WORK IN PROGRESS
Please do not quote

Why the Stock Market May Underweight Bad News: An Empirical Analysis

Anna Scherbina

Finance Department
Kellogg School of Management
Northwestern University

January 2002

Correspondence: Anna Scherbina, Finance Department, Kellogg School of Management, Northwestern University, phone: (847) 467-6175, fax: (847) 491-5719, email: a-shcherbina@nwu.edu. This paper is based on the second part of my Ph.D. dissertation. I would like to thank the members of my dissertation committee: Kent Daniel, Ravi Jagannathan, Kathleen Hagerty, Todd Pulvino, and Beverly Walther for their consistent guidance and support. I am also grateful to Torben Andersen, Bob Korajczyk, Joel Lander, Tom Lys, Bob McDonald, Iwan Meier, Chris Polk and Volker Wieland for many valuable discussions and suggestions. Finally, I would like to thank I/B/E/S for making its dataset available to me through its projects with Ravi Jagannathan and Janice Eberly. I am responsible for any remaining errors.

Abstract

It has been shown that stocks with high dispersion in analysts' earnings per share forecasts subsequently underperform otherwise similar stocks. In this paper, I document that higher-dispersion stocks tend to have a more optimistic bias and more negative subsequent revisions in the mean earnings-per-share forecast. I hypothesize that this relationship results from the unwillingness of analysts with pessimistic outlooks to post their earnings forecasts. If some investors do not have knowledge of the positive relationship between dispersion and the forecast bias, their valuations will be too optimistic whenever dispersion is high. If these investors are also dogmatic about their beliefs, the resulting market prices will also be upwardly biased whenever investors with correct valuations are impeded from selling stock (as conjectured by Miller (1977)). Consistent with this scenario, I show that dispersion affects returns around earnings announcement days only through its impact on the forecast bias. Additionally, for the group of stocks with a positive sensitivity of turnover to dispersion, the return differential between the low- and high-dispersion stocks is on average lower than for similar stocks.

I. Introduction

Since the late 1970s, theoretical literature has been debating whether equity prices tend to reflect optimism whenever opinions diverge. One strand of the literature claims that because frictions, such as short sale costs, impede the revelation of negative opinions, they thereby induce an upward bias in market prices.[1] The other, more pervasive, strand of the literature argues that market participants are able to account correctly for the negative information which is being held back, and thus produce unbiased prices.[2] Recently, the first claim has received empirical support. Diether, Malloy and Scherbina (2001) and Chen, Hong and Stein (2001) show that stocks with high level of disagreement about their value underperform otherwise similar stocks in the future, indicating that they have been initially overpriced.[3]

In this paper, I focus on dispersion in analysts' forecasts as predictor of future returns. I document that the optimistic bias in the mean earnings per share forecast is increasing in dispersion, and the future forecast revisions are decreasing in dispersion. I argue that this pattern arises because the more pessimistic analysts choose not to say anything rather than issue a low earnings-per-share estimate (this phenomenon, dubbed as self-selection in analyst coverage, was first documented by McNichols and O'Brien (1997)). Consequently, when the level of disagreement between analysts is high, the analysts who do not voice their opinion are likely to be more pessimistic, and the mean of the reported forecast will be more upwardly biased. As the uncertainty about annual earnings is resolved over the course of the year, the initially optimistic analysts are forced to revise their forecast down, and more so for the stocks where the initial bias was higher.

If some investors do not discount analysts' forecasts for the self-selection in analyst coverage, their valuations will be upwardly biased, and the bias will be increasing in dispersion. Thus,

[1] For example, Miller (1977), Morris (1996), Chen, Hong and Stein (2001) and Viswanathan (2001).

[2] For example, Diamond and Verrecchia (1987), and Hong and Stein (1999)

[3] Chen, Hong and Stein (2001) measure the magnitude of disagreement by the breath of mutual fund ownership (fraction of mutual funds holding a particular stock). Diether, Malloy and Scherbina (2001) use dispersion in analysts' earnings forecasts to measure disagreement.

dispersion may generate disagreement between investors who understand the implications of self-selection in analyst coverage and the ones who do not. This disagreement may result in the upwardly biased prices if investors with correct valuations are constrained from selling the stock, and investors with initially optimistic valuations are either dogmatic about their beliefs or mistakenly assume that other investors do not sell the stock because they agree with the price.

I provide evidence in favor of this scenario. If analysts have a different degree of disincentives from reporting low forecasts across stocks, then the relationship between the underlying analyst disagreement and the forecast bias will be different across stocks as well. In that case, it is possible to separately identify the direct effect of dispersion on returns and its effect through its influence on the forecast bias. If dispersion only affects prices because of its correlation with the forecast bias, which some investors fail to understand, then its effect on returns will be less pronounced for the stocks for which the correlation is lower, and will disappear for the stocks where there is no relationship. This is what I find in the data. Dispersion in analysts' earnings per share forecasts predicts returns around earnings announcement day only to the extent it predicts the bias in the reported mean earnings forecast.

Miller (1977) and Viswanathan (2001) argue that the mispricing will be more severe, the more difficult it is for the pessimists to sell the stock. I provide support for this conjecture. I show that the return differential between the low- and high-dispersion stocks is insignificant for the group of stocks for which turnover increases with increasing dispersion, but is positive and significant for the group of stocks for which turnover does not respond or responds negatively to dispersion.

The rest of the paper is organized as follows. Section II describes the data. Section III describes analysts' inventives and the relationship between disperion and the forecast bias. Section IV indentifies why dispersion leads to disagreement. Section V investigates the relationship between predictive power of dispersion and past earnings forecast revisions. Secion VI analyses the impact of trading on the price optimism. Section VII takes a step in asking which reporting practices lead to analyst disagreement. It shows that high accruals (the difference between reported earnings and the underlying cash flows) lead to higher rather than lower analyst agreement; and so the predictive power of accruals on future returns in independent of the predictive power of dispersion. Finally, Section VIII concludes.

II. Data Description

Analysts' earnings forecasts are taken from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail History and Summary History datasets. The Summary History dataset contains the summary statistics on analyst forecasts, such as mean and standard deviation values. These variables are calculated on the basis of all outstanding forecasts as of (ordinarily) the third Thursday of each month. The Detail History file contains individual analyst forecasts and dates on which the forecasts were issued. Each record also contains a *revision date*, i.e., the date on which the forecast was last confirmed as accurate.

There is, however, a data problem in the standard-issue Summary and Detail files that makes them unsuitable for the purposes of this paper.[4] Earnings per share forecasts are adjusted by I/B/E/S for stock splits and stock dividends that occurred since the date of the forecast in order to make them easily comparable across time. The adjusted number is then rounded to the nearest cent. This creates a potential data truncation problem for firms with high number of stock splits or stock dividends: The reported mean and/or standard deviation in analysts' forecasts will be zero if the number of stock splits is sufficiently large. At the same time, a stock with a large number of splits is most likely to have done well ex-post. Thus, observations with the standard deviation of zero (and/or mean forecast of zero) will also contain firms that have earned high returns in the future. In order to avoid implicitly using this ex-post information, I use the forecasts not adjusted for stock splits, produced by I/B/E/S per my request.

Data on stock returns, prices, and shares outstanding are taken from the Center for Research in Security Prices (CRSP) daily and monthly stock files. The accounting data come from the merged CRSP/Compustat database, extending through fiscal year 2000. If less than three months has elapsed since the latest fiscal-year-end date, accounting data for the preceding year is used.

[4] This problem was first reported in Diether, Malloy and Scherbina (2001).

Book value of equity is calculated using Compustat annual data (including Research file). I use total common equity, if available, plus balance sheet deferred taxes and investment tax credit. If total common equity is not available, I use shareholder's equity minus the value of preferred stock. For preferred stock, I use redemption value, liquidating value, or carrying value in that order, as available. The book-to-market ratio is defined as the ratio of book value to market value of equity. Market value of equity is calculated as the product of month-end share price and the number of shares outstanding.

Stocks with high dispersion tend to be smaller, possibly smaller stocks are more opaque, and the quality of public information is available is not as high as for After controlling for size, stocks with high dispersion tend to have higher analyst coverage, possibly because there is more demand for expert opinions when it is difficult to interpret available information. High-dispersion stocks tend to be value stocks that have done poorly in the past[5] and have higher systematic risk.

