects. First, while Diether et al. (2002) form portfolios monthly, Baik and Park (2003) perform yearly portfolio formation based on the dispersion at the end of December. Second, they distinctly treat firms with different fiscal year ends. In their sample, Diether et al. (2002) include all firms with different forecast-year-ends. However, forecast dispersions across firms can be different not only because analysts' disagreements differ across firms but also because forecast horizons differ. Although both papers measure forecast dispersion as the coefficient of variation, Baik and Park (2003) differentiate between firms having different fiscal year ends.

high-dispersion stocks may be fairly priced. If a firm is levered and equity is a call option on the firm's assets with an exercise price of the firm's debt, then forecast dispersion increases the value of the call option. Johnson’s evidence supports this hypothesis.

It is not clear yet whether short-sale costs drive the dispersion effect. For example, Scherbina (2001) and Park (2005) find dispersion effect even for S&P 500 stocks that are easy to short. Scherbina argues that “…while the costs of short-selling the S&P 500 stocks are low, they are not negligible”. Clearly, some evidence on the cost of shorting is desirable in tests explaining dispersion-return relationship. If stocks with high short-sale costs earn low returns, then we have direct confirmation of Miller’s theory. Some recent papers have sought to detect direct short-sale costs and study how differences of opinion impacts stock price when shorting is difficulty. For example, using a unique dataset of short-sale costs for 1926-1933 period, Jones and Lamont (2002) show that stocks that are expensive to short have low subsequent returns. Mohanaraman (2003) draws similar conclusion that more short-constrained stocks earn lower subsequent returns.

Two conditions for Miller’s overvaluation theory to hold are 1) that a stock is subject to short-sale costs, and 2) that investors disagree about firm value. Stocks differ both in the degree of differences of opinion and in their short-sale costs. Boehme, Danielsen, Kumar, and Sorescu (2009) study the interaction between the two conditions, with U.S. stocks for 1988-2002. Their measure of short-sale costs is the relative short interest, i.e., the monthly short interest divided by the number of outstanding shares. When short-sale costs are absent, forecast dispersion is positively correlated with subsequent returns. However, when present, the correlation is negative. Overvaluation exists only when both differences of opinion and short sale constraints are present.

1.3.2.2 Analyst guidance

Understanding the forecast dispersion anomaly matters not only because it links a measure of stock fundamentals to stock prices, but also because analyst disagreement is potentially under the control of firms. Managerial incentives can affect forecast dispersion. When analysts make earnings forecasts, they combine information provided by the firm with information they produce on their own. Another major reason for analyst disagreement is that some analysts may know things that other analysts do not. Thus, the two sources of information could give rise to differences of interpretation or differences of opinions among analysts; see Kandel and Pearson (1995), Harris and Raviv (1993).

Managers use quarterly earnings announcements to release information into the market. Normally, firms organize conference calls where managers discuss quarterly results and take questions from analysts. Therefore, much uncertainty is resolved around the time of quarterly earnings announcements. If the dispersion effect reflects investors' behavioral biases, we should expect more reaction from investors around quarterly earnings announcements. Expanding on this idea, Scherbina (2001) shows that about 20% of the return differential between low-and high-dispersion stocks falls in a three-day window around quarterly earnings announcement dates. Berkman, Dimitrov, Jain, Koch, and Tice (2009) also document that high-dispersion stocks earn lower returns around quarterly earnings announcements. The three-day hedge returns (returns on low- minus high- dispersion stocks) are about three times larger than the hedge returns reported by Diether et al. (2002). Thus, there are substantial benefits to focusing the analysis on quarterly earnings announcements. Concentrating on a subsample of stocks that are difficult to sell short magnifies the profitability of dispersion strategy, showing that a significant part of the dispersion effect is due to short-sale costs.

When firms provide unambiguous earnings guidance, analysts rely less on their private sources of information, thus lowering forecast dispersion. Indeed, Ali, Liu, Xu, and Yao

(2009) provide evidence that forecast dispersion is endogenously determined by the firm's earning guidance strategies. Firms with good earnings prospects provide unbiased and accurate earnings relative to firms with poor earnings prospects. Ali et al. (2009) attribute the underperformance of high-dispersion firms to the quality of future earnings and suggest that the delay in disclosing bad news about future earnings temporarily increases stock prices. They show evidence that high-dispersion firms report poor earnings in subsequent quarters. Interestingly, after controlling for future earnings surprises, high forecast dispersion actually leads to high subsequent returns (consistent with risk interpretation of dispersion).

Because firms with good news provide high quality reporting, they have low forecast dispersion. Byard and Shaw (2003) document that analyst forecast distributions for firms with a reputation for providing higher quality disclosures reflect a greater precision of analysts' both common and private information. A related argument is made by Lang and Lundholm (1996) who examine the relation between disclosure practices of firms, number of analysts, and properties of the analyst earnings forecasts. 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. In a similar vein, Ang and Ciccone (2001) claim that the forecast dispersion, measured as the standard deviation of all individual forecasts, is a proxy for firm transparency. Transparent firms that have low forecast dispersion outperform opaque firms. A hedge portfolio earns an average return of about 13% per year.

1.3.2.3 Analyst conflicts of interest

Analysts provide their research to the public with the aim to generate securities trading.[3] However, employed by brokers acting also as investment bankers, analysts face

[3] See Dubois and Dumontier (2007) and Mehran and Stulz (2007) for extensive reviews on analyst conflicts of interest.

conflicts of interest with the firms they follow. In particular, these analysts are late in incorporating bad news in their forecast revisions. This creates high forecast dispersion for firms with bad news. Avramov, Chordia, Jostova, and Philipov (2009) provide evidence that the dispersion effect concentrates among the worst rated stocks and exists only during periods of credit rating downgrades, exactly when the worst rated stocks experience large price drops. The dispersion effect also becomes insignificant after controlling for credit rating. Analyst conflicts of interest could be an explanation for their finding because credit risk analysts in rating agencies do not face the same incentives as analyst in brokerage houses. Therefore, credit analyst opinion is a more accurate proxy of firm's quality. In other words, financial distress is bad news that coupled with analyst conflicts of interest causes delays in analysts downward revising their forecast. This in turn increases forecast dispersion and explains Avramov et al. (2009) result that dispersion effect is a manifestation of credit risk.

Credit analysts have information advantage over financial analysts, especially after Reg FD. This is because under 17 CFR 243.100(b)(2)(iii) rule,[4] credit analysts have permission to access firm confidential information, so that investors following them can receive high quality credit rating. Ederington and Goh (1998) show significant negative earnings forecast revisions following credit rating downgrades, and find little change in earnings forecast around credit rating upgrades. Jung, Sivaramakrishnan, and Soderstrom (2007) confirm this result and further show that, after Reg FD, credit rating downgrades have even more impact on earnings forecast revisions. This implies that financial analysts view rating downgrades as an important source of new information about future earnings prospects, especially after Reg FD in order to compensate for the decline in public information.

Managers may want to release good news and to hide bad news. Hong, Lim, and Stein (2000) provide empirical support to this idea. Because stock linked compensation, the threat

[4] This is because the rule states that Reg FD shall not apply to a disclosure made "to an entity whose primary business is the issuance of credit ratings, provided the information is disclosed solely for the purpose of developing a credit rating and the entity's ratings are publicly available".

of takeovers, and the like, management prefers high stock prices. Thus, in order to draw market attention, managers are keen to announce good news, but negative stories are often delayed or eliminated.[5] Moreover, because of conflicts of interest, analysts are reluctant to make bad news public. Scherbina (2008) shows that future stock underperformance can be predicted by measures of withheld negative information such as a decrease in analyst coverage. Analysts with private poor earnings forecast simply prefer to stop coverage rather than disseminate bad news.

Erturk (2006) also suggests that the negative dispersion-return relationship may be attributable to the sluggish response of analysts to negative information. When some analysts are more reluctant than others to respond to bad news, it creates non-synchronous response to bad news and, as a result it generates more dispersed forecasts. In a similar spirit, Hwang and Li (2008) contend that there is no causality between forecast dispersion and return. Instead, the negative dispersion-return relationship comes from analyst incentives. After controlling for incentive-induced upward bias in the reported consensus forecast, the dispersion effect disappears. Even more, the dispersion effect only exists among firms with poor future earnings. Analysts face a difficult decision to revise their forecasts downward when there is bad news about the firm, but no such dilemma presents itself for good news. Probably, this is why the dispersion effect is present only for firms with bad news.

Ackert and Athanassakos (1997) also attribute the negative dispersion-return relationship to analyst incentives. Analyst optimism declines with forecast horizon. When much uncertainty surrounds a firm, analysts act on their incentives and release optimistic forecasts. However, when uncertainty is low, little or no optimism remains. Unfortunately, they use a sample of only 167 firms. With a larger sample of 980 firms for 1977-1989 period, Brennan et al. (1998) confirm the statistically significant inverse relationship between the

[5] On the other hand, short-sellers, once they have established a position, have an incentive to publicize the bad news. Nevertheless, because they are so few, their impact is limited.

forecast dispersion and subsequent returns. The dispersion effect is strong only during 1979-1983 period. Han and Manry (2000) also show that forecast dispersion and subsequent stock returns are negatively correlated. A hedge portfolio (long on low- and short on high-dispersion stocks) earns two-year statistically significant cumulative excess returns of 13.5%. In their view, the dispersion effect is because the market does not entirely assimilate the information contained in forecast dispersion and responds in a delayed manner.

1.3.3 Positive dispersion-return relationship

Although much of the literature narrowly focuses on the negative dispersion-return relationship, some studies show a positive relationship. For 178 firms, Cragg and Malkiel (1982) collect earnings growth estimates (for the following five years) for 1961-1968 period. To explain the variations in expected returns, they use beta and various risk factors suggested by the arbitrage pricing theory. When the variance of growth rates is added, it is highly positively significant. Additional tests show that price-earnings ratios are negatively correlated with forecast dispersion. Cragg and Malkiel (1982) conclude that forecast dispersion represents the most effective risk proxy variable. Similarly, Malkiel (1982) and Farrelly and Reichenstein (1984) show that forecast dispersion appears to be a better risk proxy than beta. Carvell and Strebel (1984) and Harris (1986) also find that high-dispersion stocks have higher subsequent returns. Using data from 1976 to 1985, Barry and Gultekin (1992) find that forecast dispersion, measured as the coefficient of variation divided by the square root of the number of analysts, produces positive returns in January and negative returns in other months. This evidence, coupled with Tinic and West (1984)'s finding that high beta stocks earn high returns only in January, may indicate that, for January, forecast dispersion proxies for risk. Avramov et al. (2009), however, find that dispersion profitability is statistically significant only in non-January months.

Subsequent works have covered larger sample of stocks. For instance, Qu et al. (2004), examining 1983-2001 period, find significant positive correlation between forecast dispersion and expected returns, where expected returns are computed based on portfolio holdings of mutual funds. They compute expected returns in the mean-variance framework based on mutual funds portfolio weights. Portfolios with higher levels of dispersion have progressively more exposure to Fama and French (1993) factors, which confirms that forecast dispersion embodies a measure of risk. For 1991-1997 period, Anderson et al. (2005) examine the dispersion-return relationship for S&P500 firms, using two different measures of forecast dispersion: standard deviation of one-year forecasts and standard deviation of growth forecasts. They find a negative relation between stocks returns and dispersion of one-year forecasts, but a positive relation for the dispersion of growth forecasts. They content that the standard deviation of growth forecasts embodies a measure of risk, while the standard deviation of one-year forecasts does not. However, both returns of dispersion factor are positively related to the S&P 500 stock returns, where the dispersion factor portfolio is long in high-dispersion stocks and short in low-dispersion stocks. In addition, not only does forecast dispersion predict return variance for the next year, but also the model using it alone provides better prediction of variance than other models.

Researchers have tried to identify the components of forecast dispersion. Barron et al. (1998) provide a model where they relate analyst earnings forecasts to public and private information. They decompose forecast dispersion into two components: uncertainty and lack of consensus. More precisely, forecast dispersion is expressed as $V(1-\rho)$, where V is the uncertainty and $(1-\rho)$ is the lack of consensus among analysts. Using the Barron et al. (1998) decomposition, Doukas, Kim, and Pantzalis (2006b) show that, after controlling for uncertainty, stocks that have high forecast dispersion or high lack of consensus earn high future returns. Thus, they support forecast dispersion being a proxy for risk. Barron et al.

(2009) also use this decomposition and find that forecast dispersion and changes in forecast dispersion, both quarterly and annually, are separate matters with separate implications. The level of forecast dispersion reflects uncertainty, but changes in forecast dispersion reflect changes in information asymmetry. In other words, a large change in dispersion, indicating high information asymmetry, suggests that there are informed and uninformed investors in the market. By contrast, when dispersion level is low, there is low uncertainty about the stock. When dispersion does not change much, investors are more likely to be trading against people with essentially the same information. Further tests show that the lack of consensus, measured by $(1-\rho)$, is positively associated with subsequent stock returns, but the uncertainty in forecast dispersion, measured by V, is negatively associated with subsequent stock returns. These results are in line with L'Her and Suret (1996) who show that increases in forecast dispersion are negatively associated with contemporaneous stock returns.

Doukas, Kim, and Pantzalis (2004) show that forecast dispersion is higher among value stocks than growth stocks. Given that 1) on average value stocks earn higher returns than growth stocks; see Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and 2) value stocks have greater exposure to forecast dispersion, they argue that forecast dispersion represents a risk factor. Further they construct a disagreement factor and show a positive (negative) and significant relationship between returns of value (growth) stocks and the disagreement factor.[6] Thus, they favor the view that investors command a premium for value stocks because these stocks are exposed to greater disagreement; see Doukas, Kim, and Pantzalis (2002). In another study, Doukas, Kim, and Pantzalis (2006a) largely replicate the negative relationship between forecast dispersion and stock returns, and show that the effect is most pronounced among small stocks and stocks having low institutional ownership. Then,

[6] To construct the disagreement factor, they rank company-year observations by forecast dispersion and form two equal-weighted portfolios based on the top 30 percent and bottom 30 percent dispersion rankings. For these portfolios, they compute monthly returns for the next 12 months. This process leads to the construction of return series of 210 monthly observations from July 1983 through December 2001. The disagreement factor is the return difference between the top 30 percent and bottom 30 percent portfolio returns.

they examine the differences of opinion under different states of earnings expectations about future stock payoffs; i.e., pessimism vs. optimism. The finding is that when analyst forecasts are optimistic, this valuation pattern reverses. The average return difference between high-dispersion and low-dispersion stocks is significantly positive across all size groups. However, when analysts' earnings expectations are pessimistic, the return spreads between high dispersion and low dispersion stocks within each size category is negative. The evidence suggests that investors tend to overvalue (undervalue) low-dispersion stocks when analysts' forecasts are optimistic (pessimistic), thus realizing low (high) subsequent returns.

Existing literature on forecast dispersion mainly focuses on stock returns. However, Güntay and Hackbarth (2010) and Mansi, Maxwell, and Miller (2006) examine the corporate bond market. Corporate bonds of high-dispersion stocks demand higher credit spreads and earn higher subsequent returns. High-dispersion firms have lower credit ratings, thus they interpret forecast dispersion as a forward-looking measure of information risk. Their result also suggest that the argument of Miller (1977) does not equally apply to bond market as it does to equity market. From their own conversations with stock dealers, Longstaff, Mithal, and Neis (2005) report that the cost of shorting corporate bonds is about five basis points, while this cost can rise to 50–75 basis points for the bonds of financially distressed firms (footnote 25). Güntay and Hackbarth (2010) further argue that this relative lack of short-sale costs for corporate bonds permits bond prices to reflect the views of both pessimistic and optimistic investors.

1.3.4 Dispersion-return relationship outside the U.S.

The vast majority of studies use U.S. data. However, there is some evidence that forecast dispersion keeps its predictive power elsewhere. Studying the German market, Dische (2002) shows that high-dispersion stocks underperform low-dispersion stocks. Hintikka (2008) and Daniševská (2004) present negative dispersion-return relationship for

Finland, France, Netherlands, and Germany, but not for the U.K. Finally, Gharghori, See, and Veeraraghavan (2007) and Zellweger, Meister, and Fueglistaller (2007) find a negative dispersion-return relationship in Australia and Switzerland, respectively. Leippold and Lohre (2009) confirm this persuasive evidence on the U.S. and major European markets. They show that the dispersion effect concentrates in a three-year window from 2000 to 2003, after the burst of so-called "dotcom bubble" when most uncertainty about high dispersion stock is resolved. It would have been highly profitable during this time to short high-dispersion stocks, but because during the "dotcom bubble" stock prices reached high levels, the authors argue that margin calls would make it unfeasible to profit from shorting high-dispersion stocks. This finding gives additional support to Miller (1977) hypothesis. The results in this subsection are also unexplained by the Fama and French (1993) and Carhart (1997) models.

1.4 Conclusion

This chapter shows that the question of whether forecast dispersion represents a risk measure or simply a noise measure of analyst disagreement is still a subject of both theoretical debate and empirical investigation. Theory suggests that the sign of the theoretical relationship between differences of opinion and expected stock returns remains an open question. For example, a number of papers contend that in the absence of short-sale costs, differences of opinion represents priced factor, produces low current prices, and generates a positive relationship between differences of opinion and subsequent stock returns. However, when short-sale costs are absent, the relation becomes negative. In summary, some studies predict a positive relationship, some derive no relationship, while others predict a negative relationship.

To review the empirical literature, I employ the widely use earnings forecast dispersion as a proxy for the differences of opinion. The empirical literature also brings conflicting evidence on the relation between contemporaneous forecast dispersion and subsequent returns. Some propose that higher dispersion introduces a larger optimistic bias into stock prices as optimistic investors bid prices up, while short sale constraints prevent pessimistic views from being reflected in stock prices, thus causing high dispersion stocks to become overpriced. This literature also reports positive correlation between forecast dispersion and commonly used measures of risk such as the beta, standard deviation of returns, and the standard deviation of earnings. Thus, they conclude that the relation between forecast dispersion and subsequent stock returns cannot have risk-based explanation. By contrast, papers supporting the positive dispersion-returns relationship show that after controlling for stock uncertainty, stocks that have high forecast dispersion or high lack of consensus earn high future returns. Thus, they support forecast dispersion being a proxy for risk.

In sum, the debate is still ongoing with a growing number of studies suggesting different explanations including short-sale restrictions and the shortcoming of using realized returns rather than the theory-suggested ex-ante expected returns, among other explanations. All these studies, however, differ in terms of sample selection and the period considered, as well as in empirical methods. Thus, many questions remain unexplored about the driving forces behind the predictive power of forecast dispersion. In the next chapters, I conduct a careful empirical investigation of the dispersion anomaly. In particular, I examine whether the negative dispersion-return relationship is due to measurement issues such as different proxies employed for analyst differences of opinion or whether the dispersion anomaly is simply due to other well-known market anomalies. I also conduct a thorough analysis on the determinants of forecast dispersion suggested by the extant literature, such as firm risk, information asymmetries, forecasting difficulties, analyst conflicts of interest and the like. In addition, I study whether the dispersion-return relationship is due to determinants of forecast dispersion or it merely proxies for other explanations of expected returns.

Table 1.1: Empirical papers on dispersion-return relationship

Papers presented in the table use forecast dispersion as a measure of differences of opinion. I examine its relation with U.S. stocks returns as opposed to e.g., corporate bond yields or European stock returns. I sort papers by year. The "Dispersion" column presents the definition of the forecast dispersion measure. The "Horizon" column shows whether the forecasted earnings are quarterly, annual, or long-term growth forecasts. The "Coverage" column provides the minimum number of analysts' forecast used to compute the forecast dispersion. The "Age" column shows the maximum age of the forecast, if any, to be included in the computation of the summary statistics, and the "Rel" column presents the empirical relationship between forecast dispersion and future stock returns in the corresponding paper.

Reference	Period	Dispersion*	Horizon**	Coverage	Age***	Rel	Key results
Cragg and Malkiel (1982)	1961-1968	std	l	2		+	Forecast dispersion explains a higher proportion of returns than the traditional beta. The results are robust to the addition of market return and national income.
Carvell and Strebel (1984)	1976-1981	$\frac{std}{\lvert avg \rvert}$	a	3		+	Develop new beta CAPM incorporating forecast dispersion that provides a better risk adjustment. Stocks with high forecast dispersion have higher subsequent returns. The results stay intact after historical beta is included.
Doukas et al. (2004)	1983-2001	$\frac{std}{price}$	a	2		+	Value stocks have higher forecast dispersion than growth stocks. The return advantage of value strategies is a reward for the greater disagreement about their future earnings. This relationship is unexplained by the Fama and French (1993) and Carhart (1997) models, augmented by the disagreement factor.
Doukas et al. (2006b)	1983-2001	$V(1-\rho)$	a	2		+	Both lack of consensus, measured by $1-\rho$, and forecast dispersion represent risk measures, after controlling for the uncertainty V.
Barron et al. (2009)	1983-2003	$V(1-\rho)$	q	2	30d	+,-	The lack of consensus, measured by $1-\rho$, is positively associated with future stock returns, but the uncertainty, measured by V, is negatively associated with future stock returns.
Qu et al. (2004)	1983-2001	$\frac{std}{price}$	a	2,5		+,-	Show significant negative correlation between forecast dispersion and subsequent realized returns. However, the correlation becomes positive between forecast dispersion and expected returns based on portfolio holdings of mutual funds.

Anderson et al. (2005)	1991-1997	std	a, l	2		+,-	Find negative returns to a dispersion of one-year forecasts, but positive returns for dispersion of growth forecasts. For the portfolio of all stocks in the S&P500 index, both measures of dispersion are positively correlated with subsequent realized returns. The predictive power of forecast dispersion remains unaffected by the addition of Fama and French (1993) and Carhart (1997) factors.
Doukas et al. (2006a)	1983-2001	$\frac{std}{\lvert avg \rvert}$	a	2	3m	+,-	When there is low forecast dispersion among analysts, the credibility of their earnings forecasts increases, and so does the confidence of investors in analysts' forecasts, causing overvaluation (undervaluation) when earnings expectations are optimistic (pessimistic).
Diether et al. (2002)	1982-2000	$\frac{std}{\lvert avg \rvert}$	a	2		-	The negative relationship is unexplained by the Fama and French (1993) and Carhart (1997) models.
Johnson (2004)	1983-2001	$\frac{std}{\lvert avg \rvert}, \frac{std}{bvps}$	a	2	6m	-	The negative association between dispersion and subsequent returns is due to the leverage effect.
Ackert and Athanassakos (1997)	1980-1991	std	a	3		-	A strategy long in low-dispersion stocks and short in high-dispersion stocks produces positive risk-adjusted returns.
Park (2005)	1982-2001	$\frac{std}{eps}$	a	2		-	Dispersion in S&P 500 stocks' earnings forecasts predicts subsequent returns, similar to Diether et al. (2002), but at the aggregate market level. The results are likewise attributed to stock prices reflecting the most optimistic valuations (in this case due to reluctance to engage in short-selling).
Brennan et al. (1998)	1977-1989	$\frac{std}{\lvert avg \rvert}$	a	2		-	The negative dispersion-return relationship remains unchanged after the inclusion of firm characteristics such as size, book-to-market, bid-ask spread, dividend yields, and momentum returns.
Han and Manry (2000)	1977-1990	$\frac{std}{price}$	a	2		-	The market does not entirely assimilate the information contained in forecast dispersion in a timely manner. The results are similar when stock returns are adjusted for beta, size, book to market ratio, and past returns.
Ang and Ciccone (2001)	1976-1997	std	a	2		-	The dispersion strategy returns are unrelated to size, book-to-market, industry, liquidity, momentum, post-earnings announcement drift, or traditional risk measures.

Baik and Park (2003)	1982-1998	$\frac{std}{\lvert avg \rvert}$	a	2		-	The negative relationship continues to hold even after even after controlling for size and book-to-market ratio.
Ciccone (2003)	1977-1996,	std	a	2		-	The predictability of forecast dispersion retains its ability even after accounting for firm size and book-to-market.
Chen and Jiambalvo (2004)	1983-2000	$\frac{std}{\lvert avg \rvert}$	a	2		-	The post-earnings-announcement drift explains the negative dispersion-return relationship - high forecast dispersion is associated with poor earnings performance that precedes negative price drifts. Fama and French (1993) and Carhart (1997) models do not account for the relatively low returns earned by high-dispersion firms.
Erturk (2006)	1983-2001	$\frac{std}{\lvert avg \rvert}, \frac{std}{bvps}$	a	2		-	Forecast dispersion results from analyst slow and non-synchronous response to negative news. The dispersion effect is strong among loser stocks with recent downward revisions and absent for winner stocks.
Sadka and Scherbina (2007)	1983-2001	$\frac{std}{\lvert avg \rvert}$	a	2		-	Trading costs increase with forecast dispersion. High forecast dispersion stocks are overpriced because forecast dispersion coincides with trading costs.
Cen, Wei, and Zhang (2007)	1983-2004	$\frac{std}{\lvert avg \rvert}$	a	2		-	The predictability of forecast dispersion on subsequent stock returns mainly comes from the denominator effect (absolute value of average forecast) rather than from the numerator effect (standard deviation) of the dispersion measure. Results are unexplained by size, book-to-market, and momentum phenomena.
Hwang and Li (2008)	1983-2006	$\frac{std}{\lvert avg \rvert}$	a	2		-	The dispersion effect disappears after controlling for the incentive-induced upward bias in consensus forecasts.
Berkman et al. (2009)	1985-2005	$\frac{std}{\lvert avg \rvert}$	a, q	2	30d	-	High differences of opinion stocks earn lower returns in the 3 days window around earnings announcements. This evidence is similar across five different proxies for differences of opinion (earnings volatility, return volatility, forecast dispersion, firm age, and share turnover).
Avramov et al. (2009)	1985-2003	$\frac{std}{\lvert avg \rvert}$	a	2		-	Credit risk subsumes dispersion effect. The profitability of dispersion is significant only during periods of credit rating downgrades. The dispersion effect is concentrated in non-investment grade firms (S&P BB+ and below). The results are robust to inclusion of short-sale costs, illiquidity, and leverage.

*std = standard deviation of analyst forecasts, avg = average analyst forecast, price = stock price prior to portfolio formation date, eps = earnings of S&P500 index, bvps = book value per share
**a=annual, q = quarterly, l = long-term
***m=months, d = days

Chapter 2: Forecast Dispersion and Stock Returns: A Re-Examination

2.1 Introduction

Explaining cross-sectional differences in average stock returns is one of the challenges of modern finance. Researchers have identified many patterns in average stock returns and because the CAPM does not explain them, they are called stock market anomalies. The number of documented market anomalies is large and continues to grow. Forecast dispersion anomaly is one of the recent market anomalies and as Chapter 1 summarizes, the empirical relationship between contemporaneous dispersion and future returns remains an open question.

Given the seemingly contradictory results in the literature, in this chapter I study 1) whether the dispersion-return relationship is robust to different dispersion measures and to longer period than considered in the extant literature, and 2) whether the dispersion-return relationship is related to other well-known financial anomalies. This is an important step to understand the unique existence of the dispersion anomaly and I contribute to the literature by studying these questions in depth. In particular, I investigate the connection of forecast dispersion anomaly with Francis, LaFond, Olsson, and Schipper (2005) accruals quality, Titman, Wei, and Xie (2004) capital investment growth, Cooper, Gulen, and Schill (2008) asset growth, and Loughran and Ritter (1995) equity issuance anomalies. Titman et al. (2004) find that high-investing firms have low future returns, and interpret their finding with investors underreacting to overinvestment. Cooper et al. (2008) observe negative correlation between firm’s asset growth and future returns, and suggest that investors overreaction to investment in asset growth causes this negative correlation. The theoretical explanation for the asset growth-return arises if the reduction in firm risk following the exercise of growth options induces a negative relationship between investment in asset growth and future returns; see Cochrane (1991) and Berk, Green, and Naik (1999). Francis et al. (2005) presents evidence of risk premium for firms with poorer earnings quality, as captured by Dechow and Dichev (2002)'s measure of accruals quality. Loughran and Ritter (1995) show that the stock performance after initial public offerings (IPOs) or seasoned equity offerings (SEOs) is poor relative to non-issuing firms, and suggest that investors may be too optimistic about the prospects of issuing firms. Similar to the forecast dispersion anomaly, these anomalies refer to firm's financial variables predicting low stock returns. I explore whether the dispersion anomaly and these four anomalies are independent effects.

My results strongly suggest that contemporaneous dispersion is negatively correlated with future stock returns. Consistent with previous studies, the dispersion effect is most pronounced among the smallest size stocks. It also appears that the negative dispersion-return link is robust to different measures of dispersion, e.g., the range, the standard deviation of forecasts scaled by price, and the exclusion of stale (old) forecasts. In addition, my analysis does not provide any discernible link between dispersion anomaly and the well-known anomalies discussed above.

The layout of this chapter is as follows. Section 2.2 presents the link of forecast dispersion with stock returns. In Section 2.3, I discuss the robustness of that relationship. Section 2.4 studies whether the dispersion anomaly is distinct from the other well-known anomalies. Section 2.5 concludes.

2.2 Dispersion-return relationship

The research problem addressed here concerns the detailed assessment of the predictability of forecast dispersion on future stock returns. The central question is whether we can achieve abnormal returns based on publicly available earnings forecasts. Yet, beginning with Cowles (1933, 1944) evidence persists that analyst advices do not produce abnormal returns. Diether et al. (2002) show the opposite - that forecast dispersion does predict stock returns. If following analysts' forecasts can make positive abnormal profits, then markets are inefficient. On the other hand, Womack (1996) argues that positive abnormal returns are limited by the search and information costs of the analysts.

Because many papers that incorporate forecast dispersion still produce conflicting results, the debate can only be resolved by means of a careful empirical investigation. I take a step in that direction and below I provide thorough examination on the relationship between forecast dispersion and stock returns by extending the analysis of previous papers to a longer period - from February 1983 to December 2007.

2.2.1 Sample characteristics

My sample merges several datasets. Analysts' earnings per share forecasts and recommendations are from I/B/E/S files. Returns are from CRSP monthly stock file that includes NYSE, AMEX, and NASDAQ stocks. For some of the tests in Section 2.4, firm accounting data from the Compustat Industrial Annual file are also used. Appendix A details the sample selection process. I first present summary statistics of the sample to provide a basis for comparison with other studies.

Table 2.1 gives an overview of sample characteristics. As shown in Panel A, in February of 1983 only 34.59% of CRSP stocks are eligible to be included in the sample. There is a clear deepening in eligible stocks over time, with the fraction of eligible stocks being 58.19% at the end of 2007. The average size of eligible stocks is 2.6 billion - that is almost twice larger than the average size of CRSP stocks, indicating that my sample is tilted toward large market capitalization firms. On average, there are 2,147 eligible firms per month with 8.77 earnings forecasts per firm.

Table 2.1: Sample characteristics

Panel A reports statistics for CRSP ordinary common shares that are traded in NYSE, AMEX, and NASDAQ by removing financial institutions. Panel B limits the sample to the eligible stocks. A stock is eligible to be included in the analysis if it has a one fiscal year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than five dollars. The period considered is February 1983 through December 2007.

Sample characteristics						
	Panel A: All CRSP stocks			Panel B: Eligible stocks		
Date	Number of firms	Average market cap (in millions)	Percentage of eligible firms	Number of firms	Average market cap (in millions)	Average number of estimates
1983/02	4,302	310.4	34.59	1,488	812.3	8.82
1983/12	4,778	321.6	34.74	1,660	841.5	9.03
1984/12	4,808	298.3	35.84	1,723	774.9	8.95
1985/12	4,672	367.1	36.99	1,728	925.3	10.07
1986/12	4,859	397.0	36.06	1,752	1018.6	9.78
1987/12	4,987	384.9	33.23	1,657	1088.2	9.90
1988/12	4,744	436.5	36.00	1,708	1142.7	10.13
1989/12	4,568	551.6	38.20	1,745	1371.6	10.07
1990/12	4,484	516.8	36.04	1,616	1378.3	10.06
1991/12	4,582	686.7	40.16	1,840	1635.6	9.29
1992/12	4,690	721.8	44.67	2,095	1549.0	8.78
1993/12	5,142	742.4	45.68	2,349	1541.4	8.54
1994/12	5,421	703.8	46.08	2,498	1460.4	8.26
1995/12	5,613	910.0	48.26	2,709	1800.5	7.98
1996/12	6,051	1024.5	51.81	3,135	1909.4	7.32
1997/12	6,096	1295.1	51.79	3,157	2415.3	7.20
1998/12	5,711	1757.5	50.60	2,890	3366.4	8.04
1999/12	5,439	2473.7	52.90	2,877	4513.9	7.92
2000/12	5,234	2236.1	43.98	2,302	4910.8	8.03
2001/12	4,601	2207.1	45.97	2,115	4652.4	8.27
2002/12	4,211	1824.0	43.62	1,837	3978.5	8.31
2003/12	3,904	2573.8	53.84	2,102	4600.2	8.72
2004/12	3,873	2883.0	56.70	2,196	4883.5	8.80
2005/12	3,801	3039.8	57.93	2,202	5080.3	8.49
2006/12	3,743	3414.7	61.29	2,294	5413.4	8.65
2007/12	3,686	3663.6	58.19	2,145	6117.1	8.53
Average	4,769	1,375	45.2	2,147	2,661	8.77

Table 2.2 brings additional descriptive statistics for the sample stocks and five portfolios equally sorted by forecast dispersion. As can be seen, although high dispersion firms have slightly lower analyst coverage and tend on average to be smaller, they are not typically small firms. The high dispersion firm has average (median) market capitalization of 984 (262) million dollars. This reflects the fact that analysts usually do not cover small firms. In addition to being smaller than the overall sample, high dispersion firms tend to have higher

value of average and median recommendations, higher standard deviation of recommendations, less buy and more sell recommendations.[7] All together, these results indicate that these firms are not performing well.

Miller (1977) argues that when investors are overconfident about the precision of their signal, differences of opinion induces excessive trading in stocks, resulting in higher trading volume (or turnover) for firms with higher differences of opinion. My empirical finding, consistent also with the previous literature, supports Miller's view that high dispersion firms have high turnover; see also Comiskey et al. (1987), Ajinkya et al. (1991). As a measure of trading volume, I use trading turnover, defined as the ratio of the number of shares traded at the month-end to the total number of shares outstanding at the month-end. Lo and Wang (2000) argue that using trading turnover as a measure of trading volume has an advantage in that it is unaffected by "neutral" changes of units such as stock splits and stock dividends. Moreover, one problem with using the number of shares traded as a measure of trading volume is that it is unscaled, therefore highly correlated with firm size. However, Chordia and Swaminathan (2000) show that the correlation between trading turnover and firm size is much lower than that between other measures of trading volume and firm size.

[7] I/B/E/S codes analyst recommendations using a 1-5 scale, with 1 signifying a strong buy, 2 a buy, 3 a hold, 4 an underperform, and 5 a sell. Thus, high value of recommendation indicates poor recommendation.

Table 2.2: The distribution of firm characteristics

This table reports the average statistics for all stocks and stocks equally sorted by five dispersion groups. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Each month stock characteristics are averaged first over the stocks in every group and then over the sample period. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2007.

Characteristic	Dispersion	Avg	Std	25%	Median	75%
Number of analysts	All	8.72	7.15	3.34	6.28	11.83
	D1	9.28	7.81	3.36	6.42	13.06
	D2	9.59	7.24	4.05	7.33	13.15
	D3	8.83	7.06	3.63	6.49	11.73
	D4	8.12	6.68	3.26	5.81	10.69
	D5	7.26	6.12	2.97	4.98	9.51
Market capitalization (in millions)	All	2,603	10,158	189	480	1,474
	D1	4,397	14,763	273	720	2,390
	D2	2,976	10,295	264	666	1,965
	D3	2,228	8,006	199	481	1,389
	D4	1,623	6,077	157	358	1,017
	D5	984	2,713	124	262	695
Turnover (%)	All	1.35	1.55	0.51	0.89	1.63
	D1	1.12	1.18	0.46	0.76	1.34
	D2	1.29	1.41	0.50	0.85	1.55
	D3	1.43	1.61	0.53	0.93	1.72
	D4	1.50	1.72	0.56	1.00	1.81
	D5	1.53	1.72	0.56	1.03	1.88
Average recommendation*	All	2.13	0.54	1.74	2.10	2.50
	D1	2.05	0.72	1.39	2.09	2.70
	D2	2.08	0.49	1.67	2.00	2.46
	D3	2.18	0.38	1.91	2.13	2.39
	D4	2.31	0.42	2.03	2.26	2.56
	D5	2.43	0.51	2.00	2.26	2.74
Median recommendation	All	2.15	0.68	1.73	2.14	2.70
	D1	2.05	0.80	1.29	2.23	2.76
	D2	2.11	0.61	1.70	2.04	2.54
	D3	2.23	0.60	1.99	2.17	2.69
	D4	2.31	0.71	1.87	2.49	2.95
	D5	2.31	0.65	2.00	2.02	2.80
Standard deviation of recommendations	All	0.74	0.33	0.59	0.76	0.92
	D1	0.30	0.24	0.00	0.40	0.52
	D2	0.69	0.07	0.63	0.69	0.75
	D3	0.90	0.06	0.85	0.90	0.95
	D4	1.13	0.07	1.08	1.11	1.17
	D5	1.51	0.25	1.39	1.41	1.53
Buy percentage	All	61.78	28.47	42.18	64.02	87.38
	D1	65.65	40.17	30.71	79.23	100.00
	D2	67.52	26.76	47.44	73.36	90.68
	D3	55.88	18.44	43.91	59.03	70.29
	D4	48.92	17.38	36.15	49.97	62.40
	D5	49.34	15.99	45.11	50.00	54.67
Sell percentage	All	3.73	8.77	0.00	0.00	3.58
	D1	1.44	5.79	0.00	0.00	0.00
	D2	2.06	7.08	0.00	0.00	0.52
	D3	3.52	6.89	0.00	0.26	4.27
	D4	9.37	9.94	0.53	7.36	14.54
	D5	17.92	17.12	0.54	16.47	29.03

*Because in year 1993 there are few recommendations in the I/B/E/S recommendations file, the period considered for the recommendations starts from January 1994 until December 2007.

2.2.2 Portfolio selection

I assign stocks to portfolios based on forecast dispersion in order to draw conclusions about average returns for these portfolios. This standard approach reduces the variability in returns; see e.g., Jegadeesh and Titman (1993). I form portfolios using three separate ranking procedures. Because the results from all three procedures are similar, I report only results from procedure 1.

In-sample breakpoints

Procedure 1: Each month, stocks are equally assigned into quintiles based on the forecast dispersion of the previous month.[8] Stocks with the lowest forecast dispersion are placed into quintile 1 (D1), and those with the highest forecast dispersion are in quintile 5 (D5). I then perform two-way sorting on size and dispersion. This procedure has been extensively used in the literature back to Banz (1981) and Basu (1983), among others. Using in-sample breakpoints, each month I equally assign stocks to quintiles based on their market capitalization of the previous month.[9] Quintile 1 includes the smallest stocks and quintile 5 includes the largest stocks. Stocks in each size quintile are further ranked into five dispersion quintiles based on the forecast dispersion of the previous month. The purpose of this two-way sorting is to hold one variable constant while investigating the impact of the other. This classification results in 25 portfolios, each of which contains 87 stocks. Stocks are held for one month.[10] I calculate monthly portfolio returns as the equal-weighted, value-weighted, and median average of returns of all stocks in a portfolio.

Procedure 2: This procedure is identical to procedure 1 except that firms are first ranked based on the dispersion and then ranked on size.

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[8] The reason portfolio formation chosen at the quintile rather than decile level is to have more firms in the portfolios. Nevertheless, I obtain similar results when forming decile portfolios.

[9] Note that sorting the stocks based on the NYSE market capitalization 20^{th}, 40^{th}, 60th and 80^{th} breakpoints does not guarantee that the portfolios will contain equal number of stocks. However, even this sorting does not significantly alter my results. Thus, I report the results of in-sample breakpoints.

[10] Section 2.3.6 presents the results when stocks are held for more than one month.

Procedure 3: This procedure independently ranks stocks based on the size and dispersion. This method is described in Reinganum (1981) and Cook and Rozeff (1984).

Alternative breakpoints

As in Fama and French (2008), stocks in each month are allocated to three size groups - micro, small, and big. The breakpoints are the 20th and 50th percentiles of previous month market capitalization of NYSE stocks. I also sort stocks into three size groups - small, medium, and large - using Cooper et al. (2008) breakpoints that are the 30th and 70th percentiles of previous month market cap of NYSE stocks. Then, in each size group, I rank stocks into further quintiles based on forecast dispersion of the previous month.

2.2.3 Portfolio returns

In-sample breakpoints

The second column of Panel A in Table 2.3 shows a strong negative relationship between average returns and forecast dispersion. In particular, for all sample stocks the average monthly return differential between low- and high-dispersion (D1- D5) portfolios is 0.66% with t-stat of 3. Not reported here, results are similar when using Newey and West (1987) standard errors with 3 as the maximum lag order of autocorrelation.[11]

The average monthly return of D1-D5 strategy declines as the average size increases. While the return differential between the low- and high-dispersion stocks is positive and significant for the smallest stocks, it becomes insignificant for stocks in the two highest

[11] In non-tabulated results, I also get similar results for firms only in NYSE, AMEX, and NASDAQ, separately; the highest return differential however is observed for NASDAQ stocks. Results remain the same for the limited sample of only December fiscal year end firms that accounts 63% of all sample firms. The unreported results indicate that equal-weighted returns on the D1-D5 portfolio excluding January returns also persist; the dispersion effect is even stronger. Specifically, monthly returns for the equal-weighted D1-D5 portfolio returns are 0.86%, t=3.84 for the full sample, 1.39%, t=7.15 for S1 size group, 0.78%, t=3.23 for S2 size group, 0.89%, t=3.17 for S3 size group. Avramov et al. (2009) also show that dispersion profitability exists only in non-January months.

market capitalization quintiles. In particular, the D1-D5 strategy for the smallest quintile earns 1.23 % monthly returns on average (14.76% annualized). Thus, it does not appear that we are simply picking up a size effect, since the two-way sorts still produce a strong negative relation between average returns and dispersion for the first three quintiles. Panel D shows that stocks in the first three quintiles together represent 6.78% of market capitalization. In Panel A and B, I present equal-weighted and value-weighted portfolio returns, respectively. As expected, within the same size quintile, value-weighted returns are close to the equal-weighted returns. However, for all stocks the average of the monthly value-weighted returns on the D1- D5 strategy reduces to 0.23% that is not statistically significant (t-stat = 0.88). This signals the overweighting of small stocks in computing equal-weighted returns. Thus, the overall evidence indicates the presence of a substantial dispersion effect.

As shown in Panel C and consistent with previous studies, contemporaneous dispersion and future return volatility are strongly positively correlated; see e.g., Athanassakos and Kalimipalli (2003). Similarly, Ajinkya and Gift (1985) report positive correlation but between forecast dispersion and implied standard deviation of stock returns; see also Graham and Harvey (1996). Harris and Raviv (1993) develop a model that investigates the role of differences of opinion (as opposed to information asymmetry) on trading volume and return volatility. They report positive relationship between forecast dispersion and return volatility. One explanation for this relationship is that analysts are more optimistic when forecast dispersion is high and thus issue more downward revisions of their forecasts that, as a result, create higher future return volatility. In Section 3.3, I conduct further analysis on the relationship between forecast dispersion and firm risk.

Table 2.3: Dispersion anomaly using in-sample breakpoints

Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market capitalization of the previous month end. Stocks in each size group are then equally sorted into five additional groups based on the forecast dispersion of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The table reports average monthly equal-weighted, average value-weighted, average median portfolio returns and average standard deviations of returns along with the percentages of market cap and number of all stocks. The period considered is February 1983 through December 2007. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Average equal-weighted returns								
		Size quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.05	0.96	1.02	1.12	1.09	1.08	-0.13	[-0.63]
D1	1.29	1.50	1.23	1.44	1.26	1.19	0.31	[1.33]
D2	1.16	1.22	1.26	1.19	1.10	1.05	0.17	[0.70]
D3	1.16	0.77	1.07	1.14	1.06	1.08	-0.31	[-1.40]
D4	0.90	0.72	0.90	1.04	1.10	1.11	-0.39	[-1.73]
D5	0.63	0.28	0.57	0.76	0.95	1.00	-0.72**	[-2.96]
D1-D5	0.66**	1.23**	0.66**	0.68*	0.30	0.20		
t(D1-D5)	[3.00]	[6.49]	[2.86]	[2.49]	[1.16]	[0.78]		
Panel B: Average value-weighted returns								
		Size quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.05	0.99	1.02	1.11	1.08	1.05	-0.06	[-0.25]
D1	1.10	1.48	1.20	1.42	1.25	1.18	0.31	[1.09]
D2	0.98	1.22	1.26	1.15	1.10	0.92	0.30	[1.13]
D3	1.11	0.79	1.08	1.12	1.02	1.01	-0.23	[-0.86]
D4	1.01	0.81	0.92	1.02	1.13	1.08	-0.27	[-1.04]
D5	0.87	0.34	0.56	0.81	0.95	1.01	-0.67*	[-2.50]
D1-D5	0.23	1.14**	0.64**	0.61*	0.30	0.16		
t(D1-D5)	[0.88]	[5.60]	[2.79]	[2.26]	[1.16]	[0.61]		
Panel C: Standard deviation of returns								
		Size quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	12.21	14.33	13.63	12.33	10.72	8.56	5.77**	[48.62]
D1	10.53	13.14	12.15	10.86	9.23	7.02	6.12**	[43.36]
D2	11.04	13.82	12.89	11.31	9.73	7.59	6.23**	[38.19]
D3	12.20	14.22	13.45	12.14	10.40	8.32	5.91**	[36.73]
D4	13.18	14.77	14.27	12.83	11.08	9.01	5.76**	[34.29]
D5	14.31	15.47	14.92	13.88	12.31	9.84	5.63**	[31.78]
D1-D5	-3.78**	-2.33**	-2.77**	-3.02**	-3.08**	-2.82**		
t(D1-D5)	[-29.33]	[-12.49]	[-16.84]	[-15.07]	[-16.57]	[-19.75]		
Panel D: Percentage of market cap and number of all stocks								
Percentage of market cap		0.77	1.92	4.09	10.17	83.04		
Percentage of number of all stocks		19.93	20.00	19.99	20.01	20.06		

Banz (1981) provides evidence that, on average, smaller firms have higher risk adjusted returns than larger firms. However, Panel A of Table 2.3 shows that small stocks do not earn higher returns than large stocks; the difference is -0.13% with a t-stat of -0.63. Ciccone (2003) also shows similar outcome for his sample. This may be due to the requirements of sample selection that biases my sample toward surviving firms that are larger than the population. On the other hand, perhaps market participants have altered their investment strategies in a way that has eliminated this source of size-return predictability. This finding is in contrast with Berk (1995), who argues that we should always observe negative relation between firm size and its return.

Fama and French (2008) and Cooper et al. (2008) breakpoints

Panel A in Table 2.4 shows that D1-D5 strategy is profitable for both micro and small stocks, earning statistically significant average monthly returns of 1.16% and 0.59%, respectively. Note that micro and small stocks together account for 64.03% of all stocks but represent only 8.17% of market capitalization.

Panel B shows that when sorting by Cooper et al. (2008)'s breakpoints, it is only the small stocks for which D1-D5 strategy earns statistically significant 1.01% monthly returns. Note that small stocks represent only 3.11% of market capitalization. Thus, the results from the alternative sorting once more confirm that dispersion effect is most pronounced for the smallest firms.

Table 2.4: Dispersion anomaly using alternative breakpoints

Panel A presents average equal-weighted portfolio returns when stocks are sorted in three size groups based on Fama and French (2008) 20th and 50th NYSE market capitalization breakpoints of the previous month. Panel B presents the average equal-weighted portfolio returns when stocks are sorted in three size groups based on Cooper et al. (2008) 30th and 70th NYSE market capitalization breakpoints of the previous month. Stocks in each size group are then sorted into five additional groups based on forecast dispersion of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than 5 are excluded from the sample. Stocks are held for one month. The table reports average monthly equal-weighted, average value-weighted, average median portfolio returns and average standard deviations of returns along with the percentages of market cap and number of all stocks. The period considered is February 1983 through December 2007. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Fama and French (2008) breakpoints

Dispersion quintiles	Size: Micro	Size: Small	Size: Big	All but Micro	All but Small	All but Big
All stocks	0.98	1.15	1.10	1.12	1.00	1.05
D1	1.43	1.39	1.21	1.29	1.24	1.36
D2	1.25	1.25	1.08	1.14	1.16	1.26
D3	0.86	1.18	1.06	1.15	1.10	1.04
D4	0.83	1.05	1.18	1.10	0.84	0.88
D5	0.27	0.80	0.98	0.90	0.57	0.50
D1-D5	1.16**	0.59*	0.22	0.39	0.66**	0.86**
t(D1-D5)	[6.34]	[2.51]	[0.88]	[1.59]	[2.99]	[4.40]
Percentage of market cap	1.53	6.64	91.82	98.47	93.36	8.18
Percentage of number of all stocks	29.15	34.88	35.97	70.85	65.12	64.03

Panel B: Cooper et al. (2008) breakpoints

Dispersion quintiles	Size: Small	Size: Medium	Size: Large	All but Small	All but Medium	All but Large
All stocks	1.02	1.12	1.10	1.11	1.02	1.05
D1	1.42	1.31	1.21	1.25	1.29	1.34
D2	1.23	1.11	1.10	1.12	1.19	1.18
D3	0.97	1.13	1.08	1.13	1.10	1.12
D4	0.82	1.15	1.08	1.12	0.83	0.89
D5	0.40	0.92	1.03	0.96	0.53	0.58
D1-D5	1.01**	0.38	0.18	0.29	0.76**	0.76**
t(D1-D5)	[5.32]	[1.53]	[0.69]	[1.14]	[3.56]	[3.63]
Percentage of market cap	3.11	14.24	82.65	96.89	85.76	17.35
Percentage of number of all stocks	42.43	37.88	19.69	57.57	62.12	80.31

2.3 Robustness checks

The most commonly used measure of analyst disagreement is the ratio of the standard deviation of forecasts to the absolute value of the average forecast. If the average forecast is zero, then they assign the stock to the highest dispersion category. Though widely used in the literature, this dispersion measure has several shortcomings. First, it requires an arbitrary decision rule when the average forecast is zero or negative. If the average forecast is zero, the stock is assigned to the highest dispersion group.[12] Second, scaling by the average forecast or actual earnings can generate a significant misclassification. For example, if actual earnings are small, there is a good chance that the forecast dispersion will be high regardless of the level of disagreement between analysts. For example, consider a normally profitable firm with regular EPS around 1 dollar per share. If for one bad year EPS is close to zero, its absolute average forecast may be one cent per share, but the range of forecasts may vary from –2 dollars to 3 dollars. Dividing standard deviation of forecasts to the absolute value of the average forecast will inappropriately classify such firm into a high dispersion group, although the 5-dollar range in the forecasts may be normal for this firm. Employing stock price as the scaling variable does not cause this type of misclassification.

Third, as shown in Panel A of Table 2.5, the distribution of this dispersion measure is highly skewed; its average is almost four times as large as the median and its standard deviation more than five times the average, thus indicating a severe outlier problem.[13] For example, we do not encounter such an outlier problem when price is used as a denominator since for this measure the average is about half of the median while the standard deviation is about twice the average. Fourth, as Cen et al. (2007) document, the predictability of forecast dispersion on subsequent stock returns mainly comes from the denominator effect (absolute value of average) rather than from the numerator effect (standard deviation) of the dispersion measure.[14]

Given the potential flaws behind the predictive power of forecast dispersion, there is a need to check the robustness of the dispersion effect across different proxies of differences of opinion. The objective of this section is to analyze this robustness check, and below I present

[12] None of the results in Chapter 2 significantly changes when firms with zero mean forecasts are assigned to the *lowest* dispersion group. Also, not reported here, even excluding observations with zero mean earnings forecasts does not affect my results.