In order to minimize the problem of bid-ask bounce, I use stocks priced at no less than $5 per share. Because I am interested in dispersion in analysts' earnings per share forecasts, I only consider stocks in the I/B/E/S database that are followed by at least two analysts. In January, 1981, the number of stocks, priced at above $5 a share and with at least two analysts following them, in the I/B/E/S and CRSP intersection, was 1239. Of these stocks, 858 were in the lowest nine NYSE market-capitalization deciles. In January 1983, the number of stocks in the I/B/E/S and CRSP intersection, with at least two analysts following them, grew to 1401. Of these, 962 were ranked in the lowest nine NYSE market-capitalization deciles. Finally, at the end of 1999, the total number of stocks in the intersection which were followed by at least two analysts became 3466, of which 2525 were in the lowest nine NYSE market capitalization deciles. For the intersection of I/B/E/S, CRSP, and Compustat datasets, the pattern is similar. However, the total number of observations available is lower because Compustat contains only a subset of stocks in CRSP. The number of stocks priced at above $5 a share and with at least two analysts following them in the intersection grew from 1049 in January 1981 to 1178 in January 1983, and

[5]Ciccone (2001).

to 1979 in December 1999. A more complete sample description is available in Table I of Diether, Malloy and Scherbina (2001).

Even though I/B/E/S has data going back to 1976, I choose the time period of January 1983 through December 2000 for tests that involve portfolio construction to allow for a larger cross-section of stocks, since the number of stocks in I/B/E/S has increased more than threefold from 1976 to 1983. Additionally, data for the Detail file only go back to 1983. However, the results of this paper are not sensitive to the time period specification.

III. Bias in Analysts' Forecasts

McNichols and O'Brien (1997) suggest that the information flow from analysts to investors is truncated, with low forecasts being censored out of the reported distribution due to analysts' incentives. This section shows that this information truncation creates a positive correlation between the level of analyst disagreement and the upward bias in the mean reported forecast. If some investors do not account for this property of analysts' forecasts, their valuations will be more optimistic the higher the level of disagreement among analysts.

A. Optimistic bias and systematic changes in the forecast error over the forecast horizon

It is documented in accounting literature that analysts' earnings forecasts are reflected in market prices.[6] Therefore, negative forecast revisions will be associated with low returns. In support of this prediction, the initial upward forecast bias and the magnitude of the future downward forecast revision are positively related to the initial dispersion in analysts' forecasts. Scherbina (2001) finds that analysts on average tend to have the more optimistic forecast errors for the quarterly earnings just before the announcement date, the higher the dispersion in the underlying forecasts. The time series of analysts' annual earnings forecasts also reveals that analysts tend to

[6]See, for example, Abdel-Khalik and Ajinkya (1982), Forbes and Skerratt (1992), Givoly and Lakonishok (1979), Gleason and Lee (2000), Gonedes, Dopuch and Penman (1976), Hawkins, Chamberlin, and W. Daniel (1984), Imhoff and Lobo (1984)and Stickel (1990).

be more optimistic in the beginning of the forecast period. The mean forecast tends to be revised downward over the forecast horizon. The magnitude of the optimistic bias and the speed of the downward revision is highest for the stocks which initially have the highest forecast dispersion. Figure 1 plots the average forecast errors, calculated as the mean forecast minus the realized annual earnings and scaled by the stock price in the beginning of the forecast horizon for stocks sorted into five portfolios based on dispersion in analysts' earnings forecasts at the beginning of the forecast period. The forecast period is defined as beginning 12 months before the fiscal year end and ending at the end of the fiscal year. Forecast error is defined as the forecast minus the actual earnings per share number. Forecast errors are averaged over portfolios and over the time period of February 1983 - December 2000. It is clear from Figure 1 that analysts are always more optimistic for high-dispersion stocks, but the downward revisions are most pronounced for these stocks as well.

Table I documents that the average downward forecast revisions are in fact higher on average for high-dispersion stocks. The differences in downward forecast revisions between the high- and the low-dispersion portfolios are positive and significant for all size groups, but higher for smaller stocks. The bottom plot on Figure 1 shows that even though the dispersion in analysts' forecasts declines over the forecast horizon, it is fairly persistent. For low-dispersion stocks it rises slightly probably as more information becomes available in the course of the year, increasing the scope for disagreement.

B. Self-selection in analyst coverage

The tension between the competing incentives to make accurate forecasts, generate sales commissions, help attract potential investment banking business, and maintain good relationship with the management of the firms they follow, creates self-selection in analysts' coverage. Analysts with pessimistic opinions tend to drop out of the forecasting pool.

An analyst's compensation is indirectly tied to his or her reputation. Firms that employ highly reputed analysts can potentially attract more trading business in exchange of offering stock recommendations of their analysts among other services. And analysts earn a percentage of the stock sales commissions generated by their employer. Analysts build reputation by issuing accurate earnings forecasts and buy/sell recommendations. This creates an incentive for analysts to research the firms they follow and derive accurate forecasts. However, besides encouraging accuracy, the incentive to generate sales commissions also encourages optimism. Not surprisingly, historically, analysts issued predominantly "strong buy" and "buy" recommendations, more rarely "hold" and even more rarely "sell" and "strong sell."

Possibly a more important concern among analysts is attracting potential investment banking business. This is illustrated by a quote from the article "Wall Street's Spin Game," which appeared in *Business Week* on 10/8/98:

"Most Wall Street research is pitched to institutional investors who pay the firm about a nickel a share in commissions. But if an analyst spends his time trying to land an initial public offering, the firm can earn 15 to 20 times that amount per share. Investment banking deals are much more lucrative for the brokerage firm. Merger advisory fees can be sweet as well..."

The incentive to attract the investment banking business encourages accuracy to the extent that analysts' reputation may be seen as reducing the information asymmetry between insiders and the outsiders to the investment banking deal. More importantly, a potential investment baking client may want their bank to have a positive outlook about their business. Thus an honest good opinion is encouraged, but an honest bad opinion is strongly discouraged by this incentive. Analysts may try adding an upward bias to their forecast, but their reputational concerns will keep a lid on this bias, after all, their compensation depends on the reputation, and the reputation depends on accuracy. Therefore, analysts will be likely to stop coverage while the outlook is bad.

Finally, analysts may not want to avoid appearing too pessimistic relative to others for the fear of repercussions from the management of the firms they follow. Analysts rely on management for information about the firm, and risk being cut off if they appear too bearish. Only in 2000 the Securities and Exchange commission instituted Regulation Fair Disclosure, a rule that prohibits selective disclosure to only some analysts or investors. But even despite of that there have been some violations, as evidenced by the article “In a Surprise Move, AOL Replaces Its Chief Financial Officer,” which appeared in *The New York Times* on 10/2/2001:

“Late last month, after the company reported its third-quarter financial results, two prominent Merrill Lynch analysts, Jessica Reif Cohen and Henry Blodget downgraded the company's stock... That decision drew an angry reaction from Mr. Kelly [the AOL's CFO] *according to several analysts, who said that the company stopped returning telephone calls from Ms. Cohen and Mr. Blodget.”*

The fear of being cut off from vital information makes analysts wary of appearing too pessimistic relative to others. Analysts may try to mimic more optimistic analysts, but if their signal is low enough, they may stop coverage altogether for the sake of their reputational concerns.

Thus, the competing analysts' incentives reward honesty when it comes to voicing optimistic opinions, but discourage it when it comes to pessimistic opinions. Therefore, if an analyst is concerned about her reputation, rather than being punished for being on the pessimistic tail of the forecast distribution, she may choose to stop coverage following a negative signal, or not revise the forecast down enough. Either way, this will cause an upward bias in the mean forecast.

McNichols and O'Brien (1997) document the self-selection in analysts' coverage. They find that analysts are more likely to issue “Strong Buy” recommendations for stocks they just started following then for the other stocks they follow. Similarly, stocks that analysts drop, tend to have lower recommendations than stocks they continue to cover. They show that this relative optimism about stocks which analysts just start to cover is not caused by intentional over-optimism. Rather, the earnings forecasts for these stocks are on average less upwardly biased than the latest forecasts for stocks that analysts end up dropping. They also find that subsequently realized return on equity is significantly higher for added stocks than for originally covered stocks and significantly higher for continuously covered stocks than for stocks that are dropped.

C. A simple model of self-selection

An analyst's incentive to stop coverage rather than ignore her signal will be stronger the more confidence she has in her signal. Therefore, both the magnitude of the upward bias in the mean forecast and dispersion in reported forecasts should depend on the precision of analysts' private signals relative to the common signals.

Indeed, if analysts with low earnings per share estimates refrain from reporting their forecasts, then the mean reported forecast will be upwardly biased. Given that analysts base their estimates both on common signals, available to all analysts, and private signals, the magnitude of the bias would depend not only on the precision of the common signal, but also on the relative precision of the private signal. If analysts perceive their private signals as precise relative to common information, they would be more willing to deviate from consensus. And the more willing they are to deviate from the consensus, the larger number of estimates will fall below the critical value, below which analysts prefer not to report their estimate, the higher will be the upward bias in the mean reported forecast. And so the bias will be higher, the higher the dispersion in the reported forecasts.