[13] Previous studies have also documented skewness in earnings forecasts; see Gu and Wu (2003) and the references therein.

[14] In a follow-up study, Cen, Wei, and Zhang (2008) show that the higher the forecasted EPS the higher the future stock returns.

the alternative definitions that are employed to test the robustness of previous results on the dispersion-return relationship.

2.3.1 Price as denominator

The first alternative measure of dispersion is the standard deviation of the analysts' forecasts as reported in the I/B/E/S Summary History file scaled by the month-end price. This measure of dispersion has been used in numerous papers including Lang and Lundholm (1996), Han and Manry (2000), and Mansi et al. (2006), among others.

2.3.2 Range as dispersion

Inexperienced analysts have a tendency to herd and herding among them is known to reduce the forecast dispersion. The motives for herding is that analysts issue forecasts that are close to the consensus in order to minimize their forecast error. De Bondt and Forbes (1999) show that analysts' coverage is also related to herding among analysts. Devenow and Welch (1996), Bikhchandani and Sharma (2001), and Hirshleifer and Teoh (2003) review the herding literature. To reduce the impact of herding on results, I define dispersion as the range, i.e., the absolute difference of maximum and minimum forecast scaled both by the absolute average of the forecasts and by the month end price. The range measure is also used as a primary measure of dispersion by Tse and Yan (2008) and Goetzmann and Massa (2005) motivated by the idea that it could be meaningfully computed especially when the number of forecasts is small.

Table 2.5: Descriptive statistics of different dispersion measures

Panel A reports summary statistics (correlation coefficients) of different dispersion measures for all stocks and stocks equally sorted by five analyst dispersion groups. Panel B presents correlation coefficients between the different dispersion measures; Pearson coefficients are above the diagonal line and Spearman coefficients are below the line. Each month dispersions are averaged first over the stocks in every group and then over the sample period February 1983 to December 2007. Forecast dispersion is measured as 1) the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the IBES Summary History file, 2) the standard deviation of the analysts' forecasts deflated by the month end price of the summary forecast report date, 3) the range scaled by the absolute value of the average forecast, 4) the range scaled by the month end price of the summary forecast report date, and 5) excluding analyst guidance; i.e., during the earnings announcement date until 90 days before the next announcement date use the forecasts for the current fiscal year end and during the 90 days before the next announcement use the forecasts of the following-fiscal-year end. Stocks with a price less than or equal 5 dollars are excluded. Because not enough forecasts are available before December 1983 in order to account for the analyst guidance, the period considered is January 1984 through December 2007.

Panel A: Summary statistics

Definition of dispersion	Dispersion	Avg	Std	25%	Median	75%
Standard deviation scaled by the absolute average forecast	All	0.20	1.10	0.02	0.05	0.12
	D1	0.01	0.01	0.01	0.01	0.02
	D2	0.03	0.01	0.03	0.03	0.04
	D3	0.06	0.01	0.05	0.06	0.07
	D4	0.12	0.03	0.10	0.12	0.15
	D5	0.97	2.60	0.25	0.37	0.73
Standard deviation scaled by the price	All	0.007	0.017	0.001	0.003	0.007
	D1	0.001	0.000	0.000	0.001	0.001
	D2	0.002	0.000	0.002	0.002	0.002
	D3	0.004	0.001	0.003	0.004	0.004
	D4	0.007	0.002	0.006	0.007	0.008
	D5	0.027	0.034	0.013	0.018	0.028
Range scaled by the absolute average forecast	All	0.51	2.99	0.06	0.13	0.30
	D1	0.03	0.02	0.02	0.03	0.05
	D2	0.08	0.01	0.07	0.08	0.09
	D3	0.15	0.03	0.13	0.15	0.17
	D4	0.29	0.07	0.24	0.28	0.35
	D5	2.30	6.82	0.58	0.86	1.66
Range scaled by stock price	All	0.02	0.04	0.00	0.01	0.02
	D1	0.00	0.00	0.00	0.00	0.00
	D2	0.00	0.00	0.00	0.00	0.01
	D3	0.01	0.00	0.01	0.01	0.01
	D4	0.02	0.00	0.01	0.02	0.02
	D5	0.06	0.08	0.03	0.04	0.06
Dispersion excluding analyst guidance	All	0.20	1.06	0.03	0.05	0.12
	D1	0.01	0.01	0.01	0.02	0.02
	D2	0.03	0.01	0.03	0.03	0.04
	D3	0.06	0.01	0.05	0.06	0.07
	D4	0.13	0.03	0.10	0.12	0.15
	D5	0.91	2.48	0.25	0.35	0.66

Panel B: Correlation coefficients

	Standard deviation scaled by the absolute average forecast	Standard deviation scaled by the price	Range scaled by the absolute average forecast	Range scaled by stock price	Dispersion excluding analyst guidance
Standard deviation scaled by the absolute average forecast		0.76	0.98	0.76	0.67
Standard deviation scaled by the price	0.79		0.76	0.99	0.32
Range scaled by the absolute average forecast	0.97	0.80		0.77	0.65
Range scaled by stock price	0.80	0.99	0.82		0.32
Dispersion excluding analyst guidance	0.60	0.30	0.57	0.30	

2.3.3 Excluding analyst guidance

During the last decade, a surprisingly high percentage of U.S. firms has fulfilled or beaten analysts' forecasts; see Brown (2001), Bartov, Givoly, and Hayn (2002). A widespread way to meet analyst expectations is to inject pessimism into their forecasts by providing analysts with negative clues, or so-called analyst downward guidance. Degeorge, Patel, and Zeckhauser (1999) show that management successfully induces analysts to lower their earnings expectations to an achievable level; see Matsumoto (2002), Baik and Jiang (2006). There is also some evidence in Bowen et al. (2002) that conference calls decrease forecast dispersion. Managers may release negative information along the year and in particular, during the last quarter of the fiscal year, in order to create a positive earnings surprise at the announcement that translates in positive abnormal stock returns. Therefore, low dispersion could lead to positive returns close to earnings releases.[15] To address the problem of analyst guidance, during the 90 days before the earnings announcement, I measure forecast dispersion for the next fiscal year end.[16] During the remaining months, dispersion is based on the current fiscal year end earnings forecasts. I/B/E/S provides earnings forecasts for the current fiscal year (up to 12 months ahead) as well as for the next fiscal year. However, since there are not enough forecasts before December 1983 to compute dispersion, the period starts in January 1984.

Table 2.6 shows a strong negative relationship between forecast dispersion and stock returns for all alternative dispersion measures. This enhances the evidence of a strong predictive power of forecast dispersion on stock returns. Hence, we are in a position to confirm that the negative dispersion-return relationship is not affected by the different

[15] One can also argue that forecast dispersion of earnings should normally decrease as time moves closer to the earnings announcement. In other words, dispersion will normally be higher at the beginning of the fiscal year than close to the earnings announcement simply because the forecast horizon is shorter; see Elton, Gruber, and Gultekin (1984). However, my primary idea here relies on the *excess* decrease of the forecast dispersion due to the analyst guidance that is unrelated to the normal change in dispersion over time.

[16] I assume that next-year these forecasts are less subject to analyst guidance than the forecasts issued in the last quarter for the current fiscal year end. As a robustness check, I also used 30 and 60 days window before the earnings announcement day, and the results remain essentially the same.

Table 2.6: Dispersion anomaly for different dispersion measures

Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market capitalization of the previous month end. Stocks in each size group are then equally sorted into five additional groups based on forecast dispersion of the previous month. In Panel A dispersion is defined as the standard deviation of the analysts' forecasts deflated by the month end price of the summary forecast report date. In Panel B and C, dispersion is defined as the range deflated by the absolute value of the average forecast and the month end price of the summary forecast report date, respectively. Panel D accounts for the analyst guidance; i.e., during the earnings announcement date until 90 days before the next announcement date use the forecasts for the current fiscal year end and during the 90 days before the next announcement use the forecasts for the following-fiscal-year end. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2007. The table reports average monthly equal-weighted portfolio returns. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Standard deviation scaled by the stock price						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.16	1.43	1.21	1.31	1.08	1.12
D2	1.15	1.17	1.22	1.10	1.04	0.99
D3	1.11	0.86	0.96	1.20	1.11	1.16
D4	1.03	0.85	0.94	1.03	1.13	1.04
D5	0.70	0.20	0.66	0.94	1.08	1.12
D1-D5	0.46*	1.23**	0.55**	0.37	0.00	0.00
t(D1-D5)	[2.54]	[6.69]	[2.78]	[1.74]	[0.00]	[0.02]
Panel B: Range scaled by absolute average forecast						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.33	1.55	1.32	1.34	1.28	1.18
D2	1.15	1.16	1.19	1.31	1.05	1.07
D3	1.01	0.80	1.06	1.08	1.06	1.10
D4	0.97	0.71	0.87	1.03	1.19	1.02
D5	0.70	0.30	0.55	0.82	0.88	1.07
D1-D5	0.63**	1.24**	0.77**	0.52*	0.40	0.12
t(D1-D5)	[3.11]	[6.41]	[3.45]	[1.96]	[1.68]	[0.48]
Panel C: Range scaled by stock price						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.17	1.43	1.16	1.23	1.16	1.11
D2	1.18	1.21	1.33	1.21	0.94	1.04
D3	1.04	0.81	0.95	1.12	1.16	1.03
D4	1.01	0.89	0.89	1.12	1.14	1.15
D5	0.82	0.23	0.71	0.92	1.04	1.09
D1-D5	0.35*	1.19**	0.45*	0.31	0.13	0.01
t(D1-D5)	[2.01]	[6.35]	[2.21]	[1.41]	[0.55]	[0.06]
Panel D: Dispersion excluding analyst guidance						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.16	1.37	1.20	1.27	1.02	1.12
D2	1.10	1.13	1.13	1.10	0.94	1.00
D3	1.07	0.71	0.99	1.17	1.05	1.03
D4	0.78	0.42	0.60	0.82	1.15	1.04
D5	0.54	0.19	0.49	0.75	0.80	1.02
D1-D5	0.61*	1.18**	0.71**	0.52	0.22	0.11
t(D1-D5)	[2.55]	[5.80]	[2.72]	[1.75]	[0.77]	[0.41]

forecast dispersion measures. This result is not surprising given the high correlation between the dispersion measures; see Panel B of Table 2.5.

2.3.4 Excluding stale forecasts

Most studies examining the dispersion-return relationship use the I/B/E/S Unadjusted Summary Statistics file to compute forecast dispersion. In I/B/E/S, however, stale forecasts are common. Stale forecasts normally tend to increase the forecast dispersion; see Barron and Stuerke (1998). I/B/E/S uses all outstanding forecasts without any limitation on the forecast age when computing summary statistics. This problem becomes more acute when analysts are not constrained to communicate their forecasts at a specific date. One feature of the I/B/E/S Summary Statistics file is that it does not contain dates of the analysts' earnings forecasts, and the issue of stale forecasts is amplified when some analysts are slow in responding to bad news and do not downgrade their forecasts; see Brown and Han (1992), Scherbina (2008), Erturk (2006), Hwang and Li (2008). Previous research estimating the accuracy of earnings forecasts shows that the most significant variable explaining the lack of accuracy is the forecast age; see Elton et al. (1984), Brown (2001), and Brown and Mohd (2003). Several recent studies address this problem and eliminate stale forecasts when computing consensus or dispersion; see Johnson (2004), Daniševská (2004), and Doukas et al. (2006a).

Because I/B/E/S consensus include stale forecasts, using it to study properties of analysts' forecasts might lead to biased conclusions. Investors may over- or under-react to old forecasts (by anchoring to the previous decision that was made too early instead of waiting for more data), hence stale forecasts maybe be overweighed when computing dispersion. To analyze the impact of stale forecasts on the results, I compute forecast dispersion by eliminating from I/B/E/S Detail Unadjusted file forecasts older than 90, 180, and 360 days before the day when I/B/E/S computes the summary statistics. I/B/E/S statistical period is the third Thursday of each month. If an analyst makes more than one forecast in a given month, only the last forecast is used in my calculations. The definition of the dispersion measure is as in Section 2.2. Limiting forecasts to those that fall within intervals offers the advantage of

Table 2.7: Dispersion anomaly excluding stale forecasts

Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market capitalization of the previous month end. Stocks in each size group are then equally sorted into five additional groups based on forecast of the previous month. Dispersion is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the average forecast after eliminating forecasts older than 90, 180, and 360 days. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 1997. The table reports average monthly equal-weighted portfolio returns. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Forecast age less than 90 days						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.44	1.45	1.40	1.49	1.35	1.50
D2	1.40	1.33	1.37	1.42	1.42	1.39
D3	1.26	0.76	1.34	1.30	1.28	1.39
D4	1.17	0.92	1.05	1.32	1.36	1.22
D5	0.70	-0.03	0.62	0.97	0.94	1.22
D1-D5	0.74**	1.49**	0.77**	0.52*	0.41	0.28
t(D1-D5)	[4.27]	[6.61]	[4.00]	[2.49]	[1.82]	[1.33]
Panel B: Forecast age less than 180 days						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.46	1.45	1.53	1.50	1.44	1.43
D2	1.40	1.34	1.43	1.34	1.37	1.29
D3	1.29	0.98	1.37	1.38	1.39	1.34
D4	1.09	0.74	1.06	1.15	1.34	1.27
D5	0.76	0.03	0.50	1.01	1.08	1.23
D1-D5	0.70**	1.42**	1.03**	0.49*	0.35	0.20
t(D1-D5)	[4.27]	[6.39]	[5.28]	[2.31]	[1.77]	[0.95]
Panel C: Forecast age less than 360 days						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.45	1.46	1.48	1.56	1.38	1.44
D2	1.42	1.33	1.42	1.41	1.41	1.33
D3	1.27	1.00	1.23	1.45	1.43	1.32
D4	1.13	0.73	1.07	1.08	1.32	1.23
D5	0.77	0.06	0.63	0.97	1.12	1.26
D1-D5	0.69**	1.40**	0.84**	0.60**	0.26	0.17
t(D1-D5)	[4.25]	[6.32]	[4.24]	[2.76]	[1.28]	[0.87]

reducing noise created by the inclusion of stale forecasts in the consensus. In addition, it provides greater reliability that changes in forecasts are related to information in the recent past.

Because in the I/B/E/S Detail Unadjusted file there are not enough forecasts starting 1998 to compute dispersion, the period considered spans from February 1983 to December 1997. Results, shown in Table 2.7, show that the elimination of old forecasts do not significantly alter results. For instance, monthly equal-weighted return for all stocks on the D1- D5 strategy (after excluding forecasts older than 90 days) is 0.74% with a t-stat of 4.27. I observe similar results when older than 180, and 360 days forecasts are eliminated. Thus, it does not appear that the exclusion of old forecasts impacts the predictable power of dispersion on stock returns.

2.3.5 Increase of analysts' minimum coverage

As Table 1.1 shows, most studies use two or three forecasts to compute forecast dispersion. However, dispersion computed from few forecasts could be a very noisy measure of disagreement. For example, Comiskey et al. (1987, p.237) concludes that "…the value of the forecast dispersion measure, as a heterogeneous expectations surrogate, is greater with the addition of more analyst forecasts". And yet, only few papers require a firm to be covered by more than two analysts; see e.g., Ajinkya et al. (1991), Qu et al. (2004), Ackert and Athanassakos (1997). De Bondt and Forbes (1999) show that as more analysts produce more forecasts, disagreement rises but only up to a point - once there are eight analysts following the firm, additional forecasts do not add to the forecast dispersion. When the sample is restricted to stocks covered by at least 5 analysts, there is still dispersion effect but it is significantly reduced; see Qu et al. (2004). Table 2.8 shows how the increase in the minimum coverage affects the results.

Equal-weighted D1-D5 portfolio returns are decreasing as the minimum coverage increases and gets insignificantly different from zero already when the data is restricted to stocks covered by at least seven analysts.[17] This result agrees with the view that dispersion computed from few forecasts is a noisy measure of analyst disagreement; however, it has a predictive power on future stock returns. Bhushan (1989) and Shores (1990), among others, note that large firms generally are more heavily followed by analysts. Hence, one reason that we do not observe any strong negative dispersion-return relation when the data is limited to extensively covered firms may be that this sample is tilted toward larger firms. And for these

[17] Limiting the sample to firms covered by seven analysts still produces on average 40 stocks in each of the 25 portfolios; hence, we can still view them as well-diversified portfolios.

Table 2.8: Dispersion anomaly increasing analyst coverage

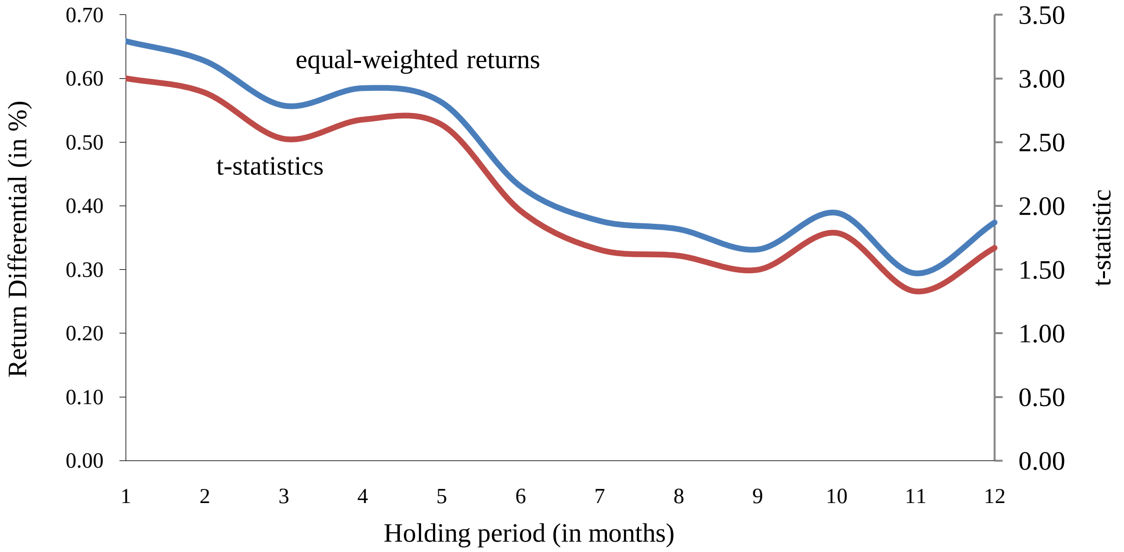
Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market capitalization of the previous month end. Stocks in each size group are then equally sorted into five additional groups based on forecast of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. I require a firm to be covered by at least 3, 4, 5, 6, and 7 analysts. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2007. The table reports average monthly equal-weighted portfolio returns. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Minimum coverage = 3						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.26	1.47	1.25	1.40	1.18	1.24
D2	1.17	1.17	1.28	1.10	1.10	1.01
D3	1.13	0.90	1.14	1.20	1.03	1.06
D4	0.95	0.74	0.94	1.03	1.13	1.07
D5	0.72	0.34	0.68	0.90	0.99	1.00
D1-D5	0.55*	1.13**	0.56*	0.51	0.20	0.24
t(D1-D5)	[2.28]	[5.23]	[2.36]	[1.83]	[0.72]	[0.95]
Panel B: Minimum coverage = 4						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.25	1.21	1.33	1.32	1.11	1.29
D2	1.14	1.11	1.35	0.98	1.21	1.00
D3	1.06	0.99	1.09	1.01	1.01	1.06
D4	1.02	0.70	1.16	1.03	1.17	1.14
D5	0.80	0.41	0.90	0.92	1.01	1.06
D1-D5	0.45	0.81**	0.43	0.40	0.10	0.23
t(D1-D5)	[1.85]	[3.34]	[1.66]	[1.43]	[0.39]	[0.89]
Panel C: Minimum coverage = 5						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.24	1.20	1.39	1.24	1.18	1.27
D2	1.13	1.18	1.15	0.99	1.23	1.05
D3	1.09	1.09	1.06	1.00	0.99	1.04
D4	1.04	0.81	1.09	1.08	1.21	1.09
D5	0.88	0.67	0.86	1.01	1.06	1.03
D1-D5	0.35	0.53*	0.52	0.23	0.12	0.24
t(D1-D5)	[1.39]	[2.23]	[1.88]	[0.86]	[0.48]	[0.94]
Panel D: Minimum coverage = 6						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.24	1.32	1.22	1.22	1.18	1.31
D2	1.12	1.24	1.09	0.95	1.22	1.07
D3	1.10	0.98	1.21	0.97	1.08	1.00
D4	1.07	0.96	1.01	1.14	1.19	1.09
D5	0.93	0.76	0.98	0.98	1.08	1.05
D1-D5	0.30	0.55*	0.23	0.23	0.11	0.26
t(D1-D5)	[1.15]	[2.17]	[0.81]	[0.85]	[0.42]	[1.02]
Panel E: Minimum coverage = 7						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.24	1.32	1.21	1.26	1.22	1.31
D2	1.12	1.22	0.97	1.10	1.17	1.03
D3	1.04	0.96	1.03	0.94	1.13	1.08
D4	1.09	0.93	1.13	1.03	1.22	1.00
D5	1.00	0.88	1.09	1.27	0.93	0.99
D1-D5	0.24	0.43	0.13	-0.01	0.29	0.32
t(D1-D5)	[0.89]	[1.59]	[0.45]	[-0.02]	[1.08]	[1.18]

firms the negative dispersion-return relationship is less pronounced, as shown by Diether et al. (2002) and also reported in Table 2.3.

Figure 1: Different holding periods

This figure plots the average equal-weighted D1-D5 portfolio returns for sample stocks. At the end of each month, stocks are ranked into quintiles based on forecast dispersion and assigned into portfolios without a lag. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are then held in the portfolio for 1 up to 12 months. The period considered is February 1983 through December 2007.



2.3.6 Different holding periods

I also hold a stock in a portfolio for periods ranging from one month to one year. At the end of each month, I rank stocks into forecast dispersion quintiles and assign into portfolios without a lag. Figure 1 shows the equal-weighted returns for D1-D5 portfolio. For relatively short holding periods, the results are similar to those of the one-month holding strategy because essentially the same stocks are selected by both strategies. This strategy delivers statistically significant equal-weighted returns up to six month, but for longer holding periods, returns for this strategy are lower and statistically insignificant. Even after six months after the portfolio formation day, a period during which any information contained in forecast dispersion should definitely have been recognized and removed from the stock price, the return difference is still 0.43% with a t-stat of 1.96. This result suggests that the market gradually notices and removes the information hidden in forecast dispersion, but even after this information is revealed, a considerable drift still occurs.

2.3.7 Dispersion as standard deviation of recommendations

One more way to investigate the relation of analysts' disagreement and stock returns is to use an alternative proxy of analyst disagreement - the standard deviation of recommendations as reported in the I/B/E/S Recommendations Summary file.[18] This measure of disagreement has several advantages. First, yearly earnings forecasts are affected by how close a firm is to the end of the fiscal year and by how important earnings guidance is for a firm. These considerations are less likely to influence the recommendations. Second, yearly forecasts typically have to be normalized to be made comparable across firms and the normalization may introduce noise in comparisons of forecasts. However, standard deviation of recommendations is directly comparable across firms so no normalization is required. Although I/B/E/S provides Recommendations Summary file starting in November 1993, the number of recommendations published in 1993 is sparse. Hence, the period considered here is from January 1994 to December 2007. The database contains 867,549 summary statistics of recommendations of U.S. firms over the sample period. To be eligible, a firm must have at least two analysts issuing recommendations. This yields an average of 2,442 firms per month.

Results, illustrated in Panel A of Table 2.9, do not suggest any discernible link between standard deviation of recommendations and future stock returns. For comparison, Panel B presents the results when dispersion is computed from earnings forecasts, using the same sample of stocks as in Panel A. Note that although the average return of D1-D5 strategy has decreased in the later period, the strong negative dispersion-return relation still holds for the smallest size group.[19] These results suggest that dispersion of recommendations and dispersion of earnings forecasts are empirically two different proxies of analyst disagreement

[18] In non-tabulated tables, I also observe similar results when dispersion is computed as the standard deviation of long-term earnings growth forecasts.

[19] That the profitable power of dispersion disappears over time is also shown in Dische (2002, p.225) and Diether et al. (2002, p.2133). Both authors explain the decreasing power of the dispersion effect by behavioral motives.

Table 2.9: Dispersion anomaly for recommendations

Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market capitalization of the previous month end. Stocks in each size group are then sorted into five additional dispersion groups based on dispersion of the previous month. Panel A reports average monthly equal-weighted portfolio returns when dispersion is defined as the standard deviation of analysts' recommendations, as reported in the I/B/E/S Summary Recommendations file. Panel B reports the same strategy returns for the same period when dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is January 1994 through December 2007. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Average equal-weighted returns using dispersion of recommendations						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	0.86	1.04	0.82	0.95	0.58	0.56
D2	1.00	1.04	1.04	0.93	0.82	0.86
D3	0.94	0.91	0.74	1.17	1.09	0.90
D4	0.89	0.57	0.77	0.93	0.92	0.94
D5	0.89	0.77	0.79	0.85	0.95	1.18
D1-D5	-0.03	0.27	0.03	0.10	-0.38	-0.63
t(D1-D5)	[-0.21]	[1.10]	[0.11]	[0.38]	[-1.34]	[-1.71]
Panel B: Average equal-weighted returns using dispersion of earning forecasts						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.08	1.47	1.08	1.23	0.94	1.00
D2	1.00	1.11	1.11	1.05	0.83	0.82
D3	1.00	0.81	0.87	0.99	0.89	0.87
D4	0.85	0.87	0.86	0.97	0.85	0.92
D5	0.64	0.33	0.52	0.77	0.99	0.98
D1-D5	0.44	1.14**	0.57	0.46	-0.06	0.02
t(D1-D5)	[1.23]	[4.10]	[1.50]	[1.07]	[-0.14]	[0.05]

- the former does not predict stock returns but the later does. Hence, more research is needed to understand the cause of this difference; see Bradshaw (2004).

2.4 The relation with other anomalies

Stock market anomalies with respect to the CAPM are patterns in average stock prices, usually related to firm characteristics. For extensive surveys of literature on market anomalies see De Bondt and Thaler (1989), Dimson and Mussavian (1998); Dimson and Mussavian (1999), Malkiel (2003), among others. Fama and French (1996) show that their three factor model (market, SMB, and HML) explains Bhandari (1988)'s leverage, De Bondt and Thaler (1985)'s reversal in long-term returns, Lakonishok, Shleifer, and Vishny (1994)'s past sales growth, E/P, and C/P anomalies. Since variables like size, E/P, leverage, and book-to-market are all scaled versions of a firm's stock price, it is reasonable to expect that some of them are redundant for explaining average returns. Chen and Zhang (2008) present another three factor model (market, investment, and productivity) that explains a number of other anomalies including Sloan (1996)'s accrual, Campbell, Hilscher, and Szilagyi (2008)'s default risk, Pontiff and Woodgate (2008)'s net shares issuance, Loughran and Ritter (1995)'s SEO/IPO, and Jegadeesh and Titman (1993)'s short-term momentum of returns. In addition, there is evidence that momentum anomaly is related to Lee and Swaminathan (2000)'s volume and Vassalou and Apedjinou (2004)'s corporate innovation anomalies. However, many other anomalies are left unexplained by the above mentioned factors, among them are the forecast dispersion anomaly, Bernard and Thomas (1989)'s earnings surprise, Pastor and Stambaugh (2003)'s liquidity, Francis et al. (2005)'s accruals quality, Ang, Hodrick, Xing, and Zhang (2006)'s idiosyncratic volatility, Cooper et al. (2008)'s asset growth, and Giovinazzo (2008)'s asset intensity anomalies.

The dispersion anomaly is another new challenge for asset pricing models, and several authors have addressed the question whether the dispersion anomaly is related to some of the well-known anomalies. For instance, in order to determine whether the results are influenced by the value anomaly, Diether et al. (2002) first classify stocks in three book-to-market groups and next into three size groups with each category. Finally, there are three dispersion groups within each of the nine categories. In all nine categories, there is a tendency for the average return to fall as dispersion increases. Another nine-way sort is done by momentum based on returns from 12 months earlier to 2 months earlier (winners versus losers), then by size and finally by dispersion. The dispersion effect is not significant among winner stocks, but it is in the predicted direction for the loser categories; see Doukas et al. (2006a). Thus, the dispersion anomaly is distinct from value and momentum anomalies.

Chen and Jiambalvo (2004) explain the negative dispersion-return relationship by the post-earnings-announcement drift. Specifically, after sorting firms by prior-period standardized unexpected earnings, the difference between the subsequent returns of high versus low dispersion firms is no longer statistically significant. The result is consistent with the findings of Erturk (2006) and Hwang and Li (2008) that the dispersion anomaly may be related to analyst incentives to underreact to bad news. Chen and Jiambalvo (2004) further test the hypothesis of Diether et al. (2002) that when dispersion is high, prices reflect the beliefs of optimistic investors. If investors holding the high dispersion stocks are optimistic, then their responses to bad news, measured as negative unexpected earnings, should be particularly strong. However, Chen and Jiambalvo (2004) show that the earnings response coefficients for high dispersion/bad news firms are lower than for low dispersion/bad news firms; see also Imhoff and Lobo (1992), Kinney, Burgstahler, and Martin (2002). These results call into question the argument that optimism accounts for the low returns earned by firms with high dispersion.

Focusing on a sample of firms rated by Standard & Poor's, Avramov et al. (2009) show that liquidity proxies such as turnover, firm size, and the Amihud (2002) illiquidity measure do not capture the dispersion effect. Sadka and Scherbina (2007) link the dispersion anomaly to trading costs. Given a decline in transaction costs, an increase in aggregate market liquidity forces the prices of high-disagreement stocks to converge down to fundamentals. This is exactly when high-dispersion stocks experience the most pronounced price corrections and the lowest returns, whereas returns on low-dispersion stocks are positively correlated with changes in aggregate liquidity. Since high- and low-dispersion stocks have an opposite relation with respect to aggregate liquidity changes, the performance of a portfolio short in high-dispersion stocks and long in low-dispersion stocks is positively related to changes in market liquidity.

The research question addressed in this section concerns whether the predictive power of forecast dispersion on stock returns can be explained by other well-known financial variables that are found to explain average stock returns. I continue this line of research and below compare the dispersion effect to other important determinants of the cross-sectional returns, not previously examined in the literature.

2.4.1 Accruals quality

Accruals quality (AQ) is a widely used measure of information risk. In a recent influential paper, Francis et al. (2005) find that poorer AQ is associated with larger costs of debt and equity, so they conclude that AQ is priced. In contrast, Core, Guay, and Verdi (2008) argue that AQ is not priced after carefully conducting several asset-pricing tests. While much research has focussed on the link between the AQ and stock returns, little has been done on the link between AQ and forecast dispersion. Hence, motivated by the idea that reporting choices affect both forecast dispersion and the AQ, my tests here examine the AQ-dispersion link. Appendix B details how AQ is measured. Average and median values of AQ are 0.085 and 0.067, respectively; all the values of AQ are in the range of 0.005 and 0.871 (not reported here).

One of the few papers studying the relationship between AQ and forecast dispersion is Cohen (2003). Based on regression analysis, he provides evidence that firms with high-quality financial reporting policies have lower forecast dispersion and higher analyst following. I go beyond this observation and show in Panel A of Table 2.10 the previous fiscal year end AQ for each portfolio. Consistent with Cohen (2003), the second column shows that high dispersion firms have indeed poorer accruals quality than low dispersion stocks. This negative relationship holds for all size groups. The largest AQ difference between low- and high-dispersion firms however is observed for the firms in S2 size quintile and equals -0.032 with a highly significant t-stat of -12.62. I also confirm the well documented fact (e.g., Table 4 in Francis et al. (2005)) that accruals quality positively correlates with the size of the firm; large firms have lower standard deviations of residuals than small firms, the difference being 0.026 with a t-stat of 7.97.

Panel B presents the average equal-weighted portfolio returns for the restricted sample. Although the spread between low- and high-dispersion portfolio returns is

Table 2.10: Dispersion and accruals quality anomalies

The table reports the average AQ and average monthly equal-weighted portfolio returns. Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market capitalization of the previous month (or AQ of the previous fiscal year end). Stocks in each size (AQ) group are then sorted into five additional groups based on forecast dispersion of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2006. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Average accruals quality (AQ)								
		Size quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	0.085	0.100	0.092	0.082	0.076	0.074	0.026**	[7.97]
D1	0.075	0.091	0.079	0.075	0.067	0.070	0.020**	[17.38]
D2	0.076	0.093	0.083	0.072	0.070	0.068	0.025**	[16.20]
D3	0.082	0.098	0.090	0.076	0.073	0.072	0.026**	[18.91]
D4	0.093	0.106	0.099	0.088	0.082	0.078	0.028**	[8.43]
D5	0.102	0.115	0.111	0.097	0.088	0.084	0.031**	[6.28]
D1-D5	-0.027**	-0.024**	-0.032**	-0.021**	-0.020**	-0.014**		
t(D1-D5)	[-9.36]	[-11.02]	[-12.62]	[-4.93]	[-4.70]	[-1.65]		

Panel B: Average equal-weighted returns by size and dispersion								
		Size Quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.14	1.15	1.23	1.12	1.17	1.05	0.10	[0.45]
D1	1.32	1.52	1.43	1.30	1.24	1.25	0.27	[1.05]
D2	1.15	1.30	1.42	1.07	1.26	1.04	0.26	[0.96]
D3	1.15	1.21	1.18	1.01	1.08	0.74	0.47	[1.74]
D4	1.14	0.97	1.20	1.18	1.14	1.15	-0.18	[-0.66]
D5	0.95	0.69	0.92	1.06	1.14	1.09	-0.40	[-1.32]
D1-D5	0.37	0.83**	0.51	0.24	0.11	0.17		
t(D1-D5)	[1.56]	[2.95]	[1.83]	[0.88]	[0.41]	[0.69]		

Panel C: Average equal-weighted returns by AQ and dispersion								
		AQ Quintiles						
Dispersion quintiles	All stocks	Small AQ1	AQ2	AQ3	AQ4	Large AQ5	AQ1-AQ5	t(AQ1-AQ5)
All stocks	1.14	1.17	1.24	1.10	1.14	1.07	0.10	[0.41]
D1	1.32	1.21	1.35	1.43	1.27	1.31	-0.10	[-0.46]
D2	1.15	1.16	1.33	1.13	1.11	0.90	0.26	[0.84]
D3	1.15	1.23	1.14	1.01	1.25	1.28	-0.05	[-0.16]
D4	1.14	1.01	1.26	1.04	1.11	1.27	-0.26	[-0.73]
D5	0.95	1.22	1.11	0.92	0.98	0.59	0.63	[1.95]
D1-D5	0.37	-0.01	0.24	0.51*	0.29	0.72*		
t(D1-D5)	[1.56]	[-0.04]	[0.93]	[2.00]	[0.99]	[2.41]		

insignificant for all stocks,[20] it is still significant for the firms in the smallest size group. Further, to explore whether AQ subsumes the predictive power of dispersion on future stock returns, I sort firms first by AQ variable and then by forecast dispersion. More precisely, each month using in-sample AQ breakpoints of the previous fiscal year end, I assign stocks into one of five AQ quintiles. Stocks with the lowest standard deviation of the residuals are placed

[20] This may be due to the additional requirement that a firm must have sufficient data in Compustat Industrial Annual file to compute AQ, which biases my sample to surviving firms that are larger and more successful than the population.

into AQ1 quintile, and those with the highest standard deviation of the residuals are in AQ5 quintile. Note that larger standard deviation of residuals is interpreted as lower earnings quality. Stocks in each AQ quintile are then ranked into five additional quintiles based on the forecast dispersion of the previous month. This sorting on average gives 30 stocks in each of the 25 portfolios. As shown in Panel C, there still exists a strong negative relation between contemporaneous dispersion and future stock returns. For example, for firms in AQ5 group the difference of average monthly equal-weighted returns of D1-D5 strategy equals significant 0.72% (t-stat=2.41%). Results are similar for the AQ3 group. Hence, it does not appear that AQ explains the puzzling dispersion-returns relation.

2.4.2 Capital investment growth

Several papers document the negative relation between investment and average returns. Cochrane (1991) is among the first to show this relation in the time series. Titman et al. (2004) find a similar relation in the cross-section and interpret the evidence as investors underreacting to overinvestment. More specifically, they show that firms that increase their level of abnormal capital investment (CI) the most tend to achieve lower stock returns for the five subsequent years. Here I study whether the effect of high forecast dispersion firms is different from the effect of CI documented by Titman et al. (2004). Similar to them, abnormal capital investment in year y is defined as follows,

$$CI_y = \frac{CE_y}{\frac{CE_{y-1} + CE_{y-2} + CE_{y-3}}{3}} - 1,$$

where CE_y is the firm's capital expenditures (#128) scaled by its total assets in year y.[21] Restricting the sample to the firms that have sufficient data in Compustat Industrial annual file produces 993 eligible firms per month. Panel A of Table 2.11 shows the distribution

[21] Using sales as the deflator, as done in Titman et al. (2004), does not significantly change the results.

characteristics of the CI variable. It reveals that small firms invest relatively more than large firms - the average difference is 0.11% with a t-stat of 7.16. Notice that the largest firms disinvest, e.g., firms in the largest size quintile disinvest with a rate of -0.022%. Not reported here, it is also interesting to note that low investment firms have high forecast dispersion than high investment firms.[22]

Panel B presents the average equal-weighted portfolio returns for this sample. Although the return differential of the D1-D5 strategy is slightly lower for the restricted sample than for the full sample, the results are largely consistent with the results obtained in Table 2.3. In particular, the D1-D5 strategy for the smallest size quintile earns 1.17 % monthly average return (t-stat=4.61%). To investigate whether CI underperformance can explain the underperformance of dispersion, I make a further two-way cut on CI and dispersion. More precisely, I form five CI groups based on the CI level of the previous fiscal year end, and then stocks in each CI group are sorted into five portfolios based on the level of forecast dispersion of the previous month. On average this sort produces 40 stocks in each of the 25 CI/Dispersion portfolios.

First, note that the results of this test, presented in Panel C, are consistent with Titman et al. (2004) showing that the spread return of low CI and high CI amounts significant 0.21% monthly return with a t-stat of 1.86. I also observe that the difference between low- and high dispersion portfolio returns is still significantly different from zero at conventional levels. More specifically, the average D1-D5 returns for CI1 and CI5 groups are highly significant with 0.6% (t-stat = 2.26) and 0.84% (t-stat = 2.93) respectively. Thus, my analysis does not suggest that the CI variable captures the dispersion effect.

[22] This finding in contrast to prior study of Gilchrist, Himmelberg, and Huberman (2005). However, their definition of dispersion of analysts' forecasts differs from the definition employed in this study.

Table 2.11: Dispersion and capital investment anomalies

The table reports average CI and average monthly equal-weighted portfolio returns. Using in-sample breakpoints each month stocks are sorted in five groups based on the level of market capitalization of the previous month (or CI of the previous fiscal year end). Stocks in each size (CI) group are then sorted into five additional groups based on forecast dispersion of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2006. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Average capital investment (CI)

Dispersion quintiles	All stocks	Size quintiles Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	0.030	0.088	0.060	0.019	0.005	-0.022	0.110**	[7.16]
D1	0.029	0.108	0.053	0.042	0.011	-0.015	0.123**	[8.09]
D2	0.019	0.080	0.045	0.024	0.007	-0.030	0.110**	[8.75]
D3	0.022	0.083	0.046	0.014	-0.002	-0.027	0.109**	[8.25]
D4	0.035	0.093	0.060	0.000	0.012	-0.017	0.111**	[5.75]
D5	0.048	0.073	0.097	0.016	-0.002	-0.022	0.095**	[4.99]
D1-D5	-0.019	0.035*	-0.045*	0.026	0.012	0.007		
t(D1-D5)	[-1.86]	[2.12]	[-2.22]	[1.77]	[0.61]	[0.73]		

Panel B: Average equal-weighted returns by size and dispersion

Dispersion quintiles	All stocks	Size quintiles Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.19	1.21	1.29	1.24	1.14	1.09	0.12	[0.55]
D1	1.39	1.70	1.51	1.50	1.22	1.31	0.40	[1.51]
D2	1.26	1.44	1.42	1.21	1.11	1.06	0.37	[1.38]
D3	1.22	1.30	1.19	1.13	1.13	0.87	0.44	[1.55]
D4	1.14	1.00	1.33	1.35	1.14	1.22	-0.22	[-0.83]
D5	0.94	0.53	0.98	1.05	1.10	1.00	-0.47	[-1.60]
D1-D5	0.44	1.17**	0.53	0.45	0.12	0.31		
t(D1-D5)	[1.83]	[4.61]	[1.87]	[1.60]	[0.46]	[1.23]		

Panel C: Average equal-weighted returns by CI and dispersion

Dispersion quintiles	All stocks	CI quintiles Small CI1	CI2	CI3	CI4	Large CI5	CI1-CI5	t(CI1-CI5)
All stocks	1.19	1.26	1.24	1.22	1.20	1.06	0.21	[1.86]
D1	1.39	1.45	1.46	1.42	1.24	1.38	0.07	[0.46]
D2	1.26	1.28	1.15	1.25	1.29	1.28	0.00	[0.00]
D3	1.22	1.50	1.27	1.23	1.27	1.01	0.49*	[2.42]
D4	1.14	1.23	1.14	1.12	1.23	1.08	0.15	[0.81]
D5	0.94	0.85	1.19	1.08	0.93	0.54	0.31	[1.42]
D1-D5	0.44	0.60*	0.27	0.34	0.31	0.84**		
t(D1-D5)	[1.83]	[2.26]	[0.98]	[1.32]	[1.21]	[2.93]		

2.4.3 Asset growth

Motivated by the work of Cooper et al. (2008), the potential candidate here to explain the dispersion effect is the total asset growth rate (AG). Exploring the predictive power of AG for stock returns, Cooper et al. (2008) find that it is the most important predictor of the future abnormal returns, and interpret their evidence as investor overreaction. In their sample covering the period of 1968-2003, firms with low AG outperformed firms with high AG by an astounding 20% equal-weighted annual return.[23] Their results is robust even for large capitalization stocks, a subgroup of firms for which other documented predictors of the cross-section (such as forecast dispersion) lose much of their predictive ability. Following Cooper et al. (2008), the AG rate is estimated as the yearly growth rate in total assets (# 6), i.e. in fiscal year end y, AG_y is measured as follows,

$$AG_y = \frac{\#6_y - \#6_{y-1}}{\#6_{y-1}}$$

Limiting the sample to the stocks that have enough data in the Compustat Industrial Annual file to compute asset growth rate yields on average 1,183 sample stocks per month. Panel A of Table 2.12, that reports distribution characteristics of the asset growth also shows that small capitalization stocks grow faster than large capitalization stocks. In non-tabulated results, I also observe a negative relation between asset growth rate and forecast dispersion. The average (median) asset growth rate over the sample period is 0.3% (0.11%) per year. My statistic slightly differs from what Cooper et al. (2008) report due to the different periods considered. Further, Panel B shows that D1-D5 strategy earns highly significant return for the equal-weighted portfolios. More specifically, the average difference between low- and high-dispersion portfolio monthly returns equals 0.57% (6.84% annualized) with a t-stat of 2.39. Although the average monthly return differential between low- and high-dispersion portfolios declines as the average size increases, it remains significant at conventional levels for the stocks in the two highest market capitalization quintiles. To study whether the AG variable can explain the anomalous relationship between forecast dispersion and stock returns, Panel C further provides the results for a two-way cut on AG and dispersion of analysts' forecasts. This sort provides 47 stocks in each of the 25 portfolios.

[23] A survey conducted by McKinsey (2007) also reveals that firms themselves knew that they were not great at capital discipline. The survey said, "17 percent of the capital invested by their companies went toward underperforming investment that should be terminated and that 16 percent of their investments were a mistake to have financed in the first place".

Table 2.12: Dispersion and asset growth anomalies

The table reports average AG and average monthly equal-weighted portfolio returns. Using in sample breakpoints each month stocks are sorted in five groups based on the level of market capitalization of the previous month end (or AG of the previous fiscal year end). Stocks in each size (AG) group are then sorted into five additional groups based on forecast dispersion of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2006. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Average asset growth (AG)								
		Size quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	0.30	0.39	0.38	0.32	0.24	0.18	0.22**	[7.62]
D1	0.29	0.43	0.40	0.31	0.24	0.15	0.28**	[14.19]
D2	0.29	0.41	0.40	0.32	0.23	0.16	0.25**	[15.42]
D3	0.31	0.41	0.38	0.34	0.25	0.16	0.24**	[13.85]
D4	0.32	0.37	0.37	0.31	0.24	0.19	0.18**	[8.32]
D5	0.31	0.33	0.35	0.30	0.23	0.23	0.10**	[2.84]
D1-D5	-0.03	0.10**	0.06*	0.01	0.00	-0.08		
t(D1-D5)	[-1.27]	[6.01]	[2.46]	[0.57]	[0.20]	[-1.85]		

Panel B: Average equal-weighted returns by size and dispersion								
		Size quintiles						
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.13	1.06	1.17	1.23	1.08	1.09	-0.03	[-0.11]
D1	1.36	1.57	1.45	1.52	1.14	1.30	0.27	[0.97]
D2	1.23	1.30	1.41	1.25	1.18	1.02	0.28	[0.99]
D3	1.22	1.05	1.12	1.14	1.07	0.94	0.11	[0.43]
D4	0.99	0.78	1.04	1.25	1.14	1.19	-0.41	[-1.45]
D5	0.79	0.47	0.76	1.01	0.92	1.00	-0.53	[-1.83]
D1-D5	0.57*	1.10**	0.70*	0.51	0.22	0.30		
t(D1-D5)	[2.39]	[4.58]	[2.55]	[1.80]	[0.82]	[1.19]		

Panel C: Average equal-weighted returns by AG and dispersion								
		AG quintiles						
Dispersion quintiles	All stocks	Small AG1	AG2	AG3	AG4	Large AG5	AG1-AG5	t(AG1-AG5)
All stocks	1.13	1.35	1.32	1.32	1.14	0.51	0.85**	[3.60]
D1	1.36	1.39	1.56	1.45	1.32	0.86	0.53	[1.94]
D2	1.23	1.47	1.35	1.36	1.25	0.84	0.63*	[2.03]
D3	1.22	1.28	1.39	1.46	1.08	0.60	0.68*	[2.20]
D4	0.99	1.35	1.30	1.34	1.18	0.20	1.15**	[4.22]
D5	0.79	1.30	0.97	0.97	0.88	-0.07	1.37**	[5.28]
D1-D5	0.57*	0.10	0.59*	0.49*	0.43	0.93**		
t(D1-D5)	[2.39]	[0.32]	[2.40]	[2.14]	[1.63]	[3.57]		

First, I confirm Cooper et al. (2008)'s finding that low asset growth firms outperform high asset growth firms. In particular, the strategy long in low AG firms and short in high AG firms earns annual 10% return with a t-stat of 3.6. Note that except for the lowest AG group, D1-D5 equal-weighted portfolio returns significantly differ from zero. The message from this test is that AG rate does not either subsume dispersion anomaly.

Table 2.13: Dispersion and equity offering anomalies

Each month I exclude stocks that have issued stocks (an IPO or a SEO) during the past 60 months. Then, using in-sample breakpoints each month stocks are sorted in five equal groups based on the level of market capitalization of the previous month end. Stocks in each size group are then sorted into five additional groups based on forecast dispersion of the previous month. Forecast dispersion is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast as reported in the I/B/E/S Summary History file. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The period considered is February 1983 through December 2007. The table reports average monthly equal-weighted portfolio returns. Numbers in brackets are the t-statistics based on standard errors adjusted for one lag autocorrelation (*5%, **1%).

Panel A: Equal-weighted returns						
		Size quintiles				
Dispersion quintiles	All stocks	Small S1	S2	S3	S4	Large S5
D1	1.30	1.49	1.34	1.44	1.21	1.26
D2	1.20	1.31	1.23	1.13	1.15	1.07
D3	1.19	1.07	1.22	1.14	1.11	1.05
D4	1.04	0.78	0.99	1.13	1.20	1.14
D5	0.69	0.35	0.50	0.88	0.95	1.11
D1-D5	0.61**	1.13**	0.84**	0.56*	0.26	0.16
t(D1-D5)	[2.71]	[5.26]	[3.50]	[2.25]	[1.02]	[0.62]

2.4.4 The effect of equity offerings

Research on long term performance of initial public offering (IPO) and seasoned equity offering (SEO) was initiated by Loughran and Ritter (1995). They show that equity-offering firms, whether an IPO or a SEO, have low long-run stock returns. To check whether the negative dispersion-return relationship is attributable to these equity-offering firms, I re-examine the dispersion-return relationship for firms that have not issued equity in any of the past 60 months. On average, 27 stocks are removed from each of the 25 portfolios, reducing the average number of stocks in these portfolios from 87 to 60. I use the Thomson Financial Global Issues Dataset to identify firms involved in any equity offering, either an IPO or a SEO.

Table 2.13 shows that the underperformance of the high dispersion firms relative to low dispersion firms still persists. Specifically, the raw return on the D1-D5 portfolio for all stocks is 0.61% per month (7.32% annualized) with a t-stat of 2.71. This empirical finding suggests that the negative dispersion-return relation is not due to the effect of equity offering, a result that is also supported by evidence from a test on value-weighted and median returns.[24]

2.5 Conclusion

In this chapter, I empirically re-examine the relationship between forecast dispersion and stock returns. Consistent with the existing literature, I provide strong evidence that contemporaneous forecast dispersion is negatively correlated with future stock returns. This effect is most pronounced in the smallest market capitalization stocks and is robust across different measures of dispersion that I consider in Section 2.3. This suggests that the market does not entirely assimilate the information contained in the forecast dispersion in a timely manner.

The significant negative dispersion-return association is robust to different measures of dispersion. However, I do not find any evident relationship between stock returns and the standard deviation of recommendations and long-term forecasts. My analysis further suggests that we cannot explain the negative dispersion-return relationship by the accruals quality, asset growth, capital investment, and equity issuance anomalies. Hence, the dispersion-return relationship is strongly negative and not directly connected to other documented anomalies. Thus, more research is needed to understand what does the forecast dispersion measure that has predictive power on stock returns, and in the next two chapters I further investigate the dispersion-return relationship.

[24] The unreported results indicate that value-weighted and median returns on the D1-D5 portfolio excluding firms that have issued new equity in any of the past 60 months also persist. Specifically, the returns for the value-weighted (median) the returns are 1.05%, t=4.56 (1.68%, t=8.25) for S1 size group, 0.84%, t=3.49 (1.46%, t=6.46) for S2 size group, 0.55%, t=2.22 (1.02%, t=4.53) for S3 size group.

Chapter 3: The Determinants of Forecast Dispersion

3.1 Introduction

How can we explain the negative correlation between contemporaneous forecast dispersion and future stock returns? What are the determinants of analyst forecast dispersion? What causes analysts to disagree in their forecasts? These are the questions of interest in this chapter. Two comprehensive reviews of the forecast literature by Givoly and Lakonishok (1984) and Brown (1993) conclude that we know very little about the determinants of forecast dispersion and how such determinants are related to one another. Schipper (1991) suggests that future research should investigate the causes of analyst disagreement and what information is impounded in analysts' forecasts. Evidence shows that forecast dispersion has several dimensions including information asymmetries and differences of opinion. On one hand, a group of analysts can have superior information. On the other hand, even when having the same information set, for example after earnings announcements, analysts revise their forecasts not necessarily in the same direction; see Bamber et al. (1997), Bamber et al. (1999), Kandel and Pearson (1995), among others.