By the next round of forecasting, all private signals received by security analysts in the previous forecasting period become known to all analysts, making the common signal more precise. Analysts once again receive private signals with the same level of precision relative to the common signal, meaning that they are more precise than the private signals they had received relative to the previous round. Because the private signals are distributed according to the normal distribution around the correct mean, but this time a smaller variance, the mean reported forecast will be lower than earlier. The drop in the forecast bias will be more pronounced the higher the level of precision in the private versus common signal because there will be more information embedded in the new cumulative signal.

This logic is illustrated more precisely by the following model. Suppose that at time zero each analyst receives the same common signal about the distribution of the firm's earnings per share:

$$s_0 = AEPS + \epsilon_0 \tag{1}$$

where $AEPS$ is the actual earnings per share number and ϵ_0 is the noise term, normally distributed around zero: $\epsilon_0 \sim N(0, \sigma_0)$. In the first round of forecasting, $t = 1$, each analyst will receive a private signal, s_{i1}:

$$s_{i1} = AEPS + \epsilon_{i1} \tag{2}$$

The noise term ϵ_{i1} is normally distributed around zero ($\epsilon_{i1} \sim N(0, \sigma_{An,1})$) and uncorrelated with the common noise term ($cov(\epsilon_0, \epsilon_{i1}) = 0$). Upon receiving the private signal, analysts i's expectation of future earnings at $t = 1$ will therefore be equal to $\frac{s_{i1}\sigma_0^2 + s_0\sigma_{An,1}^2}{\sigma_0^2 + \sigma_{An,1}^2}$. If this number happens to be k standard deviations below the mean which is based on common information ($s_0 - k\sigma_0$), the analyst will not report the forecast (in this setup, k is determined exogenously).

At the end of the period, all private signals received by analysts become common knowledge to all analysts, and the new commonly available forecast becomes more precise. At the next forecasting period, the process is repeated. It is assumed that the precision level of private relative to common information, $\frac{\sigma_{st}}{\sigma_{t-1}}$, is constant over time.

Suppose for simplicity that the earnings expectations at time zero are zero: $s_0 = 0$. Consequently, at $t = 1$, analyst i, who has received signal s_{i1} expects earnings per share to be $F_{i1} = \frac{s_{i1}\sigma_0^2}{\sigma_0^2 + \sigma_{An,1}^2}$ If the forecast falls below the critical value of $-k\sigma_0$, the forecast does not get reported. Therefore, the mean of the reported forecast after the first forecasting period will be calculated as:

$$\begin{aligned} E_0[C_1] &= E_0\left[F | F \geq -k\sigma_0\right] \\ &= E_0\left[\frac{s_{i1}\sigma_0^2}{\sigma_0^2 + \sigma_{An,1}^2} \middle| s_{i1} \geq -k\sigma_0 \frac{\sigma_0^2 + \sigma_{An,1}^2}{\sigma_0^2}\right] \end{aligned} \tag{3}$$

Substituting $\nu \equiv \frac{\sigma_{An,1}}{\sigma_0}$, since this ratio will be constant over time, the solution to equation 3 can be expressed as:

$$E_0[C_1] = \sigma_0 \frac{\nu}{1+\nu^2} \frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})} \tag{4}$$

where $f(\cdot)$ and $\Phi(\cdot)$ are the probability density and the cumulative density functions of the standard normal distribution. As is obvious from the formula 4, the bias disappears in case that the private signal is certain ($\sigma_0 = 0$), in which case all analysts will report their signal, and in the case when the private signal is pure noise ($\sigma_s = \infty$), in which case analysts will just report the common signal. Even though the expected value of the earnings is zero, the expected mean forecast will be positive, due to the truncation induced by the self-selection in analyst coverage. The positive bias increases in the degree of uncertainty in the common signal.

The bias in the consensus mean therefore is not a linear function of the relative precision of the private signal, captured by $\frac{1}{\nu}$. When private signal is very precise, the truncation-caused bias will be very small since most of the private signals received by analysts will be very close to the mean of the distribution. On the other hand, when private signals are not informative, the truncation bias will be small once again, because analysts will not be very receptive to their private signals and will cluster around the commonly known mean. Therefore, for the bias to be increasing in the relative precision of private information, private signal has to be below a certain precision level. Hence, the following claim:

Proposition 1 *Whenever the private signal is less precise than the common signal, the bias in the mean forecast increases in the relative precision of the private signal.*

Proof In the Appendix.

Dispersion in the reported analysts' forecasts can be calculated similarly:

$$\begin{aligned} E_0[\text{VAR}(C_1)] &= E_0\left[F^2|F \geq -k\sigma_0\right] - \left[E_0\left(F|F \geq -k\sigma_0\right)\right]^2 \\ &= \sigma_0^2\left(\frac{\nu}{1+\nu^2}\right)^2\left[k\frac{\nu}{1+\nu^2}\frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})} + 1 - \frac{f^2(k\frac{1+\nu^2}{\nu})}{\Phi^2(k\frac{1+\nu^2}{\nu})}\right] \end{aligned} \tag{5}$$

Dispersion in reported analysts' forecasts is closely tied to the bias. Whenever, analysts come up with more dispersed forecasts, the more of them get censored out of the reported distribution. Thus the dispersion in reported forecasts is higher in the case when the bias is higher. This is true for some values of ν, and can be summarized by the following proposition:

Proposition 2 *Whenever the private signal is less precise than the common signal, dispersion in reported analysts' forecasts increases in the relative precision of the private signal.*

Proof In the Appendix.

Since both dispersion in reported analysts' forecast and the bias in the mean reported forecast are increasing in the relative precision of private information for a certain range of parameter values, the bias and dispersion are positively correlated.

By the second round of forecasting, all signals privately received by security analysts become common knowledge. This statement may seem strong, but it may be be justified by the reasoning that analysts would have already reported their forecasts, with some of them not issuing a forecast at all, and the rest of the analysts may decipher the signals they have received. Given that there are a total of K analysts following the firm, at time 0, expected earnings by the second round of forecasting will have a mean of zero, but the standard deviation of $\sigma_1^2 = \frac{\sigma_0^2\sigma_{An,1}^2/K}{\sigma_0^2+\sigma_{An,1}^2/K} = \frac{\sigma_0^2\nu^2}{K+\nu^2}$. All else equal, the precision of the new common information is positively related to the number of analysts following the firm, and, consequently, receiving private signals. It is also positively related to the relative precision of the private signals. In the second round of forecasting, analysts receive private signals and combine them with common information. Once again, they chose not to report their forecast if it happened to be k standard deviations below the commonly-known mean ($\mu_1 = \frac{1}{1+\nu^2}\sum_{i=1}^{K} s_{i1}$), or $\mu_1 - k\sigma_1$. Since the relative precision of private to common information is constant ($\nu \equiv \frac{\sigma_{An,2}}{\sigma_1} = const$), private information becomes more precise, or $\sigma_A n$ decreases. This is a realistic assumption, since as earnings announcement approaches, the tips analysts receive become more precise. The time zero expected value of the mean reported forecast at time 2 will be calculated similarly:

$$
\begin{aligned}
E_0[C_2] &= E_0\left[F|F \geq \mu_1 - k\sigma_1\right] \\
&= E_0\left[\frac{s_{i2}}{1+\nu^2}\middle| s_{i2} \geq \mu_1 - k\sigma_{An,2}\frac{1+\nu^2}{\nu}\right] \\
&= E_0[\mu_1] + \sigma_1\frac{\nu}{1+\nu^2}\frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})}
\end{aligned}
$$

$$
\begin{aligned}
&= \sigma_0 \frac{\nu}{\sqrt{K+\nu^2}} \frac{\nu}{1+\nu^2} \frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})} \\
&= \frac{\nu}{\sqrt{K+\nu^2}} E_0[C_1] \qquad (6)
\end{aligned}
$$

$E_0[\mu_1] = 0$ since the expectation of the mean of the signals in the first forecast period is equal to the mean of the commonly-known distribution.

The bias in reported forecasts is lower in the second round of forecasting ($\frac{\nu}{\sqrt{K+\nu^2}} < 1$) even though the critical value below which the forecasts get truncated is closer to the mean than after the first period. This is because the new analysts' earnings estimates are not as dispersed as earlier, due to an increased precision of private information, so the amount of information that gets truncated out of the distribution is not as large. This effect dominates the first effect. Hence, the following proposition.

Proposition 3 *Whenever the private signal is less precise than the common signal, the drop in the expected bias in consensus forecasts is more pronounced for the stocks with higher relative precision of the private signal.*

Proof In the Appendix.