In order to broaden our knowledge on the relation between forecast dispersion and stock returns, it is essential to understand more on the determinants of forecast dispersion. Despite the important role of forecast dispersion in asset pricing, there is little research on what determines forecast dispersion. This chapter fills this gap by conducting an analysis on the determinants of forecast dispersion. I show that forecast dispersion is simultaneously associated with firm's idiosyncratic risk, firm's information environment, analysts' differing information sets, forecasting difficulty, and several other determinants suggested by the extant literature. Results are robust across different proxies for the sources of forecast dispersion.

3.2 Forecast dispersion and data

3.2.1 Forecast dispersion

Forecast dispersion *(FDisp)* is the standard deviation of individual analysts' current-fiscal-year annual earnings per share forecasts divided by the absolute value of the average earnings forecasts.[25] This measure of analyst disagreement has been widely used in the prior literature. To compute forecast statistics (standard deviation and average), I use I/B/E/S Unadjusted Detail History file that is a timeline of individual earnings forecasts unadjusted for stock splits. When computing forecast dispersion, for a given analyst I retain the most recent forecast. I use individual analyst forecasts for two reasons. First, Diether et al. (2002), Payne and Thomas (2003) and Baber and Kang (2002) show that the split-adjustment procedure can lead to wrong conclusions. Second, I/B/E/S Summary Statistics file often includes stale forecasts in computing forecast statistics; see Morse, Stephan, and Stice (1991), Brown and Han (1992), Stickel (1996), Barron and Stuerke (1998).

To ensure that prior-period financial data is available, I compute forecast dispersion on the last day of six months before firm fiscal-year-end. For example, for a firm with a fiscal-year-end of December 31st, 2009, forecast dispersion is computed on June 30th, 2009. The choice of mid-year, admittedly arbitrary, provides comparability across firms and years. Keeping forecast horizon constant for all firms is important because forecast dispersion also depends on forecast horizon. Elton et al. (1984) show evidence that forecast dispersion, computed as the standard deviation of forecasts, declines during the fiscal year and that most of the decrease occurs in the first months of the year. Finally, holding forecast horizon constant for all firms enables us to include non-December fiscal-year-end firms that comprise 37% of the sample. For December fiscal-year-end firms, Figure 2 illustrates the timeline of

[25] 25 zero-average-forecast observations are excluded from the sample representing 0.04% of all observations. There are 4,791 observations with negative average forecast that comprises about 9% of all observations. One explanation of so few negative average forecasts is the well-known upward bias in the distribution of earning forecasts; see Das, Levine, and Sivaramakrishnan (1998), Eames and Glover (2003), Stickel (1995), McNichols and O'Brien (1997).

computation of forecast dispersion. In the sample, 97% (99%) of firms report their actual earnings during the first three (six) months of the next fiscal year.

3.2.2 Other data sources

Data on stock returns, prices, and shares outstanding are from the CRSP monthly stock file. I select ordinary common shares (i.e., share codes 10 and 11) traded on NYSE, AMEX, or NASDAQ, and remove financial institutions. To minimize the problem of bid-ask spread, I follow Jegadeesh and Titman (2001) and exclude firms with a stock price less than USD 5 a share on the day when forecast dispersion is computed. To mitigate the problem of extreme values, all variables are winsorized at 0.5% and 99.5% levels. I exclude stocks followed by less than two analysts and eliminate observations with negative book value and total assets. Results are however similar when analyst coverage is set to a minimum of three, four, or five analysts.

Accounting and credit rating data is from the Compustat. Equity issuance data is from Thomson Financial Securities Data Corporation (SDC) database. SDC lists IPO and SEO issuance advisors retained on a deal, and I/B/E/S provides the name of the broker issuing a forecast. I match I/B/E/S brokers and SDC advisors using their corporate names. In most instances, the names in the two databases are qualitatively the same and can be easily matched.[26] The sample period spans from January 1983 to December 2007. I choose 1983 as a starting year because the Unadjusted Detail History file is not available prior to 1983.

3.2.3 Sample characteristics

Table 3.1 presents descriptive statistics of forecast dispersion. The sample consists of 7,920 different firms with 52,165 observations of forecast dispersion data. In 1983, 1,380

[26] I use SAS "SPEDIS" function with a maximum distance equal to 30 between I/B/E/S broker name and SDC advisor names. This procedure matches about 90% of observations in the I/B/E/S Unadjusted Detail History file.

Table 3.1: Sample characteristics

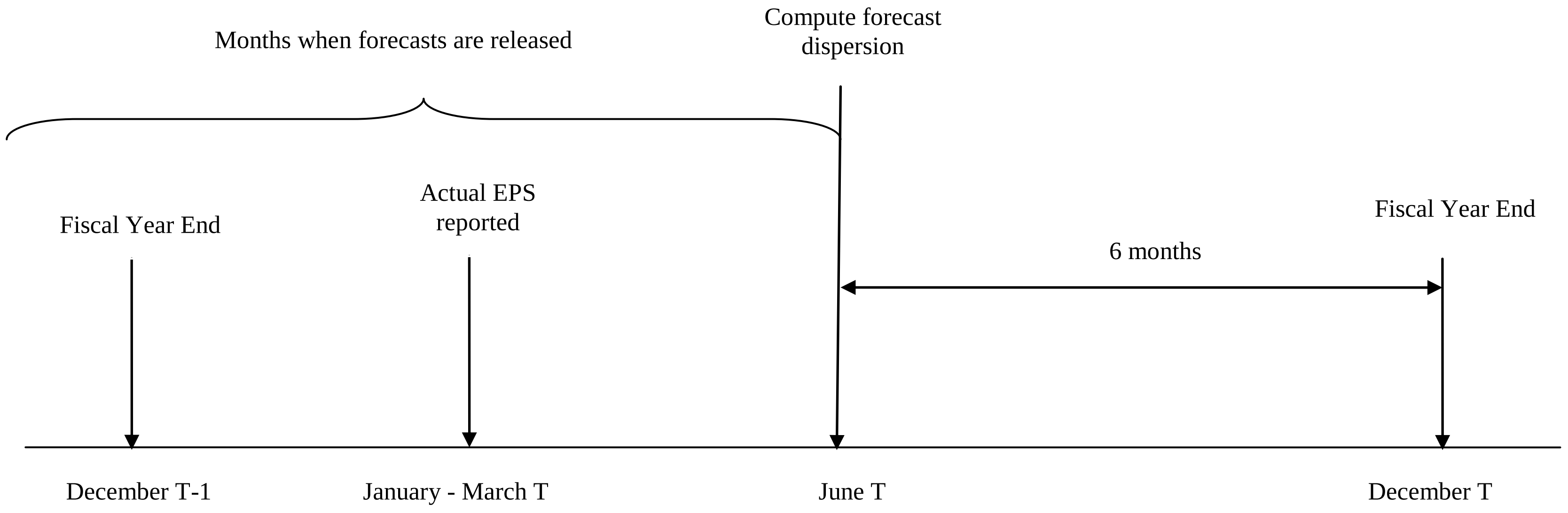
The sample consists of CRSP ordinary common shares traded on the NYSE, AMEX, and NASDAQ after removing financial institutions. Firms must also have a one fiscal year I/B/E/S earnings estimate, to be covered by two or more analysts, and have a price greater than five dollars. *FDisp* is the forecast dispersion computed as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the average forecast, excluding stocks with average forecast of zero. Market value (of equity) is the stock price times shares outstanding at the end of month when forecast dispersion is computed. The period considered is January 1983 through December 2007.

Descriptive statistics								
	Number of firms	Average number of forecasts	Average market value (in millions)	*FDisp*				
Year				Average	Std	25%	Median	75%
1983	1,380	11.91	913	0.35	0.80	0.06	0.13	0.28
1984	1,559	11.94	768	0.25	0.62	0.05	0.10	0.23
1985	1,653	11.29	889	0.30	0.76	0.05	0.11	0.25
1986	1,452	11.61	1,236	0.38	0.82	0.06	0.15	0.34
1987	1,538	11.21	1,401	0.35	0.83	0.06	0.14	0.31
1988	1,682	10.39	1,171	0.23	0.50	0.04	0.09	0.22
1989	1,728	10.35	1,279	0.22	0.60	0.04	0.08	0.18
1990	1,663	10.31	1,419	0.22	0.58	0.04	0.08	0.20
1991	1,771	9.95	1,485	0.30	0.74	0.04	0.10	0.25
1992	1,907	9.04	1,570	0.26	0.73	0.04	0.08	0.21
1993	2,139	8.54	1,560	0.21	0.57	0.03	0.06	0.18
1994	2,395	8.18	1,445	0.19	0.56	0.03	0.06	0.16
1995	2,524	7.92	1,687	0.17	0.56	0.02	0.05	0.13
1996	2,895	7.28	1,827	0.21	0.61	0.02	0.06	0.17
1997	3,064	7.18	2,079	0.17	0.52	0.02	0.05	0.13
1998	3,004	7.12	2,551	0.17	0.50	0.02	0.04	0.13
1999	2,752	7.80	3,126	0.18	0.55	0.02	0.04	0.13
2000	2,642	7.63	3,710	0.16	0.50	0.02	0.04	0.12
2001	2,136	8.12	3,780	0.19	0.53	0.02	0.06	0.16
2002	1,830	7.66	3,670	0.19	0.61	0.02	0.04	0.13
2003	1,876	8.11	3,642	0.18	0.61	0.02	0.04	0.12
2004	2,088	8.23	3,966	0.16	0.57	0.02	0.04	0.11
2005	2,125	8.17	4,262	0.15	0.51	0.02	0.04	0.10
2006	2,187	7.80	4,390	0.16	0.46	0.02	0.05	0.12
2007	2,200	8.12	4,870	0.17	0.55	0.02	0.05	0.12
Average	2,088	9.03	2,348	0.22	0.61	0.03	0.07	0.18

firms are eligible. There is a clear deepening in eligible stocks up to 3,064 firms in 1997 followed by a decrease. At the end of 2007, 2,200 firms are eligible. The number of analysts covering the firms varies from 2 analysts, the minimum to impose in order to compute the dispersion, to a maximum of 56 analysts, with an average (median) of 9 (6) analysts. Consistent with previous studies, forecast dispersion is highly skewed - its average is almost three times larger than the median; see Gu and Wu (2003). Because of analyst coverage requirements, my sample consists of relatively large firms with average market value of USD 2.3 billion. The sample consists of 48% of firms traded on NYSE and NASDAQ each, and the remaining 4% firms are traded on AMEX.

Figure 2: Timeline of computing forecast dispersion

The figure shows the timeline of forecast dispersion computation for December fiscal-year-end firms for year T. For all firms forecast horizon is 6 month prior to fiscal-year-end.



3.3 Is Forecast dispersion related to firm risk or economic uncertainty?

3.3.1 Firm risk

A number of studies suggest that one of the important determinants of forecast dispersion is firm risk; see Friend, Westerfield, and Granito (1978), Cragg and Malkiel (1982), Malkiel (1982), Farrelly and Reichenstein (1984), Carvell and Strebel (1984), and Harris (1986), among others. More precisely, these authors find a positive relationship between forecast dispersion and subsequent returns, thus conclude that forecast dispersion proxies for firm risk. Among others, Diether et al. (2002) and Irani and Karamanou (2003) show that forecast dispersion is also positively correlated with the standard deviation of returns and beta, two frequently used proxies of firm risk. Supportive theoretical work on the positive relation between forecast dispersion and return volatility are Shalen (1993) and Wang (1998). Using foreign exchange survey data, Frankel and Froot (1990) also find positive relation between forecast dispersion and return volatility.

I differentiate between systematic risk and idiosyncratic risk. As a proxy for systematic risk, I employ the widely used factors: size (SMB), book-to-market (HML) and winner minus loser factors (WML). To be precise, I estimate firm's systematic risk in the following model

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + w_i WML_t + \varepsilon_{i,t},$$

where $\varepsilon_{i,t}$ is the error term, and the subscripts *i* and *t* represent respectively firm and time when forecast dispersion is measured. All factors are computed over previous -1 to -52 weekly returns relative to the week when forecast dispersion is computed. I further employ firm's idiosyncratic risk - the residual variance $\varepsilon_{i,t}$ and denote it by $RV_{i,t}$. I use weekly returns because small stocks are not traded every day but they normally trade at least once a week. Weekly returns are thus less affected by "thin trades"; see Scholes and Williams (1977), Dimson and Marsh (1983), Maynes and Rumsey (1993), and Butler and Osborne (1998).

3.3.2 Economic uncertainty

It is reasonable to suppose that situations in which future economic state is difficult to forecast will, in general, be situations in which firm-specific earnings are also difficult to forecast, thus forecasts will differ more. This is because the state of economy is likely to influence firm earnings, at least on aggregate level. If analysts regard firm-specific earnings forecast as consisting of a systematic and idiosyncratic part of the realization, then they should also pay attention on the systematic component, i.e., the state of the economy. Hope and Kang (2005) show that economic uncertainty decreases forecast accuracy that itself affects forecast dispersion; see Elton et al. (1984) and Kwon (2002). To test this hypothesis, I include economic uncertainty in the model, proxied by the uncertainty index (*Unc*) of Anderson et al. (2009). Using the Survey of Professional Forecasters, Anderson et al. (2009) measure economic uncertainty as the dispersion of aggregate corporate profits (rather than earning forecasts of individual firms).[27]

Because the uncertainty index is available quarterly, I construct maximally correlated weekly portfolios also known as factor-mimicking portfolios for the uncertainty index. Specifically, the factor-mimicking portfolio is obtained by running the following time series regression

$$f_t = a + b^{'} B_t + \eta_t ,$$

[27] I sincerely thank Evan Anderson for kindly providing the uncertainty index. The spanning portfolios are from Kenneth French website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

where f_t is the realized value of uncertainty index and B_t denotes the time *t* excess returns (zero cost) on a vector of base assets. Following Lamont (2001) and Vassalou (2003), the base assets include the six value-weighted Fama–French portfolios constructed from the intersections of two market value and three book-to-market portfolios. The factor-mimicking portfolio is the estimated value of $\hat{a} + \hat{b}' B_t$. Following Anderson et al. (2009), to estimate the sensitivity of stock returns to uncertainty index, I employ the following model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + u_i R_{Unc,t} + \varepsilon_{i,t},$$

where $\varepsilon_{i,t}$ is the error term, the subscripts *i* and *t* represent respectively firm and time when forecast dispersion is measured, and $R_{Unc,t}$ is the factor-mimicking value of uncertainty index. The model is estimated over the previous -1 to -52 weeks relative to the week when forecast dispersion is computed.

3.3.3 Results

To examine the relationship between firm risk and economic uncertainty with forecast dispersion, I estimate the following models:

Fama-French 3 + Momentum factors (FF3+MOM)

$$FDisp_{i,t} = \alpha_1 \beta_{i,t} + \alpha_2 s_{i,t} + \alpha_3 h_{i,t} + \alpha_4 w_{i,t} + \alpha_5 \mathrm{RV}_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t},$$

Fama-French 3 factors (FF3)

$$FDisp_{i,t} = \alpha_1 \beta_{i,t} + \alpha_2 s_{i,t} + \alpha_3 h_{i,t} + \alpha_5 \mathrm{RV}_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t},$$

CAPM

$$FDisp_{i,t} = \alpha_1 \beta_{i,t} + \alpha_5 \mathrm{RV}_{i,t} + \gamma_i + \delta_t \varepsilon_{i,t},$$

CAPM+UNC

$$FDisp_{i,t} = \alpha_1 \beta_{i,t} + \alpha_6 u_{i,t} + \alpha_5 \mathrm{RV}_{i,t} + \gamma_i + \delta_t \varepsilon_{i,t},$$

Table 3.2: Dispersion, risk, and uncertainty

The dependent variable is forecast dispersion (*FDisp*), defined as the ratio of standard deviation of analyst current fiscal-year annual earnings per share forecasts to the absolute value of the average forecast. Stocks with average forecast of zero are excluded. The period considered is January 1983 through December 2007. The t-statistics are based on the standard errors clustered by firm and time (*5%, ** 1%).

	FF3 + MOM	FF3	CAPM	CAPM + UNC
β	-0.0242**	-0.0194**	-0.0327**	-0.0249**
	[-3.80]	[-2.63]	[-3.96]	[-2.96]
h	0.00249	0.00428		
	[0.59]	[0.92]		
s	0.0115**	0.0109**		
	[3.60]	[2.97]		
w	-0.0254**			
	[-4.74]			
u				-0.00103
				[-1.06]
RV	0.138**	0.140**	0.126**	0.133**
	[4.77]	[4.80]	[4.78]	[4.72]
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	52,157	52,157	52,157	52,157
Adjusted R-square	18.6	18.4	18.4	18.4

where $\varepsilon_{i,t}$ is the error term, and the subscripts *i* and *t* represent respectively firm and time when forecast dispersion is measured. To control for time trend and firm characteristics that can affect forecast dispersion, I add time δ_t and firm fixed effects γ_i.[28] Results, presented in Table 3.2, show that forecast dispersion is strongly positively related with firm's idiosyncratic risk in all specifications.[29] A one-unit increase in residual variance increases forecast dispersion by 13.8%, in the specification of FF3+MOM. In term of magnitude, this translates

[28] Results are qualitatively similar when using industry dummies instead of firm dummies. For robustness check, I employed both CRSP four-digit industry SIC code and Fama-French 12 industry classifications as industry dummies, obtained from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[29] Results are similar when estimating the models for firms with credit rating data and for firms without credit rating.

into 63% (=13.8/22) increase in forecast dispersion. Note that the average forecast dispersion is 22%. Interestingly, firm's beta is negatively correlated with forecast dispersion. This result is consistent with Diether et al. (2002, p.2130) who show that, after controlling for firm's idiosyncratic risk, firm's beta is negatively related with forecast dispersion. My result also supports Elton et al. (1984) finding that economic uncertainty plays little role in analysts' forecast error. Decomposing forecast error in economic, industry, and firm components, they find that only 3% of forecast error is attributable to misestimating economic performance and that that the biggest portion of forecast error comes from misestimating industry and firm performances. Not reported here, the results of Lagrange multiplier (LM) test show that while *FF3+MOM* significantly improves the model fit both over *FF3* and *CAPM*, *CAPM+UNC* does not results in a better fit than *CAPM*. We are in a position to confirm that forecast dispersion does not embed a classic measure of firm systematic risk (since it is negatively related to market beta and winner/loser factor) or economic uncertainty, but rather it proxies firm's idiosyncratic risk.

3.4 Are forecast dispersion and idiosyncratic risk anomalies related?

The evidence in Section 3.3 suggests that firms with high idiosyncratic risk have high dispersion. Here, I examine whether the dispersion-return relation becomes insignificant after controlling for idiosyncratic risk proxied by firm's residual variance, *RV*. Because idiosyncratic risk is negatively related associated with the cross-section of future stock returns; see Ang et al. (2006), and forecast dispersion is highly correlated with idiosyncratic risk, it is important to investigate whether idiosyncratic risk is driving the forecast dispersion effect.

Table 3.3: Dispersion and idiosyncratic risk anomalies

Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of idiosyncratic risk (proxied by the RV) of the previous month end. Stocks in each size group are then equally sorted into five additional groups based on the forecast dispersion of the previous month. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The table reports average monthly equal-weighted returns. In brackets are the t-statistics, adjusted for one lag autocorrelation, (*5%, **1%). The period considered is January 1984 through December 2007.

Panel A: First by RV then by dispersion

Dispersion quintiles	RV quintiles					RV1- RV5	t(RV1- RV5)
	Small				Large		
	RV1	RV2	RV3	RV4	RV5		
D1	1.31	1.41	1.39	1.21	0.83	0.48	[1.06]
D2	1.22	1.30	1.40	1.05	0.60	0.62	[1.31]
D3	1.28	1.32	1.16	1.02	0.38	0.89	[1.84]
D4	1.22	1.24	1.15	1.17	0.44	0.77	[1.68]
D5	1.31	1.16	1.06	0.69	0.22	1.09	[2.45]*
D1-D5	0.00	0.24	0.33	0.53	0.61		
t(D1-D5)	[0.02]	[1.80]	[1.99]*	[2.98]**	[3.11]**		

Panel B: First by dispersion then RV

Dispersion quintiles	Dispersion quintiles					D1-D5	t(D1- D5)
	Small				Large		
	D1	D2	D3	D4	D5		
RV1	1.27	1.19	1.25	1.18	1.21	0.06	[0.36]
RV2	1.38	1.33	1.28	1.23	1.03	0.35	[1.81]
RV3	1.38	1.35	1.23	1.12	0.86	0.52	[1.98]*
RV4	1.42	1.30	1.05	0.97	0.61	0.81	[2.79]**
RV5	1.01	0.82	0.52	0.37	0.12	0.89	[3.41]**
RV1-RV5	0.26	0.37	0.73	0.81	1.09		
t(RV1-RV5)	[0.67]	[0.85]	[1.55]	[1.75]*	[2.48]**		

I perform two-way sorting on *RV* and *FDisp*. Each month, stocks are equally assigned into quintiles based on the *RV* of the previous month. Stocks with the lowest idiosyncratic risk are placed into quintile *RV1*, and those with the highest idiosyncratic risk are in quintile *RV5*. Stocks in each size quintile are further ranked into five dispersion quintiles based on the *FDisp* of the previous month. Stocks are held for one month and the monthly portfolio return is the equal-weighted returns of all the stocks in a portfolio. Table 3.3 presents supporting evidence that idiosyncratic risk is not driving the forecast dispersion effect.[30] While the return

[30] As shown in Panel B, results are qualitatively similar when firms are first ranked based on their *FDisp* and then ranked based on *RV*. Results are also qualitatively similar for subsamples of rated and non-rated firms.

differential between the low- and high-dispersion stocks is positive and significant for the highest *RV* stocks, it becomes insignificant for stocks in the two smallest *RV* quintiles. Similar to results of Table 2.3, when stocks are first sorted by market capitalization and then by dispersion, D1-D5 strategy delivers statistically significant returns for three RV groups - RV3, RV4, and RV5, both in Panel A and B. In particular, the D1-D5 strategy for the largest quintile *RV5* earns 0.61 % monthly returns on average (7.32% annualized) that is statistically significant at 1% level. Thus, it does not appear that we are simply picking up a residual variance effect, since the two-way sorts still produce a strong negative relation between average returns and dispersion for the highest three *RV* quintiles. In sum, although *RV* significantly correlates with forecast dispersion (as shown in Section 3.3), the ability of forecast dispersion to predict future returns in not attributable to the predictive power of residual variance.

3.5 Explanatory variables of forecast dispersion

Here I consider a number of variables, in addition to residual variance, that prior literature shows to be associated with forecast dispersion. The precise definitions of the explanatory variables along with discussion of their influence on forecast dispersion follow. Appendix C presents detailed information on how each variable is computed.

3.5.1 Information

3.5.1.1 Information environment

Firm size is a proxy for information environment; see Bhushan (1989), O'Brien and Bhushan (1990). Large firms attract more analysts following because the cost of acquiring information is low and because of interest of more potential transactions business. Large firms also release more public information than smaller ones thus enriching their information environment. I proxy firm size by the natural logarithm of market value of equity (*LogMV*), where market value is the share price times the number of shares outstanding.

Firm's real activity is also associated with forecasting difficulty. Growth firms are difficult to analyze and forecast because of the uncertainty surrounding new projects; see Schultz (2010). Growth opportunities are also likely to be associated with information asymmetries between managers and analysts with regards to firm's future investment opportunities; see Myers (1977) and Myers and Majluf (1984). This is because managers of firms with high growth opportunities have better knowledge on their investment opportunities than analysts have. The macro-economic uncertainty in conjunction with information asymmetries should also magnify forecast dispersion. To control for the impact of growth opportunities I include the book-to-market ratio (*BM*) in the model that is also routinely used as another measure of firm risk; see e.g., Fama and French (1992), Bulkley, Harris, and Herrerias (2004).

3.5.1.2 Information flow

Another determinant that is considered to influence forecast dispersion is analysts' differing information sets. Earnings forecasts reported at different dates convey differential information impounded in them. Prior research shows that forecast accuracy is associated with forecast age because forecasts issued at different dates reflect differential information; see Clement (1999), O'Brien (1988), Bonner, Walther, and Young (2003). Therefore, it may well be that forecast dispersion is also attributable to differences in forecast ages, therefore to differences in the information impounded in them. Thus, as a proxy for analysts' differing information sets, I employ the standard deviation of forecast ages from non-conflicted analysts (*FAgeStd*). If the number of non-conflicted analysts is below two, then *FAgeStd* is set to zero. Age is the number of calendar days between analyst's last forecast for a firm and the day when forecast dispersion is computed (the last day of six months before firm's fiscal-year-end). Although several studies use trading days such as O'Brien (1988), O'Brien (1990), Das (1998), and Sinha, Brown, and Das (1997), I use calendar days such as Clement (1999), Das and Saudagaran (1998), Brown (2001), Hodgdon, Tondkar, Harless, and Adhikari (2008), among others. For example, if an analyst released his last forecast on May 15th, 2009 for a firm with a fiscal-year-end of December 31st, 2009 (for which forecast dispersion is computed on June 30th, 2009), the forecast age is 46 days.

3.5.1.3 Information asymmetries

Evidence suggests that forecast dispersion also depends on information asymmetries. For example, Lang and Lundholm (1996) find that more disclosure decreases forecast dispersion, by increasing the precision of analysts' shared information. Using conference call data, Bowen et al. (2002) show that information availability is negatively correlated with forecast dispersion. I employ two proxies for information asymmetries – the relative bid-ask spread (*BidAskSpr*) and the *Info/Noise* measure of Burlacu, Fontaine, Jimenez-Garcès, and Seasholes (2008). The bid-ask spread is the absolute value of the difference between the bid and ask prices, scaled by the middle price. When bid and ask prices are missing, I set the spread to zero and estimate the *BidAskSpr* by averaging the daily bid-ask spreads for a given firm during the previous 50 trading days relative to the day when forecast dispersion is computed. Using Admati (1985)'s noisy rational expectations equilibrium framework, from current prices Burlacu et al. (2008) construct a measure of information precision. Investors demand high return for a stock with low private information about its future dividends. Burlacu et al. (2008) define their measure as $\log(R^2/(1-R^2))$, where R^2 is from regressing stock return on its own price and the prices of other stocks in the same industry. When R^2 is a low, stock prices are relatively uninformative and the amount of private information is high. Conversely, when R^2 is high, stock prices reveal more public than private information. It is likely to be less difficult and/or less costly to gather information on firms with rich information environment than on opaque firms.