This two-period model could be easily extended to multiple forecasting periods. Thus, the self-selection in analyst coverage will lead to higher optimistic bias for the stocks with high dispersion in earnings forecasts and more pronounced downward revisions over the forecast horizon. If investors fail to account for the information truncation caused by analysts' incentives, they will form optimistic view, and will likely be disappointed in the future, much like the analysts with optimistic private signals who are likely to be forced to revise their forecasts down.

The predictions of these model are confirmed by the data, and were discussed in the beginning of this section. Figure 1 indicates that the forecast bias declines over time, and more so for high-dispersion stocks. Dispersion declines over the forecast horizon as well. The second plot of Figure 2 shows that the most pessimistic forecast declines over the forecast horizon. If one were to take the model described earlier at a face value, they would have to conclude that the truncation point below which analysts chose not to report their forecasts is above the mean. However, there could be other explanations. For example, analysts may add a deliberate bias in the beginning of the fiscal year, planning to gradually reduce it over the year.[7] In that case, the truncation point below the mean, combined with a positive initial bias will lead to the downward revision in the mean forecast. An important evidence in favor of the truncation is that the maximum forecast declines much faster that the minimum forecast. This means that the optimistic analysts have to reduce their forecast by more than just the amount of the initial bias over the fiscal year. The last three plots provide more indirect evidence in favor of the truncation explanation. They show that most forecast revisions are downward revisions, consistent with the model. On average, 16 to 24 percent of all analysts revise their forecasts down every month during the fiscal year. These numbers imply that analysts revise down a little at a time, whereas they revise up less gradually. This is consistent with the incentive not to appear too pessimistic relative to others and waiting for others to revise their forecasts down before a further downward revision. Most of the forecast revisions happen just before the end of the quarter, when analysts update their annual earnings forecasts, while they are updating their quarterly forecasts. Analysts are forced to revise their forecasts down in grater numbers towards the end of the fiscal year, when the uncertainty gets resolved rapidly.

IV. Verifying the Cause of Disagreement

If dispersion is associated with disagreement because some investors do not understand that higher dispersion leads to a higher price bias, then dispersion will have no predictive power on returns beyond its predictive power on the forecast bias. It is possible to estimate the two effects separately as long as relationship between dispersion and forecast bias varies across stocks. If analysts are more reluctant to report pessimistic forecasts for some stocks than others, the constant k such that analysts will not report below $-k\sigma$ will differ across stocks. Hence, the relationship between

[7] This behavior has been conjectured by Richardson, Teoh, and Wysocki (2001).

dispersion and bias in the consensus forecast will also differ. If the relationship between dispersion and the bias in consensus forecast is stable over time for a given stock, then it is possible to predict the forecast bias using dispersion.

It is natural to investigate whether dispersion has predictive power beyond its ability to predict the forecast error by looking at returns around earnings announcement days. At this time, most of the uncertainty about annual earnings is resolved. The models of Morris (1996) and Viswanathan (2001) predict that the resolution of uncertainty will be associated with low returns.[8]

I assume that all returns can be described by the market model with $\beta = 1$:

$$r_{it} = r_{mt} + \epsilon_{it} \tag{7}$$

where r_{it} and r_{mt} are daily log-returns on an individual stock and CRSP equally-weighted index, respectively.[9]

Assuming that day 0 is the announcement date, the cumulative abnormal return (CAR) is estimated as:

$$CAR_{it} = \frac{1}{3} \sum_{\tau=-1}^{\tau=1} (r_{i\tau} - r_{m\tau}) \tag{8}$$

Then I run the following two-stage estimation. In the first step, I look at the in-sample relationship between forecast error:

$$FE_{it} = \alpha_{0i} + \alpha_{1i}\sigma_{it} + \epsilon_{it} \tag{9}$$

where FE is the forecast error, defined as the realized earnings per share minus the consensus earnings per share forecast, scaled by the stock price as of the end of the previous quarter and σ is the standard deviation in the reported forecasts scaled by price at the end of the previous quarter.

[8]Scherbina (2001) documents that high-dispersion stocks tend to earn negative abnormal returns around the quarterly earnings announcement days.

[9]Brown and Warner (1985) find that this model performs adequately well relative to more sophisticated models.

Next, I estimate how much of the cumulative abnormal returns around announcement days are due to the predicted part of the forecast error, and how much is due to part of dispersion independent of the forecast error:

$$CAR_{it} = \beta_0(\alpha_{1i}\sigma_{it}) + \beta_1\sigma_{it} + \nu_t + u_{it} \tag{10}$$

I find that the coefficient on the predicted part of the forecast error is positive and significant (β_0 = 0.006 (t-*statistic*= 4.20)) and the coefficient on dispersion is insignificant (β_1 = 0.009 (t-*statistic*= 1.11)).[10] When only dispersion is used in the second equation, its coefficient is negative and significant. This evidence confirms that disagreement arises because some investors do not discount analysts' forecasts for the self-selection bias.

V. Earnings forecast revisions

If dispersion predicts the likelihood that the mean forecast will be revised down, the past forecast revision may capture the tendency of the forecast to be revised down even better than dispersion. Chan, Jegadeesh and Lakonishok (1998) document that revisions in mean analysts' forecasts are positively autocorrelated. They also show that the revisions in the mean earnings forecast help predict the cross-section of stock returns. They call this phenomenon "earnings momentum." I calculate revision in the mean forecast over the previous n months as the difference between the current earnings-per-share forecast and the forecast for the same fiscal year end n months ago and scaled by the absolute value of the current month's mean forecast (observations with the mean forecast of zero are removed from the sample). I then add earnings forecast revisions for the previous one to six months ($Rev1$ to $Rev6$) and the cross-product of dispersion in analysts' forecasts and forecast revisions to the cross-sectional regression of next month's returns, alongside the constant term ($Const.$), size ($ln(ME)$), book-to-market ratio ($ln(BE/ME)$), dispersion in analysts' forecasts (*Disp.*), and residual analyst coverage (*Resid. Cov.*), defined in the previous section.

[10] I still need to correct the standard errors of these estimates for the fact that α_{1i} was also estimated.

Table II shows regression coefficients. Coefficients on $ln(ME)$, $ln(BE/ME)$ and *Res. Cov.* are insignificant and are not reported. The constant term is always significant, and is not reported either. Dispersion loses significance when forecast revision spans the previous six month. This means that by that point, the revision variable incorporates the predictive power embedded in dispersion. As hypothesized earlier, calculating the change in the mean forecast over the previous half-a-year, reduces transitory changes in the mean forecast and subsumes the predictive power of dispersion. Not surprisingly then, when the cross product of the forecast revision and dispersion is included in the regression, it comes out negative. This regression specification invariably makes the dispersion variable negative and significant. This means that when the mean earnings forecast was revised up, a high current level of dispersion indicates low future returns.

Table III further investigates this nonlinearity. *Dummy* equals 1 when the forecast revision over the previous six months has been positive. As expected, the product of the dummy variable and dispersion is always negative and significant. The dummy itself is significant: The fact that the previous forecast revision has been positive raises expected future returns. These returns will be higher the higher was the forecast revision, but less so for stocks with higher dispersion in analysts' forecasts, large-cap stocks, and value stocks. Daniel and Titman (1999) document that price momentum is less pronounced for value stocks; Jegadeesh and Titman (1993) also show that larger firms are less susceptible to price momentum. The same appears to be true for the earnings momentum.

A. The January effect

In order to see whether the pattern of the return differential between the low- and high-dispersion stocks over the year, follows the pattern of the downward earnings forecast revisions, I form five portfolios based on dispersion in analysts' earnings forecasts as of the previous month. I then run monthly Fama and French (1993) regression of the return differential between the low- and high-dispersion stocks on the size, book-to-market, market, and momentum factors. The alphas from the regressions are Newey-West adjusted for autocorrelation. Because I use only 18 years of data, the statistical power of the test is not very high. Therefore, I use the 10% rather than 5% level to determine the statistical significance. Figure 2 plots alphas for the Fama-French four-factor alphas surrounded by the dotted lines, representing the 10% significance bounds, calculated using the t-statistics corresponding to 18 observations.

The first graph uses all stocks. It shows that the return differential, while positive and significant on average, is negative and significant in January. As it turns out, both low- and high-dispersion portfolios do well in January, but the high-dispersion portfolio earns significantly higher returns.

I then proceed to see how the January effect holds for different size groups. I sort all stocks into size quintiles based on the level of market capitalization as of the last month. Within each size group, I sort stocks into quintiles based on dispersion in analysts' forecasts and calculate the four-factors Fama-French alphas on the return differentials by size. The January effect is not present for the smallest size quintile. It is present but insignificant for the second and third smallest size quintile. But it is negative and significant for the largest two size quintiles.

However, since the majority of stocks in my sample have December fiscal year end, the January effect may have something to do with the initial over-optimism at the beginning of a fiscal year. Therefore, I separate stocks by the fiscal year end. I have at least 27 stocks per portfolio on average for March, June, September and December fiscal year ends. For other months as fiscal year ends I have much fewer stocks, which would mean too much idiosyncratic noise. I do the same calculations for the stocks with different fiscal year ends, and find that the January effect is negative and significant for all of them, except for September fiscal year end. Therefore, the January effect seems to be independent of the beginning-of-fiscal year phenomenon.

I hypothesize that the January effect is caused by tax-related selling or selling by mutual funds which is motivate by window-dressing of high-dispersion stocks (which are likely to be past losers) in December and buying them back in January (hence, the high return differential in December and the low on in January). However, further research is in order.

VI. Sorting on the Responsiveness of Turnover to Dispersion

As conjectured by Miller (1977) and Viswanathan (2001), the optimistic bias in stock prices will be lower the less constrained are the pessimistic investors from selling stock. Scherbina (2001) attempted to test this conjecture by trying to assess the costliness of taking a short position in a stock. However, she found no relationship between her proxies for short-sale costs and future returns.

Here I use turnover instead for estimating how easy it is to trade based on disagreement. Whenever the level of disagreement is high, pessimistic investors will sell the stock by either taking a short position in a stock or selling off their holdings. If disagreement is consistently associated with high turnover, then pessimistic views can easily get into prices, and stocks with high levels of disagreement will not earn subnormal returns. If, on the other hand, pessimistic investors face high costs of selling, their views will not get reflected in prices, and stocks with high levels of disagreement will earn low subsequent returns.

I use an approach first suggested by Viswanathan. For each stock, I regress turnover (defined as a ratio of monthly trading volume to the total number of shares outstanding as of the end of the month) on dispersion in analysts' earnings per share forecasts, size and book-to-market ratio in a time series regression. I then assign stocks into two groups based on whether the regression coefficient on dispersion is positive or not.

I find that for the group of stocks for which turnover increases with dispersion, the return differential between the low- and high-dispersion stocks is not as high as for the group of stocks for which turnover does not increase with dispersion, as shown in Table IV. This result supports the hypothesis that whenever there is trading based on negative information, the mispricing is ameliorated.[11]

[11] Viswanathan sorts stocks based on responsiveness of short interest to dispersion and finds that the returns differential between the high- and low-dispersion stocks is lower for the group of stocks with a higher responsiveness coefficient. Additionally, I repeat the same exercise by estimating the responsiveness of total institutional holdings and the breadth of institutional ownership to dispersion, and find similar result: Whenever institutions trade in response to increased dispersion, the return differential is less pronounced.

In the future, I intend to identify whether mispricing persists for some stocks because they are illiquid or because they are in the domain of the less sophisticated investors.

VII. Which Factors Influence Analyst Disagreement?

A. Accruals

This is the first step in explaining what causes disagreement among analysts. Accruals represent the difference between reported earnings and the underlying cash flows. Accounting principles allow for some leeway in the timing and amount of costs and revenues recognized, and as a result, the reported earnings may differ from the underlying cash flows. Sloan (1996) has first documented that stocks with high accruals subsequently underperform stocks with low accruals. Chan, Jegadeesh and Lakonishok (2001)–CJL'01 from now on–undertake a detailed study of the sources of the predictive power of accruals. They examine three alternative hypotheses:
1) High accruals arise from earnings manipulation designed to fool investors, and returns drop as investors catch on.
2) A component of accruals, working capital, tends to rise with the rise in sales. High accruals are thus correlated with the strong past growth in sales. If investors systematically overestimate the future sales growth from the short past history, they will likely be disappointed in the future, and so high accruals will lead to low returns.
3) Several components in accruals are known to be correlated with the business conditions. An increase in inventories may coincide with slowing sales, and an increase in accounts payable may signify that a firm is having trouble making its payments; so both may indicate adverse business conditions. While the the change in inventories enters the formula for accruals with a positive sign, change in accounts payable enters with a negative sign. If investors underreact to these indicators of the business conditions, and the inventories effect dominates, then accruals will forecast future returns simply because they are correlated with the buildup in inventories.

CJL'01 find strong evidence in support of the first hypothesis: firms with high accruals tend to have experienced a large increase in accruals and deterioration in cash flows over the prior year. The high past earnings growth tends to continue for a while, even as the accruals component is high, before it starts to eventually deteriorate. This suggests deliberate earnings manipulation.

By decomposing accruals into a component predicted by the past trends in sales growth and the one which is not, CJL'01 do not find support for the second hypothesis. Finally, they observe that changes in inventory is the most important component of accruals in predicting future returns. At the same time, changes in accounts payables is negatively rather than positively correlated with future returns (as is consistent with the third rather than first hypothesis, since an increase in accounts payable lowers accruals, but indicates adverse business conditions). These observations lend support to the third hypothesis: the overall accruals number is an indicator of a firm's business conditions. It is important to note that the first and the third hypotheses are not mutually exclusive: Management may desire to manipulate earnings when business conditions start to deteriorate.

It is not immediately clear how accruals should be correlated with the level of disagreement among analysts. The practice of earnings management may lead to an increased agreement for two reasons: (1) analysts know what the target earnings number is and expect that the management will be able to meet it; (2) management may directly communicate the target earnings number to the analysts. In this case, the predictive power of the dispersion in analysts' forecasts will be independent of the predictive power of accruals, because it is only the stocks with high level of dispersion that earn subnormal returns. Stocks with low levels of dispersion do not earn high abnormal returns.

On the other hand, earnings management creates a disconnect between the actual firm performance and the reported earnings. When a firm's management does not communicate with analysts, then in addition to evaluating the firm's financial performance, analysts must also assess its ability to keep up the earnings manipulation practice, which may create a higher scope for disagreement. In this case, the practice of earnings management may lead to a higher average level of dispersion in analysts' forecasts.

Insofar as part of the predictive power of accruals lies in the correlation with the business conditions, high accruals may lead to higher levels of disagreement whenever analysts differ in their ability to account for the business cycle.

In case that high accruals coincide with high levels of analyst disagreement, the predictive power of dispersion in analysts' forecasts may turn out to be subsumed by the predictive power of accruals. To test whether this is the case, I form portfolios of stocks in the intersection of I/B/E/S, CRSP and Compustat based on independent sorts on accruals and dispersion in analysts' forecasts and evaluate portfolio returns. I use Sloan's (1996) definition of accruals:

$$\begin{aligned} Accruals &= \Delta CA - \Delta CL - DEP \\ &= (\Delta AR + \Delta INV + \Delta OCA) - (\Delta AP + \Delta OCL) - DEP \end{aligned} \tag{11}$$

where ΔCA is the change in non-cash assets (which can be further decomposed as the the sum of change in accounts receivable, ΔAR, change in inventories, ΔINV, and change in other current assets, ΔOCA); ΔCL is the change in current liabilities excluding short-term debt and taxes payable (which is further decomposed as the sum of change in accounts payable, ΔAP, and change in other current liabilities, ΔOCL); and DEP is depreciation and amortization.

I sort stocks into quintiles based on the level of accruals. Within each quintile, I sort stocks into quintiles based on dispersion in analysts' earnings per share forecasts. Portfolios are formed every month, returns are equally- weighted. The time period under consideration is February 1983 through December 2000. As can been seen from Table V, the return differential between low- and high-dispersion stocks is positive and significant within each accruals-based quintile and is slightly increasing with the level of accruals. The bottom table shows that there is considerable variability in the level of dispersion within each accruals quintile, but on average the high-accruals quintile has lower levels of dispersion. Since these are smaller stocks, and dispersion tends to be positively correlated with size, this further shows that high accruals firms tend to have higher levels of analyst agreement. This evidence is consistent with the assumption that whenever management indulges in earnings management, it tends to communicate the target earnings number to analysts. Hence, the predictive power of accruals is independent of the predictive power of dispersion. For the entire sample, the return differential between the low- and high-accruals firms is on average 0.54 percent per month, while the return differential between the low- and high-dispersion stocks is on average 0.63 percent per month. The second number is more economically significant, but less statistically significant because the time series of returns is more volatile.

VIII. Conclusion

Dispersion in analysts' earnings per share forecasts is correlated with an optimistic bias in the mean reported forecast. This happens because analysts prefer not to report their forecasts when they are sufficiently pessimistic relative to their peers. Failure of some investors do not understand the correlation between dispersion and bias in the consensus forecasts leads to disagreement about the stock value. This is evidenced by the fact that only those stocks with strong negative correlation between forecast error and dispersion earn low returns around quarterly earnings announcement days.