3.5.2 Change in rating

The change in credit rating reflects credit agency's (e.g., Standard & Poor's) assessment on firm's credit quality. I proxy change in firm risk by the change in Standard & Poor's long-term issuer credit rating during the past twelve months (Δ*Rat*). Negative Δ*Rat* indicates deterioration in credit rating. For firms not covered by credit analysts (i.e., with no credit rating), Δ*Rat* is replaced by the change of Altman (1968)'s Z-Score (Δ*ZScr*). The Z-Score is a widely used measure of default probability computed as a linear combination of five financial ratios. Previous literature shows that the Z-Score is highly accurate in predicting bankruptcy within two years. I expect a negative association between Δ*Rat* *(*Δ*ZScr)* and *FDisp* meaning that credit rating deterioration increases forecast dispersion because of financial analysts' non-synchronous response to bad news about a firm.

3.5.3 Forecasting difficulty

A number of studies present positive relationship between complexity of forecasting task and analysts' forecasts error; see Clement (1999), Lang and Lundholm (1996), Duru and Reeb (2002), among others. Elton et al. (1984) document persistency in forecasting difficulty, i.e., if analysts made large errors in the previous year, they are likely to make large errors in the current year too. Comiskey, Mulford, and Porter (1986) support forecast error as an effective measure of forecasting difficulty. I follow Comiskey et al. (1986) and proxy the forecasting difficulty by the relative forecast error (*RelFE*) of the previous year. It is the absolute difference between average (consensus) forecast and actual earnings divided by the actual earnings. Zero actual earnings observations are excluded from the sample.[31] Actual earnings are from I/B/E/S Actual Unadjusted file. For example, forecast error for a firm with December 2000 fiscal-year-end is the absolute value of the difference between the consensus earnings forecast at June 2000 and the actual earnings for December 2000 divided by the actual earnings for December 2000. In other words, analysts' prior aggregate forecast error measures forecasting difficulty.

3.5.4 Herding

Analysts' herding behavior is another influential factor driving forecast dispersion. Welch (2000) and Jegadeesh, Kim, Krische, and Lee (2004) show that analysts herd more when recent returns are positive. In other words, when recent stock returns are positive and the consensus is optimistic, analysts herd toward the consensus. Using the classification method adopted in the analyst herding literature, I classify a forecast as bold if it is above both the prevailing consensus and the most recent forecast issued by the same analyst, or else below both; see Clement (1999), Gleason and Lee (2003), Kumar (2010). All other forecasts are classified as herding forecasts, and the proportion of herding forecasts proxies for analyst herding (*Herd*).

3.5.5 Conflicts of interest

The choice of how frequently and when analysts revise their forecast may not only depend on their forecasting ability and/or new information but also on their conflicts of interest with a firm they follow. Because of the conflicts of interest, conflicted analysts should be slow in incorporating bad news in their forecast revisions while non-conflicted analysts are

[31] There are only 87 zero-actual observations that accounts for 0.21% of all observations.

not; see Lin and McNichols (1998), Ljungqvist, Marston, and Wilhelm (2006). This asymmetric behavior among analysts creates high forecast dispersion, especially for firms with bad news that are followed by both conflicted and non-conflicted analysts; see Erturk (2006), Hwang and Li (2008), Scherbina (2008). To proxy analyst conflicts of interest, I compute the proportion *p* of conflicted (non-conflicted) analysts and calculate the information entropy as $ConfInt_{i,t} = p_{i,t}Log\left(p_i\right) + \left(1 - p_{i,t}\right)Log\left(1 - p_{i,t}\right)$. Everything else equal, this functional attains its maximum when conflicted and non-conflicted analysts are in equal proportion. This is exactly when analyst conflicts of interest has its highest impact on forecast dispersion. Analysts are marked as conflicted if they work for an investment bank that led or co-led IPOs or SEOs before the current earnings forecasts.

I further differentiate between loser and winner firms, and compute stock past performance as the compounded stock returns over the past -1 to -12 months (*PastRet*). If *PastRet* is negative then the firm is classified as loser firm, otherwise, it is classified as winner. The hypothesis is that poor past returns lead analysts to diverge more in their forecasts, thus increasing forecast dispersion. Indeed, there is evidence that forecast dispersion differ for profit vs. loss firms; see Das (1998), Han and Manry (2000), Brown (2001), Agrawal et al. (2006), Ciccone (2001), among others. Chan, Jegadeesh, and Lakonishok (1996) find that although some analysts downward their forecasts following poor stock price performance, on average analysts remain overly optimistic in their forecasts. They conjecture that "… analysts may remain optimistic and wait for additional confirmatory evidence of poor earnings before slowly modifying their estimates". Erturk (2006) and Hwang and Li (2008) contend that when analysts are slow in responding to bad news, coupled with analyst conflicts of interest, it results in more dispersed forecasts.

3.6 Empirical model and results

3.6.1 Descriptive statistics

Table 3.4 presents descriptive statistics for forecast dispersion and its determinants. In my sample Standard & Poor's rated firms account about 30% of the sample firms which is consistent with Avramov et al. (2009) statistics. For both rated and non-rated firms, average forecast dispersion is more than three times larger than the median. Consistent with the general finding in literature it shows that forecast dispersion is highly skewed; see also Johnson (2004), Verardo (2009), Gu and Wu (2003), Athanassakos and Kalimipalli (2003), among others. Rated firms have an average of USD 5.9 billion market value that is about 2.5 times larger than the average firm. The average (median) difference between market value of equity for rated versus non-rated firms is approximately USD 4.9 (USD 1.4) billion. Note that ΔRat and $\Delta ZScr$ have negative average values indicating that my sample firms have deteriorating credit conditions. Not reported here, the average value of *ZScr* is 7.7 and *Rat* of 14 that corresponds to BBB Standard & Poor's rating. The percentage number of forecasts issued by investment banks is about 85% (87%) for rated (non-rated) firms. *ConfInt* equals 0.34 (0.26) for (non-) rated firms.[32] Similar statistics of conflicts of interest is also reported in Ertimur, Sunder, and Sunder (2007). Note that residual variance for a rated firm is almost half of that of non-rated firms – indicating that credit analyst following significantly decreases information asymmetries about a firm thus reducing firm's idiosyncratic risk. I observe similar statistics for the other explanatory variables such as *BM*, *Herd*, *RelFE* between rated and non-rated firms.

Table 3.5 report Pearson and Spearman correlations between forecast dispersion and its explanatory variables. I observe strong positive correlation between *FDisp* and *RV*. There

[32] *ConfInt* attains its maximum at 0.7 when the percentage number of forecasts issued by investment banks is 50%.

Table 3.4: Descriptive statistics of explanatory variables

Panel A (B) reports the descriptive statistics on variables in the regression model for (non-) rated firms. Appendix C presents detailed information on how each variable is computed.

Panel A: Descriptive statistics for rated firms						
Variables	Obs	Avg	Std	25%	50%	75%
FDisp	13,117	0.20	0.60	0.02	0.06	0.16
RV	13,117	0.23	0.28	0.08	0.14	0.27
Log(MV)	13,117	7.53	1.51	6.51	7.49	8.49
MV (in millions)	13,117	5,927	12,398	672	1,781	4,848
BM	13,117	0.62	0.43	0.31	0.52	0.82
FAgeStd	13,117	0.12	0.19	0.00	0.00	0.19
BidAskSpr	13,117	0.01	0.01	0.00	0.00	0.01
Info/Noise	13,117	-1.52	0.56	-1.87	-1.49	-1.14
ΔRat	13,117	-0.03	0.67	0.00	0.00	0.00
RelFE	13,117	0.57	1.93	0.04	0.12	0.38
Herd	13,117	0.29	0.26	0.06	0.25	0.46
ConfInt	13,117	0.34	0.24	0.00	0.39	0.54
%InvBank	13,117	0.85	0.14	0.77	0.86	1.00
Panel B: Descriptive statistics for non-rated firms						
Variables	Obs	Avg	Std	25%	50%	75%
FDisp	22,233	0.20	0.58	0.03	0.06	0.16
RV	22,233	0.41	0.43	0.15	0.28	0.51
Log(MV)	22,233	5.91	1.29	4.99	5.86	6.75
MV (in millions)	22,233	981	3,088	146	349	852
BM	22,233	0.54	0.40	0.26	0.44	0.71
FAgeStd	22,233	0.06	0.14	0.00	0.00	0.00
BidAskSpr	22,233	0.01	0.02	0.00	0.01	0.02
Info/Noise	22,233	-1.45	0.55	-1.78	-1.41	-1.08
ΔZScr	22,233	-0.64	6.43	-1.11	-0.05	0.67
RelFE	22,233	0.65	2.02	0.06	0.16	0.46
Herd	22,233	0.28	0.30	0.00	0.21	0.50
ConfInt	22,233	0.26	0.28	0.00	0.00	0.54
%InvBank	22,233	0.87	0.18	0.75	1.00	1.00

is also statistically significant positive correlation between *FDisp* and *RelFE* (a surrogate for forecasting difficulty or earnings predictability), meaning that when forecasting task complexity is high, analysts' forecast differ more. Consistent with the prior findings in the literature, I also observe negative correlation between *FDisp* and *Herd*; see also Hwang and Li (2008), Erturk (2006), Scherbina (2008), and Lobo and Tung (2000). This suggests that

Table 3.5: Correlation of explanatory variables

Panel A (B) reports the correlations among the variables for (non-) rated sample. Pearson coefficients are above the diagonal line and Spearman coefficients are below the line. Appendix C presents detailed information on how each variable is computed.

Panel A: Correlation coefficients for rated firms

	FDisp	*RV*	*Log(MV)*	*BM*	*FAgeStd*	*BidAskSpr*	*Info/Noise*	*ΔRat*	*RelFE*	*Herd*	*ConfInt*
FDisp		0.29	-0.24	0.21	0.15	-0.06	0.04	-0.11	0.49	-0.06	0.18
RV	0.14		-0.36	-0.04	-0.25	0.31	0.10	-0.05	0.36	-0.05	-0.21
Log(MV)	-0.15	-0.26		-0.41	0.31	-0.21	-0.10	0.05	-0.28	0.11	0.12
BM	0.15	0.07	-0.38		0.01	0.01	0.04	-0.16	0.18	-0.09	0.05
FAgeStd	0.03	-0.18	0.18	0.02		-0.30	-0.01	-0.01	-0.04	0.10	0.70
BidAskSpr	0.05	0.24	-0.34	0.14	-0.17		0.03	-0.01	0.03	-0.06	-0.30
Info/Noise	0.02	0.07	-0.10	0.02	-0.01	0.05		-0.01	0.06	0.03	0.00
ΔRat	-0.11	-0.07	0.04	-0.17	-0.01	-0.02	0.00		-0.14	0.01	-0.03
RelFE	0.18	0.15	-0.17	0.11	-0.01	0.07	0.02	-0.11		0.00	0.04
Herd	-0.05	-0.01	0.09	-0.10	0.04	-0.06	0.02	0.01	0.00		0.05
ConfInt	0.04	-0.20	0.17	0.00	0.51	-0.17	0.00	-0.03	0.01	0.00	

Panel B: Correlation coefficients for non-rated firms

	FDisp	*RV*	*Log(MV)*	*BM*	*FAgeStd*	*BidAskSpr*	*Info/Noise*	*ΔZScr*	*RelFE*	*Herd*	*ConfInt*
FDisp		0.18	-0.20	0.20	0.16	-0.01	-0.02	-0.12	0.42	-0.08	0.17
RV	0.12		-0.28	-0.21	-0.31	0.32	0.06	-0.11	0.26	-0.02	-0.29
Log(MV)	-0.11	-0.14		-0.37	0.26	-0.50	-0.09	0.13	-0.25	0.14	0.15
BM	0.13	-0.14	-0.32		0.13	0.03	0.02	-0.15	0.17	-0.11	0.15
FAgeStd	0.05	-0.19	0.20	0.13		-0.36	-0.05	0.02	0.00	0.07	0.65
BidAskSpr	0.04	0.11	-0.55	0.14	-0.20		0.07	-0.10	0.06	-0.09	-0.30
Info/Noise	-0.02	0.02	-0.09	0.01	-0.04	0.08		0.01	0.01	0.03	-0.03
ΔZScr	-0.04	-0.14	0.07	-0.04	0.01	-0.05	0.02		-0.14	0.00	0.03
RelFE	0.16	0.12	-0.14	0.13	-0.01	0.09	0.01	-0.05		0.00	0.04
Herd	-0.06	0.02	0.10	-0.11	0.01	-0.07	0.04	0.01	0.01		0.03
ConfInt	0.04	-0.22	0.15	0.14	0.50	-0.22	-0.03	0.04	0.00	-0.02	

when analysts herd less in their forecasts, it creates larger forecast dispersion. As predicted, forecast dispersion is also related to information flow/arrival. In particular, *FAgeStd* is positively correlated with *FDisp*, suggesting that forecast dispersion is high when large firms have low forecast dispersion. Contrary to the prediction, I observe a positive correlation between *FDisp* and *BM*, suggesting that growth firms have larger forecast dispersion than value firms. This result is however consistent with Doukas et al. (2004).

3.6.2 Empirical model

The empirical method to examine the determinants of forecast dispersion is by regressing forecast dispersion on its determinants discussed in Section 3.5. I split the sample into two subsamples – firms with credit rating data and firms without credit rating. For rated firms the specification of the baseline model is as follows:

$$\begin{aligned} FDisp_{i,t} = {} & \beta_1 ResidVar_{i,t} + \beta_2 Log(MV)_{i,t} + \beta_3 BM_{i,t} + \beta_4 FAgeStd_{i,t} + \beta_5 Info/Noise_{i,t} \\ & + \beta_6 \Delta Rat_{i,t} + \beta_7 RelFE_{i,t} + \beta_8 Herd_{i,t} + \beta_9 ConfInt_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $\varepsilon_{i,t}$ is the error term, and the subscripts *i* and *t* represent respectively firm and time when forecast dispersion is measured. To control for time trend and firm characteristics that can affect forecast dispersion, I add time δ_t and firm fixed effects γ_i.[33] For non-rated firms, Δ*Rat* is replaced with the yearly change in Altman's Z-Score (Δ*ZScr*). Because one lag is necessary for computing *RelFE*, the period considered for the regression analysis of non-rated firms is January 1984 through December 2007. For the specification including Δ*Rat*, the sample starts in January 1986 because of data availability.

When dealing with panel data, there can be strong residual correlation within firms over time (time-series dependence) as well as strong residual correlation across firms for a given period (cross-sectional dependence). These time-series and cross-sectional residual correlations create a bias in ordinary least squares (OLS). To account for these correlations, t-statistics are calculated with firm- and time-clustered standard errors, using the procedure in Cameron, Gelbach, and Miller (2006), Petersen (2009), and Thompson (2009).

[33] Results are qualitatively similar when using industry dummies instead of firm dummies. I tried CRSP four-digit industry SIC code and Fama-French 12 industry classifications, obtained from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

3.6.3 Results

Panel A of Table 3.6 presents regression results from estimating equation (1). Column (1) reports results for the sample of firms rated by Standard & Poor's, column (2) is for firms without rating, and column (3) reports results for the full sample. As predicted, the coefficient of *RV* is significantly positive in all specifications. This implies that high firm idiosyncratic risk leads analysts to issue more dispersed forecast.[34] A 1% increase in residual variance increases forecast dispersion by 0.15% for rated firms and 0.14% for the full sample. As Panel B shows, the results are robust to the exclusion of *RV* from equation (1). The coefficient of *Log(MV)* is also highly significant in all specifications. For example, for rated firms an increase in firm's market value by 2.7 times decreases forecast dispersion by 6.48% - that is 30% of the average.

Contrary to the prediction, I obtain statistically significant positive coefficient for the BM ratio. This finding suggests that value firms have higher forecast dispersion than growth firms. To provide context, the average BM ratio is equal to 0.62 for rated firms, and 0.54 for non-rated firms. Thus, keeping the book value constant, for rated firms a decrease in firm's market value by 2.6 (=1.62/0.62) times increases the BM ratio by one unit. This in turn increases forecast dispersion by about 0.17 that is 77% of average forecast dispersion. Other researchers have shown such result; see Ciccone (2001) and Doukas et al. (2004). Because value firms often earn high returns, Doukas et al. (2004) conclude that "…value investment strategies yield higher returns because value stocks are riskier, in the sense that investor disagreement about their future growth in earnings is greater than it is about growth stocks".

[34] Results not reported here remain unchanged when residual variance is replaced by total variance.

Table 3.6: Explaining forecast dispersion

The dependent variable is forecast dispersion (*FDisp*), defined as the ratio of standard deviation of analyst current fiscal-year annual earnings per share forecasts to the absolute value of the average forecast. Stocks with average forecast of zero are excluded. See Appendix C for the definitions of explanatory variables. The period considered is January 1984 through December 2007. Numbers in brackets are the t-statistics, based on the standard errors clustered by firm and time (*5%, ** 1%).

	Panel A			Panel B		
Explanatory variable (predicted sign)	(1) Rated firms	(2) Non-rated firms	(3) All firms	(1) Rated firms	(2) Non-rated firms	(3) All firms
RV (+)	0.150*	0.120**	0.138**			
	[2.42]	[3.26]	[4.68]			
Log(MV) (-)	-0.0648**	-0.0298*	-0.0517**	-0.0708**	-0.0319*	-0.0551**
	[-2.87]	[-2.29]	[-5.31]	[-3.13]	[-2.52]	[-5.35]
BM (-)	0.170**	0.271**	0.215**	0.179**	0.269**	0.218**
	[2.65]	[6.03]	[5.71]	[2.79]	[6.01]	[5.77]
FAgeStd (+)	0.101*	0.106*	0.108**	0.0968*	0.100*	0.0996**
	[2.19]	[2.35]	[3.03]	[2.09]	[2.24]	[2.80]
Info/Noise (-)	-0.000942	-0.0161	-0.0136	0.00135	-0.0160	-0.0127
	[-0.09]	[-1.69]	[-1.92]	[0.13]	[-1.68]	[-1.81]
ΔRat/ΔZScr (-)	-0.0452**	-0.000745	-0.000805	-0.0487**	-0.000892	-0.000979
	[-3.58]	[-1.08]	[-1.15]	[-3.83]	[-1.22]	[-1.21]
RelFE (+)	0.0250**	0.0240**	0.0272**	0.0260**	0.0256**	0.0287**
	[4.00]	[6.07]	[8.54]	[4.14]	[6.45]	[8.74]
Herd (-)	-0.0658**	-0.0819**	-0.0735**	-0.0651**	-0.0814**	-0.0728**
	[-3.85]	[-5.66]	[-6.70]	[-3.78]	[-5.57]	[-6.46]
ConfInt(+)	-0.0152	0.00745	0.0101	-0.0151	0.00740	0.00803
	[-0.29]	[0.36]	[0.47]	[-0.28]	[0.35]	[0.36]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,117	22,233	35,350	13,117	22,233	35,350
Adjusted R-squared	26.2	28.7	25.1	26.0	28.5	24.8

Focusing on rated firms, I further show that firms with rating downgrades (i.e., negative Δ*Rat*) have high forecast dispersion. On average, one-notch decrease of credit rating quality (e.g., from BB+ to BB) increases forecast dispersion by about 4.5%. To better place the magnitude of this estimate, recall that the average forecast dispersion is 22%. Thus, one-notch decrease of credit rating increases forecast dispersion by about 20% (~ 4.4/22) of the average.

I do not observe any explanatory power for $\Delta ZScr$, the change in Altman's Z-Score. One potential explanation is that this score does not add any piece of new information while credit risk analysts incorporate information that goes beyond accounting information. Taken together, my findings provide additional support that firm idiosyncratic risk is an important component of forecast dispersion; see also Malkiel (1982), Williams (1977), Johnson (2004), Qu et al. (2004), Doukas et al. (2004), among others.

Interestingly, information asymmetry does not have significant impact on forecast dispersion. Note that when *Info/Noise* is used to proxy for the information asymmetry, it has differential impact on forecast dispersion for rated versus non-rated firms. For rated firms, the coefficient of Info/Noise is insignificant -0.09% and -1.61% for non-rated firms, significant at 10% level. This differential impact indicates that credit analysts affect the information environment of rated firms by issuing credit rating that reflects their assessment on firm's credit quality. Table 3.7 presents the results when *BidAskSpr* is used to proxy for the information asymmetry. I observe no discernible association between information asymmetries and forecast dispersion, and the coefficient of *BidAskSpr* is statistically insignificant in all specifications. In sum, it does not seem that information asymmetry surrounding a firm is a significant source of forecast dispersion.

Corroborating previous results in the literature, I find that analyst herding decreases forecast dispersion. Consistent with the view that forecasting difficulty leads to higher forecast dispersion, my results show that the difficulty of forecasting (proxied by *RelFE*) increases forecast dispersion.[35] *FAgeStd* is also highly positively significant implying that

[35] Cohen, Hann, and Ogneva (2007, p.272) state that "prior to the early 1990s, I/B/E/S did not always adjust actual earnings to exclude items not forecasted by analysts, thereby creating a mismatch between its actual (realized) and forecasted (expected) earnings". My findings, however, remain unchanged when the sample is restricted to data after 1993 when is likely to be free of the I/B/E/S adjustment error.

Table 3.7: Explaining forecast dispersion with bid-ask spread

The dependent variable is forecast dispersion (*FDisp*), defined as the ratio of standard deviation of analyst current fiscal-year annual earnings per share forecasts to the absolute value of the average forecast. Stocks with average forecast of zero are excluded. See Appendix C for the definitions of explanatory variables. The period considered is January 1984 through December 2007. Numbers in brackets are the t-statistics, based on the standard errors clustered by firm and time (*5%, ** 1%).

	Panel A			Panel B		
Explanatory variable (predicted sign)	(1) Rated firms	(2) Non-rated firms	(3) All firms	(1) Rated firms	(2) Non-rated firms	(3) All firms
RV (+)	0.151*	0.120**	0.137**			
	[2.42]	[3.26]	[4.67]			
Log(MV) (-)	-0.0663**	-0.0264	-0.0512**	-0.0718**	-0.0286*	-0.0546**
	[-3.04]	[-1.94]	[-5.10]	[-3.28]	[-2.14]	[-5.18]
BM (-)	0.172**	0.271**	0.216**	0.180**	0.268**	0.218**
	[2.63]	[6.06]	[5.71]	[2.75]	[6.05]	[5.78]
FAgeStd (+)	0.100*	0.107*	0.108**	0.0964*	0.101*	0.0998**
	[2.18]	[2.37]	[3.07]	[2.09]	[2.26]	[2.82]
BidAskSpr (+)	-0.608	0.497	0.0269	-0.376	0.477	0.0294
	[-0.43]	[0.84]	[0.06]	[-0.27]	[0.78]	[0.06]
ΔRat/ΔZScr (-)	-0.0452**	-0.000764	-0.000834	-0.0487**	-0.000911	-0.00101
	[-3.58]	[-1.11]	[-1.21]	[-3.83]	[-1.26]	[-1.26]
RelFE (+)	0.0250**	0.0239**	0.0272**	0.0260**	0.0255**	0.0287**
	[4.01]	[5.99]	[8.51]	[4.15]	[6.36]	[8.70]
Herd (-)	-0.0658**	-0.0833**	-0.0745**	-0.0650**	-0.0827**	-0.0738**
	[-3.84]	[-5.79]	[-6.79]	[-3.76]	[-5.69]	[-6.54]
ConfInt(+)	-0.0158	0.00746	0.00960	-0.0155	0.00739	0.00760
	[-0.30]	[0.37]	[0.44]	[-0.29]	[0.36]	[0.34]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,117	22,233	35,350	13,117	22,233	35,350
Adjusted R-squared	26.2	28.7	25.1	26.0	28.4	24.8

forecasts issued at different points in time are more dispersed, due to differences of information reflected in them. Mozes (2003) and Dunn and Nathan (1998) also show that when analysts revise their forecasts at different speed, forecast dispersion increases. The coefficient of *ConfInt* is insignificantly different from zero suggesting that the presence of investment banking analysts does not affect forecast dispersion. However, as shown in

Table3.8, analysts' conflict of interest is only present during periods of bad news, proxied by stock return's decreases. It is the asymmetry of analysts' behavior (conflicted vs. non-conflicted) with respect to bad news that contributes to the increase in forecast dispersion.

Results for loser vs. winner firms

Avramov et al. (2009) show that dispersion strategy concentrates among worst rated firms and is significant only during periods of deteriorating credit conditions. Hwang and Li (2008), Erturk (2006), hypothesize that the effect of analyst conflicts of interest on forecast dispersion is stronger for loss firms than for profit firms. Here, I test whether analyst conflicts of interest has differential impact for profit vs. loss firms, using the following extended model:

$$\begin{aligned} FDisp_{i,t} = {} & \beta_1 ResidVar_{i,t} + \beta_2 Log(MV)_{i,t} + \beta_3 BM_{i,t} + \beta_4 FAgeStd_{i,t} \\ & + \beta_5 Info/Noise_{i,t} + \beta_6 ChgRat_{i,t} + \beta_7 RelFE_{i,t} + \beta_8 Herd_{i,t} \\ & + \beta_9 ConfInt_{i,t} 1_{\{Past Ret_t \geq 0\}} + \beta_{10} ConfInt_{i,t} 1_{\{Past Ret_t < 0\}} + \gamma_i + \delta_t + \varepsilon_{i,t} \end{aligned} \qquad (2)$$

The main interest is on β_9 and β_{10}. The results presented in Table 3.8 confirm that following stock return plunges, analyst conflicts of interest increases forecast dispersion in all specifications. This result brings additional support to the hypothesis that when firm's past stock performance is poor, the conflicted analysts are sluggish in revising their forecasts downward while the non-conflicted analysts are not; see Hwang and Li (2008), Erturk (2006), Lobo and Tung (2000), Han and Manry (2000), Brown (2001), among others. Chan et al. (1996) also show that analysts are in general slow in responding to bad news, and that stocks experiencing low past returns are associated with downward revisions in analyst estimates.