I also document that while high-dispersion stocks underperform the low-dispersion stocks on average over the year, they outperform them in January. The phenomenon is similar to the one observed in momentum returns, which has been explained by tax-related selling, and requires further analysis.

As predicted by Miller (1977) and Viswanathan (2001), the upward bias in prices will be most pronounced whenever pessimistic investors are most constrained from selling the stock. Consistently, I find that the return differential between the high- and the low-dispersion stocks is lower for the group of stocks for which turnover responds positively to increases in dispersion.

Finally, earnings management is associated with lower levels of disagreement among analysts. More research is required to answer which reporting practices cause analysts to disagree.

References

Abdel-khalik, A. and B. Ajinkya, 1982, "Returns to informational advantages: The case of analysts' forecast revisions," *The Accounting Review* October: 661-680.

Brown, S. J., J. B. Warner, 1985, "Using daily stock returns: The case of even studies", *Journal of Financial Economics* 14, 3-31.

Chan, L.K.C., N. Jegadeesh, and J. Lakonishok, 1996, "Momentum Strategies," *The Journal of Finance* 51, 1681-713.

Chan, L.K.C., N. Jegadeesh, and J. Lakonishok, 2001, "Earnings quality and stocks returns: the evidence from accruals," NBER Working Paper 8308.

Chen, J., H. Hong and J. Stein, 2001, "Breadth of ownership and stock returns," Manuscript, Stanford University

Clement, M., 1999, "Analyst forecast accuracy: do ability, resources, and portfolio complexity matter?" *Journal of Accounting and Economics* 27, 285-303.

Ciccone, S., 2001, "Analyst forecast properties, financial distress, and business risk," Manuscript, University of New Hampshire.

Diamond, D. and R. Verrecchia, 1987, "Constraints on short-selling and asset price adjustment to private information," *Journal of Financial Economics* 18, 277-311.

Diether, K., C. Malloy and A. Scherbina (2001) "Differences of opinion and the cross-section of stock returns," *The Journal of Finance*, forthcoming.

Fama, E and J. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy* 81, 607-636.

Forbes W. and L. Skerratt, 1992, "Analysts' forecast revisions and stock price movements," *Journal of Business Finance and Accounting* June: 555-564.

Gervais, S., R. Kaniel and D. Mingergrin, 2001, "The high-volume return premium," *The Journal of Finance*, 56, 877-919

Givoly, D. and J. Lakonishok, 1979, "The information content of financial analysts' earnings forecasts," *Journal of Accounting and Economics* March: 165-185.

Gleason, C. and C. Lee, 2000, "Characteristics of price informative analyst forecasts," Working paper, University of Arizona.

Gonedes, N., N. Dopuch, and S. Penman, 1976, "Disclosure rules, information production, and capital market equilibrium: The case of forecast disclosure rules," *Journal of Accounting Research* Spring: 89-137.

Hawkins, E., S. Chamberlin, and W. Daniel, 1984, "Earnings expectations and security prices," *Financial Analysts Journal* September/October: 24-37.

Hong, H., and J. Kubik, 2001, "Analyzing the analysts: Career concerns and biased earnings forecasts," *Journal of Finance*, forthcoming.

Hong, H., T. Lim and J. Stein, 1999, "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies," Manuscript, Stanford University.

Hong, H. and J. Stein, 1999, "Differences of Opinion, Rational Arbitrage and Market Crashes," NBER Working Paper 8151.

Imhoff, E. and G. Lobo, 1984, "Information content of analysts' composite forecast revisions," *Journal of Accounting Research* Autumn: 541-554.

Jegadeesh, N. and S. Titman, 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency," *Journal of Finance* 48, 65-91

Lee, C.M.C. and B. Swaminathan, 2000, "Price momentum and trading volume," *The Journal of Finance* 55, 2017-2069.

McNichols, M. and P. O'Brien, 1997, "Self-selection and analyst coverage," *Journal of Accounting Research* 35, 167-199.

Miller, E., 1977, "Risk, uncertainty, and divergence of opinion," *Journal of Finance* 32, 1151-1168.

Morris, S., 1996, "Speculative investor behavior and learning," *Journal of Financial Economics* 111, 1111-1133.

Pownall, G., P. Simko and G. Waymire, 2001, "The economic significance of large short interest increases," Manuscript, Emory University.

Richardson, S, S.H. Teoh and P. Wysocki "The walkdown to beatable analyst forecasts: the roles of equity issuance and insider trading incentives," 2001, Manuscript, University of Michigan.

Scherbina, A., 2001 "Stock prices and differences of opinion: Empirical evidence that prices reflect optimism," Manuscript, Northwestern University.

Sloan, Richard G., 1996, "Do stock prices fully reflect information in accruals and cash flows about future earnings?" *Accounting Review* 71, 289-315.

Stickel, S., 1990, "Predicting individual analyst earnings forecasts," *Journal of Accounting Research* Autumn: 409-417.

Viswanathan, S., 2001, "Strategic trading, heterogeneous beliefs and short constraints," Manuscript.

Appendix

Proof of Proposition 1:
Let $x \equiv k\frac{1+\nu^2}{\nu}$. Then the expectation at $t = 0$ of consensus at $t = 1$ can be expressed as:

$$E_0[C_1] = \sigma_0 \frac{k}{x} \frac{f(x)}{\Phi(x)}$$

Under this formulation, the effect of changing relative precision in the expected bias can be expresses as:

$$\frac{\partial E_0[C_1]}{\partial \nu} = \frac{\partial E_0[C_1]}{\partial x} \frac{\partial x}{\partial \nu}$$

This function is x, since the denominator is increasing in x, and the numerator is decreasing in x. Therefore, the expected value of the bias is increasing in the relative precision, $\frac{1}{\nu}$, or decreasing in ν, whenever x is increasing in ν. This will be the case when

$$\frac{\partial x}{\partial \nu} = k(-\frac{1}{\nu^2} + 1) > 0 \qquad \text{or} \qquad \nu > 1$$

This means that when $\frac{\sigma_s}{\sigma_0} > 1$, or the private signal is less precise than the common signal, the bias in mean reported analysts' forecasts will be increasing in the relative precision of the signal. *Q.E.D.*

Proof of Proposition 2:
Once again, introducing a new variable $x \equiv k\frac{1+\nu^2}{\nu}$, the formula 5 for dispersion in reported analysts' forecasts can be rewritten as:

$$E_0[VAR(C_1)] = \sigma_0^2 \frac{k^2}{x^2} \left[x\frac{f(x)}{\Phi(x)} + 1 - \frac{f^2(x)}{\Phi^2(x)} \right] = \sigma_0^2 k^2 \left[\frac{f(x)}{x\Phi(x)} - \frac{f^2(x)}{x^2\Phi^2(x)} + \frac{1}{x^2} \right]$$

The partial derivative of this equation with respect to ν can be expressed as:

$$\frac{\partial E_0[VAR(C_1)]}{\partial \nu} = \sigma_0^2 k^2 \left[\frac{\partial}{\partial x} \left(\frac{f(x)}{x\Phi(x)} \right) \left(1 - 2\frac{f(x)}{x\Phi(x)} \right) - \frac{1}{2x^3} \right] \frac{\partial x}{\partial \nu}$$

This expression is negative as long as $1 - 2\frac{f(x)}{x\Phi(x)}$ is positive. But as long as the condition for the Proposition 1 is satisfied ($\nu < 1$), $x > 2k$ and $2\frac{f(x)}{x\Phi(x)} < 1$, as long as k is high enough (for example, 1 and above). *Q.E.D.*

Proof of Proposition 3:
Expected change in bias is equal to:

$$E_0[C1] - E_0[C_2] = E_0[C_1] \left(1 - \frac{\nu}{\sqrt{K^2 + \nu^2}} \right)$$

The derivative with respect to the inverse relative precision is equal to:

$$\frac{\partial (E_0[C1] - E_0[C_2])}{\partial \nu} = \frac{\partial E_0[C1]}{\partial \nu} \left(1 - \frac{\nu}{\sqrt{K^2 + \nu^2}} \right) - C_1 \frac{K^2}{(K^2 + \nu^2)^{3/2}} < 0$$

Because when private signal is less precise than the common signal, conditions for the proposition 1 to hold are met, and the partial derivative of the first-period bias with respect to the relative inverse precision of the private information is negative. *Q.E.D.*

Table I
Average Change in the Forecast Bias

At the end of the third month of each fiscal year, stocks are sorted into five portfolios based on dispersion in analysts' earnings earnings per share forecasts. Forecast bias is defined as the mean reported forecast net the realized earnings, scaled by the stock price at the end of the time of portfolio assignment. End of the forecast period is defined as the end of the first month of the following fiscal year. Change in the forecast bias is the change in bias from the end of previous to the end of current month. It is averaged over portfolios by the number of months remaining until the end of the forecast period and then averaged over the entire forecast horizon. The difference in the monthly change the forecast bias between the low- and high-dispersion portfolios if first calculated over the months remaining until the end of the forecast period and then averaged over the entire forecast horizon. The t-statistics are adjusted for autocorrelation.

Dispersion Quintiles	Size Quintiles small *S1*	*S2*	*S3*	*S4*	large *S5*	All Stocks
D1 (low)	-0.15	-0.11	-0.09	-0.09	-0.09	-0.10
D2	-0.18	-0.13	-0.10	-0.11	-0.08	-0.11
D3	-0.20	-0.16	-0.12	-0.10	-0.09	-0.13
D4	-0.24	-0.23	-0.19	-0.13	-0.12	-0.17
D5 (high)	-0.35	-0.29	-0.32	-0.22	-0.16	-0.28
D1-D5	0.21[a]	0.18[a]	0.22[a]	0.13[a]	0.07[a]	0.19[a]
t-statistic	5.93	5.69	7.26	8.65	4.91	8.79

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

Table II

Fama-MacBeth Regressions of Monthly Returns on Stock Characteristics and Earnings Forecast Revisions

This table presents coefficients of the Fama-MacBeth (1973) regression of returns on a constant term and previous month's stock characteristics. These include: $\ln(ME)$ – the logarithm of firm's market value; $\ln(BE/ME)$ – the logarithm of the ratio of the firm's book value of equity as of the previous fiscal year to the market value of equity (if less than three months elapsed since the fiscal year end date, then the book value of equity for the year before that is used); *Resid. Cov.* – the residual from monthly regressions of $\ln(1 + analyst\ coverage)$ on $\ln(ME)$ and $\ln(BE/ME)$; *Disp.* – the ratio of the standard deviation of the analyst earnings per share forecasts for the current fiscal year to the absolute value of the mean forecast (observations with the mean forecast of zero are deleted from the sample); *Rev*1, *Rev*2, *Rev*3, *Rev*4, *Rev*5, and *Rev*6 – changes in the mean reported earnings per share forecasts for the current fiscal year over the previous 1, 2, 3, 4, 5, and 6 months respectively, scaled by the mean value of the most recent mean forecast. Coefficients on $\ln(ME)$, $\ln(BE/ME)$, and *Resid. Cov.* are insignificant and are not reported. The coefficient on the constant term is always significant, but is not reported either. Returns are in percent; the t-statistics appear in parentheses. The period of analysis is February 1980 to December 2000.

Disp.	Rev1	Rev2	Rev3	Rev4	Rev5	Rev6	Disp.* Rev1	Disp.* Rev2	Disp.* Rev3	Disp.* Rev4	Disp.* Rev5	Disp.* Rev6
-0.117^a	0.323^a	-	-	-	-	-	-	-	-	-	-	-
(-2.88)	(5.19)	-	-	-	-	-	-	-	-	-	-	-
-0.169^a	0.479^a	-	-	-	-	-	-0.045	-	-	-	-	-
(-3.04)	(4.57)	-	-	-	-	-	(-1.63)	-	-	-	-	-
-0.081^c	-	0.212^a	-	-	-	-	-	-	-	-	-	-
(-1.88)	-	(4.94)	-	-	-	-	-	-	-	-	-	-
-0.135^b	-	0.347^a	-	-	-	-	-	-0.013	-	-	-	-
(-2.13)	-	(5.41)	-	-	-	-	-	(-1.04)	-	-	-	-
-0.112^b	-	-	0.105^a	-	-	-	-	-	-	-	-	-
(-2.20)	-	-	(2.75)	-	-	-	-	-	-	-	-	-
-0.175^a	-	-	0.188^a	-	-	-	-	-	-0.018^b	-	-	-
(-2.63)	-	-	(3.46)	-	-	-	-	-	(-2.33)	-	-	-
-0.106^c	-	-	-	0.086^a	-	-	-	-	-	-	-	-
(-1.87)	-	-	-	(2.72)	-	-	-	-	-	-	-	-
-0.202^a	-	-	-	0.133^a	-	-	-	-	-	-0.011^c	-	-
(-2.88)	-	-	-	(2.93)	-	-	-	-	-	(-1.89)	-	-
-0.090^c	-	-	-	-	0.077^a	-	-	-	-	-	-	-
(-1.85)	-	-	-	-	(3.55)	-	-	-	-	-	-	-
-0.181^a	-	-	-	-	0.137^a	-	-	-	-	-	-0.005	-
(-2.73)	-	-	-	-	(4.12)	-	-	-	-	-	(-0.76)	-
-0.043	-	-	-	-	-	0.089^a	-	-	-	-	-	-
(-0.82)	-	-	-	-	-	(4.46)	-	-	-	-	-	-
-0.151^b	-	-	-	-	-	0.129^a	-	-	-	-	-	-0.005
(-2.14)	-	-	-	-	-	(4.38)	-	-	-	-	-	(-1.25)

^{a,b,c} Statistically significant at the 1, 5, and 10 percent levels, respectively

Table III
Fama-MacBeth Regressions With Assumed Nonlinearities

This table presents coefficients of the Fama-MacBeth (1973) regression of returns on a constant term and previous month's stock characteristics. These include: $\ln(ME)$ – the logarithm of firm's market value; $\ln(BE/ME)$ – the logarithm of the ratio of the firm's book value of equity as of the previous fiscal year to the market value of equity (if less than three months elapsed since the fiscal year end date, then the book value of equity for the year before that is used); *Resid. Cov.* – the residual from monthly regressions of $\ln(1 + analyst\ coverage)$ on $\ln(ME)$ and $\ln(BE/ME)$; *Disp.* – the ratio of the standard deviation of the analyst earnings per share forecasts for the current fiscal year to the absolute value of the mean forecast (observations with the mean forecast of zero are deleted from the sample); *Rev*6 – changes in the mean reported earnings per share forecasts for the current fiscal year over the previous six months, scaled by the mean value of the most recent mean forecast; *Dummy* equals to 1 if $Rev6 > 0$ and 0 otherwise. Returns are in percent; the t-statistics appear in parentheses. The period of analysis is February 1980 to December 2000.

Const.	ln(ME)	ln(BE/ME)	Disp.	Rev6	Resid. Cov.	Dummy	Dummy* Disp.	Dummy* Rev6	Dummy* ln(ME)	Dummy* ln(BE/ME)	Dummy* Res. Cov.
1.75^b	-0.003	0.023	-	0.089^a	0.090	-	-	-	-	-	-
(2.51)	(-0.06)	(0.26)	-	(5.42)	(0.79)	-	-	-	-	-	-
1.79^b	-0.006	0.023	-0.043	0.089^a	0.092	-	-	-	-	-	-
(2.58)	(-0.11)	(0.26)	(-0.82)	(4.46)	(0.82)	-	-	-	-	-	-
1.93^a	-0.017	0.050	-0.067	0.060^a	0.144	0.666	-	-	-	-	-
(2.80)	(-0.34)	(0.60)	(-1.31)	(3.24)	(1.28)	(8.40)	-	-	-	-	-
1.96^a	-0.018	0.054	-0.060	0.057^a	0.142	0.714	-0.827^b	-	-	-	-
(2.85)	(-0.35)	(0.61)	(-1.02)	(2.61)	(1.27)	(8.80)	(-2.44)	-	-	-	-
1.95^a	-0.015	0.058	-0.066	0.054^b	0.147	0.667^a	-1.098^a	0.786^b	-	-	-
(2.84)	(-0.29)	(0.65)	(-1.13)	(2.41)	(1.31)	(8.20)	(-3.33)	(2.35)	-	-	-
1.46^b	0.072	0.143	-0.064	0.051^b	0.121	2.607^a	-1.129^a	0.580^c	-0.299^a	-0.266^a	0.143
(2.07)	(1.44)	(1.18)	(-1.08)	(2.30)	(0.99)	(5.08)	(-3.25)	(1.72)	(-9.95)	(-4.27)	(1.18)

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

Table IV

Portfolio Returns by Sensitivity of Turnover to Dispersion in Analysts' Earnings Per Share Forecasts

Monthly turnover (defined as total trading scaled by the total number of shares outstanding at the end of the month) is regressed on dispersion in analysts' earnings per share forecasts (defined as the standard deviation in the outstanding forecasts scaled by the absolute value of the mean forecast, with observations where the mean forecast is zero excluded from the sample), log-market capitalization value and the book-to-market ratio in a times series regression for each stock. Stocks with the positive coefficients on dispersion are assigned to one group, and the rest of the stocks are assigned to another group. Stocks within each of the two groups are then sorted into three market capitalization groups and three dispersion groups within each market capitalization group based on the values as of the previous month. Average returns for each group are then calculated by equally-weighting individual returns (portfolios are reassigned every month, and stocks with share prices of less than $5 are exclued from the portfolios). Time period is February 1983-December 2000. t-statistics in parentheses are adjusted for autocorrelation.