In terms of economic magnitude, 1% increase in *ConfInt* increases forecast dispersion by 0.07%, during times of stock return decreases. By contrast, we do not observe any significant

Table 3.8: Explaining forecast dispersion for loser vs. winner firms

The dependent variable is forecast dispersion (*FDisp*), defined as the ratio of standard deviation of analyst current fiscal-year annual earnings per share forecasts to the absolute value of the average forecast. Stocks with average forecast of zero are excluded. See Appendix C for the definitions of explanatory variables. The period considered is January 1984 through December 2007. Numbers in brackets are the t-statistics, based on the standard errors clustered by firm and time (*5%, ** 1%).

	Panel A			Panel B		
Explanatory variable (predicted sign)	(1) Rated firms	(2) Non-rated firms	(3) All firms	(1) Rated firms	(2) Non-rated firms	(3) All firms
RV (+)	0.149*	0.117**	0.136**			
	[2.40]	[3.19]	[4.61]			
Log(MV) (-)	-0.0623**	-0.0280*	-0.0492**	-0.0682**	-0.0299*	-0.0524**
	[-2.74]	[-2.20]	[-5.03]	[-2.99]	[-2.42]	[-5.07]
BM (-)	0.162**	0.257**	0.203**	0.170**	0.254**	0.205**
	[2.59]	[5.82]	[5.67]	[2.73]	[5.78]	[5.73]
FAgeStd (+)	0.103*	0.106*	0.108**	0.0988*	0.101*	0.101**
	[2.24]	[2.40]	[3.17]	[2.14]	[2.29]	[2.93]
Info/Noise (-)	-0.000933	-0.0159	-0.0133	0.00135	-0.0158	-0.0124
	[-0.09]	[-1.66]	[-1.89]	[0.14]	[-1.66]	[-1.78]
ΔRat/ΔZScr (-)	-0.0441**	-0.000587	-0.000609	-0.0475**	-0.000719	-0.000772
	[-3.53]	[-0.87]	[-0.87]	[-3.78]	[-1.00]	[-0.96]
RelFE (+)	0.0250**	0.0239**	0.0271**	0.0259**	0.0254**	0.0285**
	[4.00]	[6.07]	[8.56]	[4.13]	[6.44]	[8.74]
Herd (-)	-0.0623**	-0.0790**	-0.0696**	-0.0615**	-0.0782**	-0.0688**
	[-3.84]	[-5.55]	[-6.71]	[-3.75]	[-5.47]	[-6.46]
$ConfInt\,1_{\{\text{PastRet} \geq 0\}}$ *(-)*	-0.0477	-0.0368	-0.0314	-0.0482	-0.0400	-0.0353
	[-0.95]	[-1.41]	[-1.29]	[-0.96]	[-1.51]	[-1.42]
$ConfInt\,1_{\{\text{PastRet} < 0\}}$ *(+)*	0.0222	0.0650**	0.0706**	0.0230	0.0690**	0.0711**
	[0.35]	[2.65]	[2.63]	[0.36]	[2.79]	[2.60]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,117	22,233	35,350	13,117	22,233	35,350
Adjusted R-squared	26.2	28.8	25.2	26.1	28.6	24.9

impact of analyst conflicts during rating upgrades. One explanation that conflicts only matter for financially distressed firms is because financial analysts at investment banks do not revise their earnings forecasts (or do so only partially or with a delay) after credit analysts issue their rating change. Credit analysts in rating agencies do not face the same incentives as analyst in investment banks. Therefore, credit analyst opinion is a more accurate proxy of the quality of firm. This may explain the finding of Avramov et al. (2009) that the dispersion effect becomes insignificant after controlling for credit rating.

3.7 Conclusion

This chapter examines the determinants of one of the most commonly used measures of analyst disagreement - the earnings forecast dispersion. Regression analysis shows that forecast dispersion is a complex concept and that it simultaneously contains information about firm-specific risk, firm past performance, analysts' differing information set, forecasting difficulty, and analyst herding. In addition, I observe that analyst conflicts of interest matters for loser firms and has no significant impact on forecast dispersion for winner firms. One explanation is that financial analysts at investment banks do not revise their earnings forecasts (or do so only partially or with a delay) after bad news about a firm. Overall, the results suggest that caution should be employed when using forecast dispersion as a measure of only firm riskiness or forecasting difficulty, or the like. These results are important not only to understand what causes analyst disagreement but also, as I will show in Chapter 4, to further understand the observed negative relationship between forecast dispersion and stock returns.

Chapter 4: Does Forecast Dispersion Matter for Stock Returns?

In this chapter, I investigate whether the dispersion anomaly is existent after controlling for the determinants of forecast dispersion. The ability of determinants to explain the dispersion anomaly would indicate the lack of direct relationship between forecast dispersion and stock returns, while the inability would strengthen the uniqueness of dispersion anomaly.

4.1 Introduction

Most previous tests trying to explain the forecast dispersion anomaly use portfolio sorts. My aim in this chapter is to present additional tests that avoid some of the problems of earlier studies. Roll (1977) and Lo and MacKinlay (1990) criticize the use of portfolios and suggest using individual stocks in tests of asset pricing models. Roll (1977) argues that the portfolio formation process, by concealing possibly return relevant stock characteristics within portfolio averages, will make it difficult to reject the null hypothesis of no effect on returns. Lo and MacKinlay (1990) make an opposite point, that if the researcher forms portfolios based on characteristics that prior research has shown to be relevant for expected returns, he will be inclined to reject the null hypothesis too often due to a "data-snooping bias." Although both critics seem at odds, they are complementary rather than competing; portfolio formation may both make some return-irrelevant characteristics appear significant, and disguise the empirical relevance of other return-relevant characteristics.

This chapter assesses whether incorporating determinants of forecast dispersion as conditioning information in asset-pricing models helps capture the impact of the dispersion effect on raw and risk-adjusted returns of individual stocks. In other words, I study whether forecast dispersion is priced in a cross-sectional analysis based on stocks (and not portfolios) after accounting for the effect of APT-type factors and determinants of forecast dispersion. Lo and MacKinlay (1990) argue that portfolio formation procedures based on some empirically motivated characteristic can lead to the spurious conclusion that that characteristic has a significant effect on returns. Following Avramov and Chordia (2006), stock level beta is allowed to vary with firm's market value of equity and book-to-market ratio as well as with macroeconomic variables. Although none of the models examined fully capture the forecast dispersion effect, it becomes less important in the conditional models and is no longer significant for the sample of rated firms. Furthermore, consistent with Avramov and Chordia (2006), I show that the conditional models capture the momentum effect.

4.2 Methodology

I evaluate the influence of forecast dispersion on stock returns using the conditional multi-factor model developed by Brennan, Chordia, and Subrahmanyam (1998). I follow Avramov and Chordia (2006) and first run regressions of excess stock return on asset pricing factors with loadings that vary in cross-section and over time with firm's market value of equity and the book-to-market ratio, as well as with macroeconomic variables. I then run cross-sectional regressions of risk-adjusted returns, rather than gross returns, as dependent variables on the firm characteristics including firm's market value of equity, residual variance, book-to-market ratio, momentum, and forecast dispersion (the main variable of interest). Under the null hypothesis of exact pricing, all these characteristics should be insignificant. The use of risk-adjusted returns in asset pricing tests intends to address the error-in-variables bias in estimating the cross-section regression coefficients in finite samples.

Brennan et al. (1998) propose the following K-factors model that generates stock returns:

$$R_{i,t} = E_{t-1}\left(R_{i,t}\right) + \sum_{k=1}^{K} \beta_{i,k,t-1}\left[f_{k,t} - E_{t-1}\left(f_{k,t}\right)\right] + \varepsilon_{i,t} ,$$

where $R_{i,t}$ is the realized return for stock i at time t, and $f_{k,t}$ is the return on the k'th risk-factor mimicking portfolio at time t, $\beta_{i,k,t\text{-}1}$ is the conditional beta corresponding to the k'th factor, E_{t-1} is the conditional expectations operator, and $E_{t-1}\left(\varepsilon_{i,t} \mid f_{k,t}\right) = 0$. The factor model expresses the unanticipated factor return, $f_{k,t} - E_{t-1}\left(f_{k,t}\right)$, as a linear regression on the unanticipated part of the factors. The exact or equilibrium version of the APT implies that expected returns can be written as:[36]

$$E_{t-1}\left(R_{i,t}\right) = R_{f,t} + \sum_{k=1}^{K} \beta_{i,k,t-1} E_{t-1}\left(f_{k,t}\right),$$

where $R_{f,t}$ is the return on the riskless asset at time t. From the above two equations, we can now write realized returns as:

$$R_{i,t} = R_{f,t} + \sum_{k=1}^{K} \beta_{i,k,t-1} f_{k,t} + \varepsilon_{i,t},$$

and risk-adjusted returns as:

$$R^{*}_{i,t} = R_{i,t} - R_{f,t} - \sum_{k=1}^{K} \hat{\beta}_{i,k,t-1} f_{k,t},$$

where $\hat{\beta}_{i,k,t-1}$ is the estimated conditional beta from the first-pass time-series regression over the entire period. The null hypothesis is whether forecast dispersion has incremental explanatory power for stock returns above the risk factors. To do this, I regress the risk-adjusted returns $R^{*}_{i,t}$ against the vector of M firm characteristics $Z_{m,t\text{-}1}$:

$$R^{*}_{i,t} = \alpha_{0,t} + \sum_{m=1}^{M} \alpha_{m,t} Z_{m,t-1} + \eta_{i,t}$$

[36] See Shanken (1985) and Connor and Korajczyk (1988) for the definition and discussion of an approximate factor model.

Firm characteristics are divided into two groups. The control variables in the first group are firm's residual variance, change in Z-Score, market value, book-to-market ratio, turnover, and momentum that are known to be related with expected stock returns. In the second group, I have forecast dispersion that is the main variable interest. I run the estimation monthly and obtain a sequence of vectors $\alpha_{m,t,}$ $t = 1\ldots T$. Testing $\bar{\alpha}_{m,t} = 0$ asks whether $Z_{m,t\text{-}1}$ can predict stock returns over their role as linear instruments for the betas.

I follow Avramov and Chordia (2006) and consider the following asset pricing models: (1) CAPM, (2) Fama and French (1993) three factor model, (3) Fama and French model augmented by the Jegadeesh and Titman (1993) momentum factor, and (4) Fama and French model augmented by the Pastor and Stambaugh (2003) liquidity factor.[37] Time varying beta is a linear function of market value, book-to-market ratio, and a macroeconomic variable:

$$\beta_{i,t-1} = \beta_{i,0} + \beta_{i,1} z_{t-1} + (\beta_{i,2} + \beta_{i,3} z_{t-1}) MV_{i,t-1} + (\beta_{i,4} + \beta_{i,5} z_{t-1}) BM_{i,t-1},$$

where z_{t-1} is the corporate spread as an indicator of the state of the economy, measured as the differential between BAA and AAA rated corporate bond yields from Moody's.

4.3 Data

4.3.1 Sample selection

My sample merges several datasets of U.S. firms spanning January 1983 to December 2007. To address concerns that the U.S. Summary History file makes use of analysts' forecasts that are no longer current, I calculate the month-end averages and standard deviations from the individual earning forecasts in the unadjusted Detail History file; see Diether et al. (2002), Payne and Thomas (2003), and Baber and Kang (2002). Forecast

[37] I use the Pastor-Stambaugh value-weighted liquidity traded factor that is long in high sensitivity to liquidity stocks and short in low sensitivity to liquidity stocks.

dispersion, *FDisp*, is the standard deviation of annual earnings forecasts scaled by the absolute value of the average earnings forecast (with zero average-earnings forecast observations excluded). Stocks followed by fewer than two analysts are excluded.

Stock returns for U.S. common stocks are from CRSP monthly stock file. I select ordinary common shares (share codes 10 and 11) traded in NYSE, AMEX, and NASDAQ, and remove financial institutions. To be included in the sample, the stock must have at least 36 months return data. Observations on firm characteristics such as firm's market value and B/M ratio lagged two months must be also available. I use the CRSP value-weighted returns to proxy for market returns.

Firm accounting data is from the Compustat Industrial Annual file. To mitigate the problem of extreme values, all variables for regression analysis are winsorized at 0.5% and 99.5% levels. Observations with negative book value, market value, and total assets are eliminated. To ensure that the accounting variables are known before the returns they are used to explain, as in Fama and French (1992), minimum 6-month gap between fiscal year-end and the return date is required. In other words, the value of book-to-market ratio for July of year t to June of year $t + 1$ is computed using accounting data as of the end of year $t\text{-}1$. For the risk-adjustment, the control variables are market value, book-to-market ratio, turnover, and past cumulative returns. Variables are defined in Appendix D.

4.3.2 Sample characteristics

The total number of different firms in my sample is 5,257 with 562,129 valid forecast dispersion data. Table 4.1 presents the time-series averages of the cross-sectional averages and standard deviations of firm characteristics. Firms on average (median) have USD 2.17 (0.44) billion market value, with an average excess return of 0.87% per month. Firm's market

Table 4.1: Sample characteristics

The table reports the time-series averages of the cross-sectional summary statistics for 5,257 distinct firms having forecast dispersion data. Each month firm characteristics are averaged first over the stocks and then over the sample period. Excess return is the firm excess return over 1-month Treasury bill rate. *FDisp* is the ratio of standard deviation of analyst current fiscal-year annual earnings per share forecasts to the absolute value of the average forecast (with zero-average forecast observations excluded). *ResidDisp* and *ExplainDisp* are the residual and explanatory part of *FDisp. RV* is the residual variance and $\Delta ZScr$ is the change in Altman's Z-Score. *MV* is the market value in billions of dollars and *BM* is the book-to-market ratio. *NYTurn* (*NDTurn*) is turnover of NYSE-AMEX (NASDAQ) stocks. *Ret2-3*, *Ret4-6*, and *Ret7-12* are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month, respectively. The period considered is January 1983 through December 2007.

Characteristics	Avg	Std	25%	Median	75%
Excess return (%)	0.87	12.72	-6.07	0.25	6.96
FDisp	0.25	0.72	0.03	0.07	0.19
ResidDisp	0.35	0.52	0.17	0.26	0.37
ExplainDisp	0.18	0.11	0.10	0.17	0.25
RV	0.41	0.39	0.15	0.29	0.53
$\Delta ZScr$	-0.41	4.91	-0.79	-0.02	0.55
MV (in billions)	2.17	6.42	0.16	0.44	1.37
BM	0.63	0.57	0.27	0.48	0.81
Turn(%)	12.80	12.85	4.98	8.66	15.68
NYTurn(%)	4.70	7.35	0.03	1.02	7.10
NDTurn(%)	8.10	13.48	0.00	1.85	11.23
Ret2-3(%)	2.70	16.97	-7.41	1.75	11.50
Ret4-6 (%)	4.40	21.12	-8.39	2.85	15.03
Ret7-12 (%)	9.70	32.58	-10.18	5.93	24.16

value is highly skewed, therefore in the regression analysis I employ the logarithm transform of *MV*. Excess return is firm's raw return less 1-month Treasury bill rate. The average monthly turnover for NYSE-AMEX (NASDAQ) firms is 4.7% (8.1%). The average (median) book-to-market ratio of all stocks is 0.63 (0.48); this is lower than the statistics in Avramov and Chordia (2006) indicating that my sample is tilted toward growth firms with high market value due to the requirement of analyst following.

4.4 Results

I empirically asses the relationship between forecast dispersion and future stock returns in a time-varying beta framework for individual firms. I estimate the asset pricing models at monthly frequency. Following Brennan et al. (1998), firm characteristics are deviations from the cross-sectional averages and are lagged two months with respect to the excess returns or the risk-adjusted returns that are the dependent variables in the regressions. This is to ensure any spurious association between the prior month return and the current month return caused by thin trading or bid-ask spread effects. To minimize the problem of bid-ask bounce, I follow Jegadeesh and Titman (2001) and exclude stocks priced at less than USD 5 lagged two months. A significant coefficient indicates that the firm characteristic under consideration is related to the cross-section of individual risk-adjusted return.

4.4.1 Excess returns

To begin with, Panel A of Table 4.2 presents the Fama-MacBeth coefficient estimates for the cross-sectional regressions of risk-unadjusted excess returns on forecast dispersion. *FDisp* is strongly significant for all specification except for rated firms. This result is in contrast with Avramov et al. (2009) who show statistically significant negative dispersion-return association for rated firms. I further examine whether *FDisp* stays significant after accounting for firm characteristics that are best known to be associated with stock returns. *FDisp* remains significant after the control variables. This is consistent with my previous results and prior literature. Lagged returns are predominantly statistically significant, confirming earlier findings of Avramov and Chordia (2006) and Brennan et al. (1998).

4.4.2 Risk-adjusted returns

Here, I examine whether the relationship between *FDisp* and stock returns remains significant after Brennan et al. (1998)'s risk-adjustment. Panel B of Table 4.2 presents the Fama-MacBeth coefficient estimates for the cross-sectional regressions with risk-adjusted excess returns as dependent variables. The main interest is in the coefficient of *FDisp* and it is highly significant at 1% level for all risk-adjusted returns. This indicates that risk-adjustment

Table 4.2: Results for forecast dispersion

Coefficient estimates are time-series averages of cross-sectional OLS regressions. The dependent variable in the first column is the excess return. In the second, third, fourth, and fifth columns it is the risk-adjusted excess return with respect to CAPM, Fama and French (1993) three factor model, Fama and French model augmented by the Jegadeesh and Titman (1993) momentum factor, and Fama and French model augmented by the Pastor and Stambaugh (2003) liquidity factor, respectively. *FDisp* is the ratio of standard deviation of analyst current fiscal-year annual earnings per share forecasts to the absolute value of the average forecast (with zero-average forecast observations excluded). *RV* is the residual variance and Δ*ZScr* is the change in Altman's Z-Score. *MV* is the market value in billions of dollars and *BM* is the book-to-market ratio. *NYTurn* (*NDTurn*) is turnover of NYSE-AMEX (NASDAQ) stocks. *Ret2-3*, *Ret4-6*, and *Ret7-12* are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month, respectively. *NDDum* is a dummy variable for NASDAQ stocks and equals 1 is the stock is traded in NASDAQ and 0 otherwise. The variables are the deviations from their cross-sectional averages in each month and lagged two months with respect to the current month. Stocks priced at less than $5 lagged two months are excluded. $\bar{R}^2$ is the time-series averages of the monthly adjusted R^2. t-statistics are in brackets (*5%, **1%). All coefficients are multiplied by 100. The period considered is January 1983 through December 2007.

	Panel A: Excess return				Panel B: Risk-adjusted return				Panel C: Risk-adjusted return (time-varying)			
	Rated	Non-Rated	All	All	CAPM	FF3	FF3+MOM	FF3+LIQ	CAPM	FF3	FF3+MOM	FF3+LIQ
FDisp	0.315	-0.197**	-0.197**	-0.103*	-0.143**	-0.143**	-0.126**	-0.133**	-0.367**	-0.141	-0.319*	-0.196
	[0.52]	[-2.63]	[-3.05]	[-2.15]	[-3.11]	[-3.56]	[-3.36]	[-3.57]	[-4.00]	[-1.37]	[-2.38]	[-1.39]
RV				-0.163	-0.602**	-0.391*	-0.293	-0.392**	1.193**	2.045**	0.364	1.653**
				[-0.61]	[-2.95]	[-2.45]	[-1.88]	[-2.66]	[2.80]	[4.45]	[0.66]	[3.76]
Δ*ZScr*				-0.0000396	0.00272	0.00131	0.0000194	0.000312	-0.00114	0.000477	-0.00534	0.0370
				[-0.01]	[0.38]	[0.22]	[0.00]	[0.06]	[-0.06]	[0.02]	[-0.23]	[1.51]
Log(MV)				-0.0267	-0.0141	0.0182	0.0347	0.0227	-0.156**	-0.701**	-0.351**	-0.682**
				[-0.69]	[-0.38]	[0.96]	[1.96]	[1.26]	[-3.69]	[-16.34]	[-6.77]	[-12.22]
BM				0.0476	0.0780	-0.212**	-0.174**	-0.298**	-0.244	-0.619**	-0.329*	-1.342**
				[0.45]	[0.85]	[-3.55]	[-3.11]	[-5.21]	[-1.48]	[-4.07]	[-1.97]	[-7.93]
NYTurn				-2.258**	-2.739**	-1.602**	-1.174*	-1.378**	1.005	1.129	2.010	-0.854
				[-2.96]	[-4.18]	[-2.87]	[-2.24]	[-2.61]	[1.06]	[1.15]	[1.83]	[-0.86]
NDTurn				-1.857**	-2.150**	-1.032*	-0.852*	-0.918*	-5.631**	-7.109**	-3.662**	-3.934*
				[-3.13]	[-4.37]	[-2.58]	[-2.29]	[-2.52]	[-7.53]	[-7.43]	[-3.02]	[-2.45]
Ret2-3				0.633	0.783**	0.739**	0.726**	0.766**	-0.0993	0.511	1.095	0.868
				[1.89]	[2.61]	[2.62]	[2.83]	[2.85]	[-0.15]	[0.67]	[1.45]	[1.11]
Ret4-6				1.428**	1.448**	1.250**	1.123**	1.174**	1.020	1.130	1.656*	1.079
				[5.54]	[5.94]	[5.87]	[5.96]	[5.87]	[1.74]	[1.68]	[2.54]	[1.52]
Ret7-12				0.616**	0.633**	0.559**	0.461**	0.518**	0.466	0.793	1.056*	0.817
				[3.85]	[4.23]	[4.15]	[3.81]	[4.21]	[1.03]	[1.59]	[2.16]	[1.52]
NDDum				0.150	0.148	0.277**	0.222**	0.269**	-1.625**	-1.537**	-0.794**	-0.733**
				[1.43]	[1.45]	[4.13]	[3.54]	[4.34]	[-11.61]	[-13.40]	[-6.20]	[-5.27]
Constant	0.837*	0.746*	0.715*	0.632	-0.102	-0.163*	-0.0437	-0.145*	0.118	1.139**	0.673**	1.108**
	[2.52]	[2.14]	[2.29]	[1.95]	[-0.70]	[-2.55]	[-0.80]	[-2.39]	[0.74]	[9.81]	[5.55]	[8.72]
Observations	173,449	332,836	506,285	443,113	443,113	443113	443,113	443,113	443,113	443,113	443,113	443,113
$\bar{R}^2$ (%)	4.11	0.35	0.34	7.28	5.79	3.59	3.31	3.43	5.73	4.62	3.02	3.56

by none of the considered factor models is able to capture the negative relationship between forecast dispersion and stock returns. Leippold and Lohre (2009) show that dispersion effect concentrates in a 3-year window from 2000 to 2003, after the burst of so-called “dotcom bubble” when most uncertainty about high dispersion stock is resolved. This finding supports Miller (1977) view that high forecast-dispersion stock prices reflect the valuation of optimists in the presence of high short-sale costs. As a result, forecast dispersion effect could be traced to either time-varying risk premia or time-varying asset pricing misspecification, or both. Thus, the forecast dispersion profitability could vary with business cycle. I modify the first pass regression to account for time-varying alpha that includes a vector of business cycle variable consisting of corporate spread, term spread and the 3-month Treasure bill yield.

Panel C of Table 4.2 shows that forecast dispersion remains highly correlated with time-varying risk-adjusted returns. This indicates that even when alpha varies with macroeconomic variables, the impact of forecast dispersion on cross-section of expected returns unrelated to business cycle variable is still highly significant. However, forecast dispersion becomes statistically insignificant for FF3 and FF3+LIQ time-varying specification, suggesting that forecast dispersion strategy is related to liquidity. This supports the finding of Sadka and Scherbina (2007) that stocks with high forecast dispersion have also high transaction costs, therefore preventing investors to exploit the dispersion strategy that has persisted through the years. $\Delta ZScr$ is not significant in any specification suggesting that the discreteness of $\Delta ZScr$ creates major impediment in predicting probability of default. Because financial ratios that are necessary to compute the Z-Score are available annually, the default probability of a firm is unchanged for twelve months. It is also noteworthy that some of the coefficients and constant terms in Panel C are different in magnitude from Panel B; see also Avramov and Chordia (2006, footnote 16) for a similar outcome. Interestingly, the relationship between stock returns and residual variance becomes positive when alpha varies with business cycle; see Ang et al. (2006). Note also that lagged return variables are insignificant in almost all specifications suggesting that macroeconomic variables eliminate momentum profitability.

4.4.3 Residual and explained dispersion

The inability of the well-known risk-based asset pricing models to explain forecast dispersion effect suggests that forecast dispersion does not only proxy for firm's riskiness. Next, I examine whether variables that explain forecast dispersion can capture the negative dispersion-return relationship, by decomposing *FDisp* into its two components - residual dispersion and explained dispersion. Explained dispersion (*ExplainDisp*) is the explanatory part of forecast dispersion from equation (1) as discussed in Chapter 3, and the residual dispersion (*ResidDisp*) is the difference between forecast dispersion and the explained dispersion.[38] Table 4.3 shows that while *ResidDisp* remains strongly negatively correlated with both excess return and risk-adjusted returns in most specifications, *ExplainDisp* does not predict stock returns. In addition, when alpha varies with macroeconomic variables, the impact of *ResidDisp* is reduced, indicating that the dispersion strategy returns varies with business cycle.

The asset-pricing framework above uses single stocks in cross-sectional tests that allow risk and expected return to vary with conditioning information. Next, I construct portfolios based on *ResidDisp*, in order to draw conclusions about average returns for different classes of stocks. Each month, stocks are equally assigned to one of quintiles based on their market value of the previous month. Quintile 1 includes the smallest stocks and quintile 5 includes the largest stocks. Stocks in each size quintile are further ranked into five dispersion quintiles based on the *ResidDisp* of previous month. The purpose of this two-way

[38] Results are similar when *ResidDisp* is defined using equation (2) of Chapter 3.

sorting is to hold one anomaly variable constant and to investigate the impact of the other. For the full sample this classification results in 25 portfolios that contain an average of 57 stocks. Monthly portfolio return are calculated as the equal-weighted and value-weighted returns of all the stocks in a portfolio. Stocks are held for one month. Consistent with regression results, Table 4.4 shows strong negative relationship between *ResidDisp* and stock returns.

Focusing on equal-weighted portfolios, I show that for all sample firms (non-rated firms) the average monthly return differential between low- and high-dispersion, the D1- D5 portfolios, is 0.34% (0.28%) with t-stat of 2.47 (2.27). Although for all firms the model explaining forecast dispersion reduces the dispersion effect (for comparison see Panel A of Table 2.3), the two-way sort still produces a strong negative relation between stock returns and residual dispersion. Note that for rated firms residual dispersion eliminates the dispersion strategy across all size groups. For comparison, the dispersion strategy for the same sample of rated firms yields average monthly return of 0.67% with a t-stat of 2.38 for the smallest size group only, not reported here. Taken together, although factors that explain forecast dispersion are able to reduce the dispersion profitability, the overall evidence indicates the presence of a dispersion effect.

Table 4.3: Results for residual and explained dispersion

Coefficient estimates are time-series averages of cross-sectional OLS regressions. The dependent variable in the first column is the excess return. In the second, third, fourth, and fifth columns it is the risk-adjusted excess return with respect to CAPM, Fama and French (1993) three factor model, Fama and French model augmented by the Jegadeesh and Titman (1993) momentum factor, and Fama and French model augmented by the Pastor and Stambaugh (2003) liquidity factor, respectively. *ResidDisp* and *ExplainDisp* are the residual and explanatory part of *FDisp*. *RV* is the residual variance and $\Delta ZScr$ is the change in Altman's *Z*-Score. *MV* is the market value in billions of dollars and *BM* is the book-to-market ratio. *NYTurn* (*NDTurn*) is turnover of NYSE-AMEX (NASDAQ) stocks. *Ret2-3*, *Ret4-6*, and *Ret7-12* are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month, respectively. *NDDum* is a dummy variable for NASDAQ stocks and equals 1 if stock is traded in NASDAQ and 0 otherwise. The variables are the deviations from their cross-sectional averages in each month and lagged two months with respect to the current month. Stocks priced at less than $5 lagged two months are excluded. $\bar{R}^2$ is the time-series averages of monthly R^2. The t-statistics are in brackets (*5%, **1%). All coefficients are multiplied by 100. The period considered is January 1984 through December 2007.

	Panel A: Excess return				Panel B: Risk-adjusted return				Panel C: Risk-adjusted return (time-varying)			
	Rated	Non-Rated	All	All	CAPM	FF3	FF3+MOM	FF3+LIQ	CAPM	FF3	FF3+MOM	FF3+LIQ
ResidDisp	-0.0829	-0.246*	-0.214*	-0.108	-0.160*	-0.152**	-0.137**	-0.153**	-0.407**	-0.0814	-0.335*	0.0297
	[-0.84]	[-2.25]	[-2.52]	[-1.61]	[-2.46]	[-2.66]	[-2.60]	[-2.88]	[-3.70]	[-0.64]	[-2.04]	[0.18]
ExplainDisp	0.241	0.928	0.547	-0.325	-0.404	-0.0973	-0.0752	-0.0640	-1.474*	-0.427	0.346	-0.982
	[0.47]	[1.82]	[1.11]	[-0.93]	[-1.24]	[-0.32]	[-0.26]	[-0.22]	[-2.42]	[-0.56]	[0.37]	[-1.04]
RV				-0.256	-0.669**	-0.297	-0.184	-0.234	0.919*	2.016**	1.296*	1.489**
				[-0.82]	[-2.73]	[-1.53]	[-0.97]	[-1.32]	[2.04]	[4.10]	[2.22]	[2.78]
$\Delta ZScr$				-0.00115	0.00403	0.00351	-0.0000184	0.00157	-0.00961	-0.00354	0.0136	0.0234
				[-0.15]	[0.53]	[0.52]	[-0.00]	[0.24]	[-0.46]	[-0.14]	[0.58]	[1.01]
Log(MV)				0.0340	0.0421	0.0509*	0.0586*	0.0520*	-0.0504	-0.661**	-0.479**	-0.681**
				[0.77]	[1.03]	[2.04]	[2.47]	[2.19]	[-1.00]	[-10.34]	[-6.48]	[-9.52]
BM				0.0256	0.0746	-0.189**	-0.163*	-0.266**	-0.165	-0.406*	-0.444**	-0.952**
				[0.24]	[0.76]	[-2.64]	[-2.45]	[-3.85]	[-0.95]	[-2.48]	[-2.82]	[-5.11]
NYTurn				-1.838*	-2.374**	-1.468*	-0.992	-1.259*	1.767	0.868	1.066	-0.235
				[-2.43]	[-3.65]	[-2.53]	[-1.80]	[-2.29]	[1.95]	[0.91]	[1.08]	[-0.22]
NDTurn				-1.202*	-1.579**	-0.801*	-0.581	-0.786*	-5.288**	-7.310**	-5.446**	-6.045**
				[-2.09]	[-3.25]	[-1.97]	[-1.49]	[-2.06]	[-6.73]	[-8.48]	[-5.39]	[-5.85]
Ret2-3				0.406	0.621	0.740*	0.691*	0.756**	0.154	0.633	1.194	0.805
				[1.12]	[1.88]	[2.40]	[2.44]	[2.60]	[0.22]	[0.79]	[1.48]	[0.98]
Ret4-6				1.408**	1.523**	1.360**	1.220**	1.296**	1.349*	1.399*	1.868**	1.358*
				[4.87]	[5.69]	[5.73]	[5.80]	[5.73]	[2.28]	[2.06]	[2.88]	[1.98]
Ret7-12				0.712**	0.714**	0.627**	0.526**	0.603**	0.413	0.786	0.976	0.922
				[4.07]	[4.30]	[4.13]	[3.82]	[4.28]	[0.86]	[1.46]	[1.88]	[1.73]
NDDum				0.204	0.207	0.322**	0.260**	0.306**	-1.742**	-1.610**	-1.108**	-0.961**
				[1.87]	[1.96]	[4.61]	[3.97]	[4.70]	[-11.58]	[-13.02]	[-7.97]	[-6.84]
Constant	0.666*	0.761*	0.721*	0.612	-0.144	-0.177*	-0.0436	-0.152*	0.0687	1.079**	0.938**	1.122**
	[2.28]	[2.24]	[2.36]	[1.82]	[-0.93]	[-2.57]	[-0.72]	[-2.33]	[0.40]	[8.27]	[6.96]	[7.81]
Observations	147,477	236,783	384,260	374,629	374,629	374,629	374,629	374,629	374,629	374,629	374,629	374,629
$\bar{R}^2$ (%)	1.63	0.88	0.98	7.89	6.41	4.09	3.76	3.91	6.37	5.07	3.68	4.08

Table 4.4: Dispersion anomaly for residual dispersion

Using in-sample breakpoints each month stocks are equally sorted in five groups based on the level of market value of the previous month end. Stocks in each size group are then equally sorted into five additional groups based on the residual dispersion (*ResidDisp*) of the previous month. Stocks with an average forecast of zero are assigned to the highest dispersion group, and stocks with a price less than or equal 5 dollars are excluded from the sample. Stocks are held for one month. The table reports average monthly equal-weighted returns. In brackets are the t-statistics, adjusted for one lag autocorrelation, (*5%, **1%). The period considered is January 1984 through December 2007.

Panel A: All firms

Dispersion quintiles	All stocks	Size quintiles Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.08	0.93	1.11	1.16	1.10	1.12	-0.18	[-0.87]
D1	1.23	1.27	1.26	1.30	1.21	1.06	0.21	[0.79]
D2	1.18	1.11	1.14	1.17	1.07	1.17	-0.06	[-0.26]
D3	1.04	0.99	1.12	1.16	1.01	1.09	-0.10	[-0.49]
D4	1.07	0.88	1.05	1.24	1.18	1.11	-0.23	[-0.88]
D5	0.90	0.43	0.97	0.97	1.03	1.16	-0.73	[-2.75]**
D1-D5	0.34	0.84	0.29	0.33	0.18	-0.10		
t(D1-D5)	[2.47]*	[4.61]**	[1.57]	[1.60]	[0.86]	[-0.50]		

Panel B: Non-rated firms

Dispersion quintiles	All stocks	Size quintiles Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.09	0.94	1.07	1.21	1.14	1.10	-0.16	[-0.70]
D1	1.17	1.04	1.20	1.20	1.21	0.90	0.14	[0.46]
D2	1.20	1.21	1.10	1.21	1.37	1.05	0.15	[0.60]
D3	1.06	0.96	1.27	1.20	0.89	1.19	-0.23	[-0.82]
D4	1.15	1.06	1.17	1.35	1.18	1.12	-0.06	[-0.20]
D5	0.89	0.46	0.62	1.08	1.05	1.24	-0.78	[-2.24]*
D1-D5	0.28	0.58	0.57	0.12	0.16	-0.34		
t(D1-D5)	[2.27]*	[2.60]**	[2.56]*	[0.53]	[0.73]	[-1.57]		

Panel C: Rated firms

Dispersion quintiles	All stocks	Size quintiles Small S1	S2	S3	S4	Large S5	S1-S5	t(S1-S5)
All stocks	1.05	0.85	1.11	1.14	1.10	1.05	-0.20	[-0.85]
D1	1.01	0.84	1.14	1.15	1.03	0.99	-0.15	[-0.46]
D2	1.08	0.84	1.13	1.20	1.05	0.96	-0.13	[-0.50]
D3	1.08	0.99	1.13	1.02	1.08	0.99	0.00	[-0.01]
D4	1.10	0.75	1.16	1.16	1.25	1.11	-0.36	[-1.23]
D5	0.98	0.83	0.99	1.17	1.07	1.19	-0.36	[-1.14]
D1-D5	0.03	0.02	0.15	-0.03	-0.04	-0.19		
t(D1-D5)	[0.17]	[0.06]	[0.52]	[-0.10]	[-0.17]	[-0.96]		

4.5 Conclusion

The chapter investigates whether multi-factor asset pricing model with and without time-varying beta can explain the negative relationship between forecast dispersion and future stock returns. The models considered are (1) CAPM, (2) Fama and French (1993) three factor model, (3) Fama and French model augmented by the Jegadeesh and Titman (1993) momentum factor, and (4) Fama and French model augmented by the Pastor and Stambaugh (2003) liquidity factor. My results show that none of these models captures the forecast dispersion effect when the market beta varies with firm's market value, book-to-market ratio and the corporate spread. My analysis further suggests that the dispersion-return relationship is related to aggregate liquidity and business-cycle risk factors. In addition, the negative relationship between forecast dispersion and stock returns is significantly weaker after accounting for the determinants that explain forecast dispersion.

Conclusion

This dissertation contributes to the literature in an important and active area of financial markets research - explaining the relationship between forecast dispersion and stock returns. One of the most influential early studies is Diether et al. (2002) showing evidence that stocks with lower forecast dispersion earn higher future returns. They explain the negative relationship between dispersion and future returns by market frictions and interpret forecast dispersion as a proxy for the differences of opinion. They attribute this finding to Miller (1977) hypothesis that in the presence of short-sale costs, stock prices are determined by the optimistic investors who bid the prices up. This interpretation is however contrary to previous thought that forecast dispersion is a proxy for risk; see Malkiel (1982), Farrelly and Reichenstein (1984), and Carvell and Strebel (1984), among others.

A growing number of studies suggest that tests of forecast dispersion that employ stock returns face several challenges. Analyst forecast dispersion has long been considered a proxy for investor heterogeneity, assuming that the disagreement among analysts reflects disagreement among investors. Based on the notion that investor disagreement is one of the factors to trigger trade, forecast dispersion is also used to study trading volume around information events such as earnings announcements. Over time, investors revise their expectations thereby generating transactions. In conjunction with revision in earnings forecasts, forecast dispersion explains turnover; see Ajinkya et al. (1991). Roulstone (2003) shows that forecast dispersion is negatively associated with stock liquidity thus conclude that analysts reduce information asymmetry by providing public information to market participants.

In Chapter 1, I conduct a thorough review of the literature on the differences of opinion-return relationship, paying special attention to the use forecast dispersion as a proxy of differences of opinion. As reviewed, the literature is split on the relationship between forecast dispersion and stock returns both in terms of the direction of the relationship and in terms of the role of forecast dispersion. Therefore, to understand the causes of the relationship between forecast dispersion and stock returns, I perform a detail examination of the dispersion anomaly.

This research adds to the existing literature on the role of forecast dispersion on stock returns. My results can be summarized as follows. First, I find that the dispersion anomaly persists on a longer period from February 1983 to December 2007 that includes the sample periods considered in the previous studies. This negative relationship between contemporaneous forecast dispersion and future stock returns is also robust to different dispersion measures. In addition, I examine the relation with other market anomalies that are known to predict low future stock returns. In particular, my results show that forecast dispersion anomaly is not due to accruals quality, capital investment growth, asset growth, and equity issuance anomalies.

Second, I add to the literature with a detail analysis of determinants of forecast dispersion. My analysis shows that forecast dispersion is simultaneously related to a number of factors including firm riskiness, analysts' herding and conflicts of interest, forecast difficulty, and the differences in information impounded in each forecast. The motivation to consider these sources of forecast dispersion stems from empirical facts observed between forecast dispersion and its determinants.

Third, using individual stocks, in Chapter 4 I test a risk-based asset pricing models applying four different specifications to adjust for risk. Regardless of the method used for risk-adjustment, there is a strong negative relation between average returns and forecast dispersion. However, accounting for the determinants of forecast dispersion and allowing beta to vary with firm's market value, book-to-market ratio, and business cycle variables, reduces the dispersion-return relationship. Further tests show that the determinants of forecast dispersion account for half of the profitability of dispersion strategy, thus substantiating the importance of the determinants of forecast dispersion in understanding the dispersion anomaly. In sum, my findings corroborate previous results that forecast dispersion is an important determinant of stock returns.

Appendix A: Sample selection

I/B/E/S provides analysts' earnings forecasts in the U.S. Detail History and Summary History files. Both Summary and Detail files suffer from a rounding problem that makes them unsuitable for computing summary statistics. In these files, I/B/E/S adjusts the earnings per share for stock splits and stock dividends after the date of the forecast in order to smooth the forecast time series. The adjusted number is then rounded to the nearest cent. For firms with large numbers of stock splits or stock dividends, earnings-per-share forecasts (and the summary statistics associated with earnings) are reported as zero. To avoid this problem, I rely on the raw forecasts that are not adjusted for stock splits. I/B/E/S also provides Unadjusted Summary Statistics file that contains summary statistics for analyst forecasts, including average, median, and standard deviation, as well as information about the number of analysts making forecasts and the number of upward and downward revisions. These summary statistics are ordinarily calculated on the third Thursday of each month. For each stock, the coverage in any given month equals to the number of I/B/E/S analysts who provide fiscal year on earnings estimates in that month. From I/B/E/S, I select U.S. stocks that in I/B/E/S Unadjusted Summary Statistics file have at least two EPS estimates denominated in U.S. dollar (USD). At least two analysts must cover each stock in order to compute forecast dispersion.

Data on stock returns, prices, volume, and shares outstanding are from CRSP. I select ordinary common shares (SHRCD = 10 and 11) that are traded in NYSE (EXCHCD = 1), AMEX (EXCHCD = 2) and NASDAQ (EXCHCD = 3) and remove financial institutions ($6000 \leq$ SICCD$\leq$ 6999). To reduce the potential effects of outliers on the results and to minimize the problem of illiquid stocks and the bid-ask spread, I follow Jegadeesh and Titman (2001) and exclude firms with a stock price of $5 or less at the portfolio formation date.

Appendix B: Measuring accruals quality

The accruals quality (AQ) metric I use is based on Dechow and Dichev (2002) regression model that posits a relation between current period working capital accruals and operating cash flows in the prior, current, and future periods. Following McNichols (2002) discussion of this model, I also include the change in revenues and property, plant and equipment (PPE) as additional explanatory variables. The unexplained portion of the variation in working capital accruals is an inverse measure of accruals quality (a greater unexplained portion implies poorer quality). I adopt Francis et al. (2005) indirect approach to calculate total accruals that uses information from the balance sheet and income statement:

$$TCA_{j,y} = \alpha_{0,j} + \alpha_{1,j} CFO_{j,y\text{-}1} + \alpha_{2,j} CFO_{j,y} + \alpha_{3,j} CFO_{j,y+1} + \alpha_{4,j} \Delta \mathrm{Re}\,v_{j,y} + \alpha_{5,j} PPE_{j,y} + \varepsilon_{j,y},$$

where

$TCA_{j,y} = \Delta CA_{j,y} - \Delta CL_{j,y} - \Delta Cash_{j,y} + \Delta STDEBT_{j,y}$	is firm j's total current accruals in year y
$CFO_{j,y} = NIBE_{j,y} - TA_{j,y}$	is firm j's cash flow from operations in year y
$NIBE_{j,t}$	is firm j's net income before extraordinary items in year y (#18)
$TA_{j,y} = \Delta CA_{j,y} - \Delta CL_{j,y} - \Delta Cash_{j,y} + \Delta STDEBT_{j,y} - DEPN_{j,y} = TCA_{j,y} - DEPN_{j,y}$	is firm j's total accruals in year y
$\Delta CA_{j,y}$	is firm j's change in current assets (#4) between year y-1 and year y
$\Delta CL_{j,y}$	is firm j's change in current liabilities (#5) between year y-1 and year y
$\Delta Cash_{j,y}$	is firm j's change in cash (#1) between year y-1 and year y
$\Delta STDEBT_{j,t}$	is firm j's change in debt in current liabilities (#34) between year y-1 and year y
$DEPN_{j,y}$	is firm j's depreciation and amortization expense (#14) in year y

$\Delta \mathrm{Rev}_{j,y}$	is firm j's change in revenues (#12) between year y-1 and year y
$PPE_{j,y}$	is firm j's gross value of PPE (#7) in year y

I require that each firm-year observation has data and estimate the AQ for each of 48 industry groups with at least 20 firms in year y; see Fama and French (1997). Consistent with the prior literature, I winsorize extreme values at 1% and 99% levels, i.e., values less than the 1% percentile or greater than the 99% percentile are set to be the values of the 1% and 99% percentiles, respectively. Annual cross-sectional estimations yield firm- and year-specific residuals, that form the basis for the accruals quality metric: $AQ_{j,y} = \sigma(\varepsilon_j)_y$ is the standard deviation of firm *j*'s residuals, $\varepsilon_{j,y}$, calculated over years *y-4* through *y*. Because $\sigma(\varepsilon_j)_y$ is based on five annual residuals, my sample is restricted to firms with at least 7 years of data (recall that estimating the AQ requires both lead and lag cash flows). This restriction likely biases the sample towards firms that are larger and more successful. The unexplained portion of the variation in working capital accruals is an inverse measure of accruals quality (a greater unexplained portion implies a poorer quality). Because the AQ metric requires one lead cash flow observation, the period considered spans until December 2006 starting from February 1983.

Appendix C: Definitions of explanatory variables

FDisp	Forecast dispersion is the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts divided by the absolute value of the average forecast (with zero-average-forecast observations excluded from the sample). Forecast dispersion is computed at the end of six months before fiscal-year end.
Unc	The uncertainty index of Anderson et al. (2009) measured as the standard deviation of the aggregate corporate profits (rather than earning forecasts of individual firms).
Beta	The estimated systematic risk from a market model regression, estimated over previous -1 to -52 weekly returns.
RV	The residual variance over previous -1 to -52 weekly returns, relative when forecast dispersion is computed. I assume a single factor return generating process and measure the firm level idiosyncratic risk relative to the traditional Capital Asset Pricing Model (CAPM): $$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{i,t},$$ where $R_{i,t}$ is the return on stock *i* at week *t*, $R_{f,t}$ is the risk free rate at week *t*, and $R_{m,t}$ is the market return at week *t*. The risk free rate is the 1-month Treasury bill rate, and market return is the CRSP value-weighted market index. Weekly return is the daily compounded return over a given week.
Log(MV)	The natural logarithm of market value (in millions) computed as stock price times number of shares outstanding.
BM	Book-to-Market ratio is the total assets (#6) minus liabilities (#181) plus deferred taxes and investment tax credit (#35), minus book value of preferred stock (in the following order: redemption value (#56) or liquidating value (#10) or carrying value (#130) divided by the market value.

FAgeStd The annualized (divided by 365) standard deviation of forecast ages from non-conflicted analysts. Age is the number of calendar days between analyst's last forecast for a given firm and the day when forecast dispersion is computed. If the number of non-conflicted analysts is below two, the *FAgeStd* is set to zero.

BidAskSpr The average of the daily bid-ask spreads over the previous 50 days relative to the day when forecast dispersion is computed. The daily bid-ask spread is the absolute value of the difference between the bid and ask prices, scaled by the middle price.

Info/Noise The Info/Noise measure of Burlacu et al. (2008) computed as $\ln(R^2/(1-R^2))$ where R^2 is from regressing firm weekly returns on its lagged stock price, and four value-weighted industry returns, over previous -1 to -52 weeks as follows:

$$r_{i,t} = \alpha_0 + \beta_1 P^N_{i,t-1} + \beta_2 P^N_{SIC4\backslash i,t-1} + \beta_3 P^N_{SIC3\backslash 4,t-1} + \beta_4 P^N_{SIC2\backslash 3,t-1} + \beta_5 P^N_{SIC1\backslash 2,t-1} + \varepsilon_{i,t},$$

where

$r_{i,t}$ is firm's compounded return over a given week

$P^N_{i,t-1}$ is firm's normalized stock price

$P^N_{SIC4\backslash i,t-1}$ is calculated using stocks with the same 4-digit SIC code as stock i, but excluding stock i

$P^N_{SIC3\backslash 4,t-1}$ is calculated using stocks with the same 3 digit SIC codes but different 4 digit SIC codes

$P^N_{SIC2\backslash 3,t-1}$ is calculated using stocks with the same 2 digit SIC codes but different 3 digit SIC codes

$P^N_{SIC1\backslash 2,t-1}$ is calculated using stocks with the same 1 digit SIC codes but different 2 digit SIC codes

At time *t*, the normalized price equals $\prod_{k=1}^{t}(1+r_{i,k}) / \prod_{k=1}^{t}(1+r_{m,k})$, where $r_{m,k}$ is the compounded CRSP value-weighted market return over a given week. The cumulative market and stock returns are set to 1 in January 1982.

Δ*Rat* Rating change is the change in S&P Long Term Issuer Credit Rating for firm j during the past 12 months.

$$\begin{cases} 0, & \text{if no change in rating} \\ \text{Rating}_{j,t}\text{-Rating}_{j,k}, & \text{if change in rating during } t\text{-}12<k<t \end{cases}$$

The entire spectrum of ratings is as follows: AAA=22, AA+=21, AA=20, AA−=19, A+=18, A=17, A−=16, BBB+=15, BBB=14, BBB−=13, BB+=12, BB=11, BB−=10, B+=9, B=8, B−=7, CCC+=6, CCC=5, CCC−=4, CC=3, C=2, D=1.

ΔZScr Yearly change in Altman (1968)'s Z-Score computed as

$$\Delta ZScr = 1.2\cdot\Delta X1 + 1.4\cdot\Delta X2 + 3.3\cdot\Delta X3 + 0.6\cdot\Delta X4 + 0.999\cdot\Delta X5,$$

where
X1 = working capital/total assets = #179/#6
X2 = retained earnings/total assets = #36/#6
X3 = earnings before interest and taxes/total assets = #178/#6
X4 = market value equity/book value of total liabilities = (#199·#25)/#181
X5 = sales/total assets = #12/#6

RelFE Previous year's relative forecast error, computed as the absolute difference between average (consensus) forecast and actual earnings divided by actual earnings. Actual earnings are as reported in I/B/E/S Actual Unadjusted file adjusted for stock splits. Zero-actual-earnings observations are excluded.

Herd The proportion of herding forecasts where an analyst's forecast is classified as herding if it is between the prevailing consensus and the most recent forecast issued by the same analyst.

ConfInt $ConfInt = -pLn(p) - (1-p)Ln(1-p)$, where p is the proportion of conflicted analysts. Analyst is marked as conflicted if he works for an investment bank that led or co-led any IPO or SEO.

PastRet Compounded return over the previous -1 to -12 months relative to the month when forecast dispersion is computed.

Appendix D: Definitions of control variables

Excess return	Excess return is firm's raw return less risk-free rate, where risk-free rate is the 1-month Treasury bill rate.
FDisp	Forecast dispersion is the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts (unadjusted for stock splits) divided by the absolute value of the average earnings forecasts. Zero average-forecast observations are excluded.
CorpSpr	Corporate spread is Moody's BAA-AAA corporate bond yield spread.
TermSpr	Term spread is Moody's term yield spread defined as the long-term U.S. government bond yield minus the yield on three-month U.S. Treasury bills.
Yield	Moody's yield on three-month U.S. Treasury bills.
Turn	Turnover is the ratio of trading volume to the number of shares outstanding.
MV	Market value (in billions) is the price per share times shares outstanding.
BM	Book-to-Market ratio is the total assets (#6) minus liabilities (#181) plus deferred taxes and investment tax credit (#35), minus book value of preferred stock (in the following order: redemption value (#56) or liquidating value (#10) or carrying value (#130) divided by market value.
RetM-N	Cumulative return over the past M to N months relative to the current month, i.e., $\prod_{t=M}^{N}(1+r_t)-1$ where r_t is the stock return in month *t*. For example, *Ret4-6* is the cumulative returns over the previous fourth through the previous sixth months.

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