Returns

Dispersion	Coefficient > 0			Coefficient ≤ 0		
	Small Cap	Medium Cap	Large Cap	Small Cap	Medium Cap	Large
low	1.64	1.58	1.50	1.61	1.48	1.38
medium	1.38	1.40	1.46	1.14	1.50	1.41
high	0.99	1.28	1.32	0.36	0.96	1.16
low-high	0.65[a]	0.31[c]	0.18	1.25[a]	0.52[a]	0.22
t-statistic	(3.18)	(1.67)	(0.96)	(6.62)	(2.68)	(0.97)

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

Average Dispersion and Response Coefficient (below)

Dispersion	Coefficient > 0			Coefficient ≤ 0		
	Small Cap	Medium Cap	Large Cap	Small Cap	Medium Cap	Large Cap
low	0.02	0.02	0.02	0.02	0.02	0.02
	368.89	286.40	256.18	-1107.36	-196.42	-187.34
medium	0.07	0.05	0.04	0.08	0.06	0.05
	250.73	245.61	202.14	-259.91	-164.67	-123.77
high	0.61	0.41	0.29	0.86	0.63	0.46
	147.44	108.51	115.05	-327.73	-75.55	-62.91

Table V

Portfolio Returns by Accruals and Dispersion in Analysts' Earnings Forecasts

Stocks in the intersection of I/B/E/S, CRSP and Compustat are sorted into quintiles based on the level of accruals as of the previous fiscal year; within each accruals-based quintile, stocks are sorted into quintiles based on dispersion in analysts' earnings per share forecasts as of the previous month. Dispersion is defined as the ratio of the standard deviation in earnings forecasts to the absolute value of the mean forecast (stocks with the mean forecast of zero are assigned to the higher dispersion-based quintile). Accruals are defined as the change in non-cash current assets minus the change in current liabilities excluding short-term debt and taxes payable and minus depreciation and amortization, and calculated using data for the previous fiscal year. Portfolios are constructed every month and returns are equally-weighted. Time period is February 1983-December 2000. t-statistics in parentheses are adjusted for autocorrelation.

Returns

	Accruals Quintiles						
Dispersion Quintiles	low *A1*	*A2*	*A3*	*A4*	high *A5*	*A1-A5*	All stocks
D1 (low)	1.62	1.72	1.68	1.54	1.32	-	1.56
D2	1.61	1.28	1.49	1.58	0.94	-	1.38
D3	1.55	1.61	1.37	1.36	1.15	-	1.40
D4	1.34	1.51	1.47	1.48	0.65	-	1.26
D5 (high)	1.08	1.15	0.91	0.85	0.43	-	0.93
D1-D5	0.54[c]	0.57[b]	0.77[a]	0.68[a]	0.88[a]	-	0.63[a]
	(1.68)	(2.14)	(2.80)	(2.89)	(2.99)		(2.62)
All stocks	1.44	1.45	1.38	1.36	0.90	0.54[a]	-
						(4.13)	

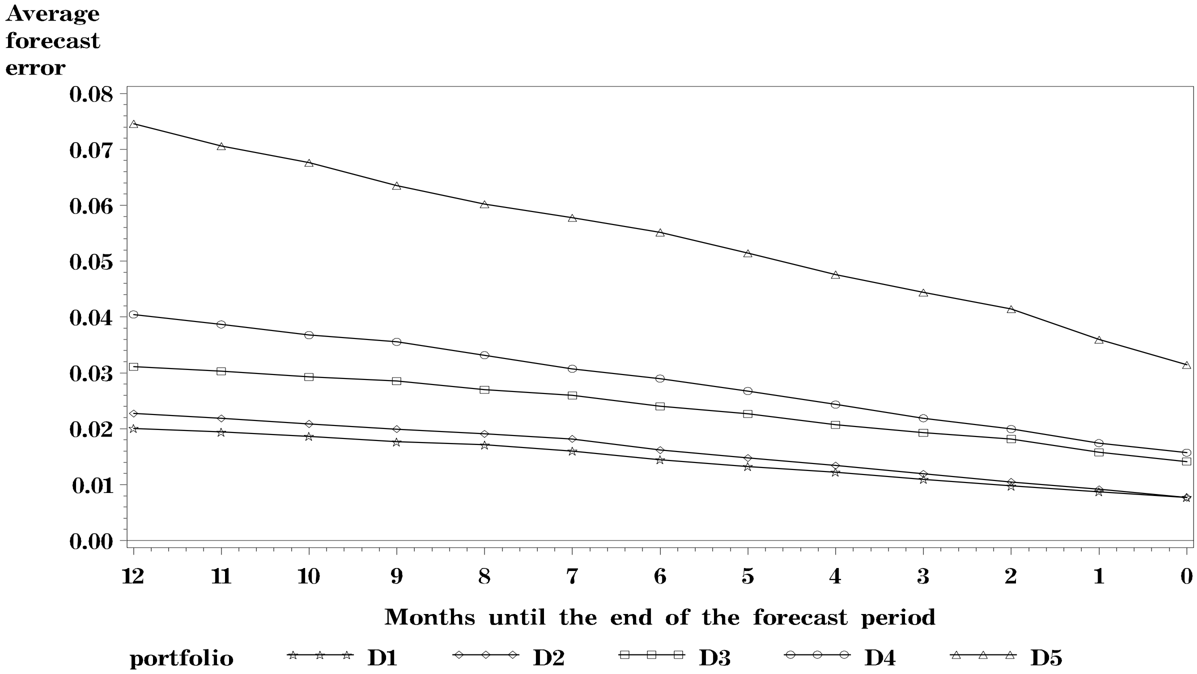
[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

Average Forecast Dispersion and Market Capitalization (in millions of $)

	Accruals Quintiles					
Dispersion Quintiles	low *A1*	*A2*	*A3*	*A4*	high *A5*	All Stocks
D1 (low)	0.015	0.014	0.013	0.012	0.011	0.013
	$4,423	$4,622	$3,877	$3,520	$1,501	$3,490
D2	0.039	0.031	0.029	0.027	0.029	0.031
	$3,419	$3,756	$3,164	$2,751	$1,235	$2,839
D3	0.077	0.056	0.049	0.046	0.051	0.054
	$2,452	$3,214	$2,324	$2,052	$1,027	$2,244
D4	0.162	0.111	0.093	0.088	0.098	0.107
	$1,458	$2,135	$1,178	$1,331	$845	$1,584
D5 (high)	1.383	0.842	0.777	0.739	0.716	0.895
	$858	$1,125	$1,132	$866	$508	$916

Figure 1
Forecast Errors

At the end of the previous fiscal year, stocks are sorted into five portfolios based on dispersion in analysts' earnings earnings per share forecasts for the current fiscal year. Forecast error is defined as the mean reported forecast minus the realized earnings, scaled by the stock price at the time of portfolio assignment. End of the forecast period is defined as the current fiscal year end. Forecast error is averaged over portfolios by the number of months remaining until the end of the current fiscal year.



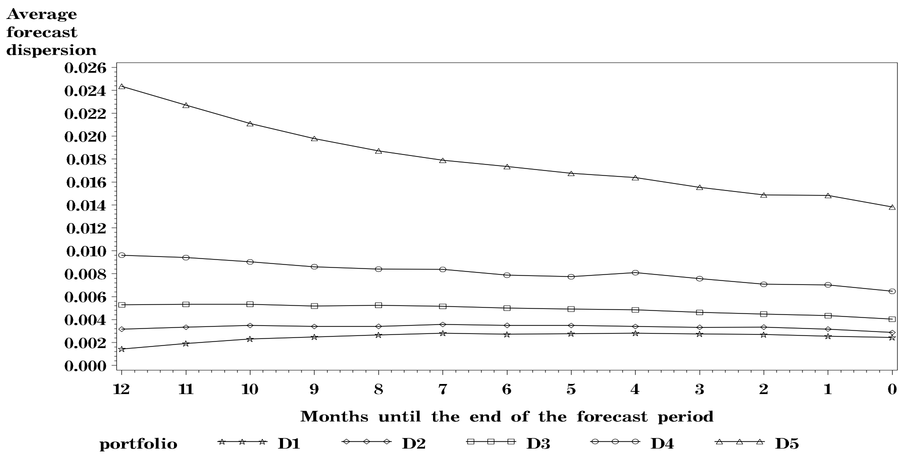
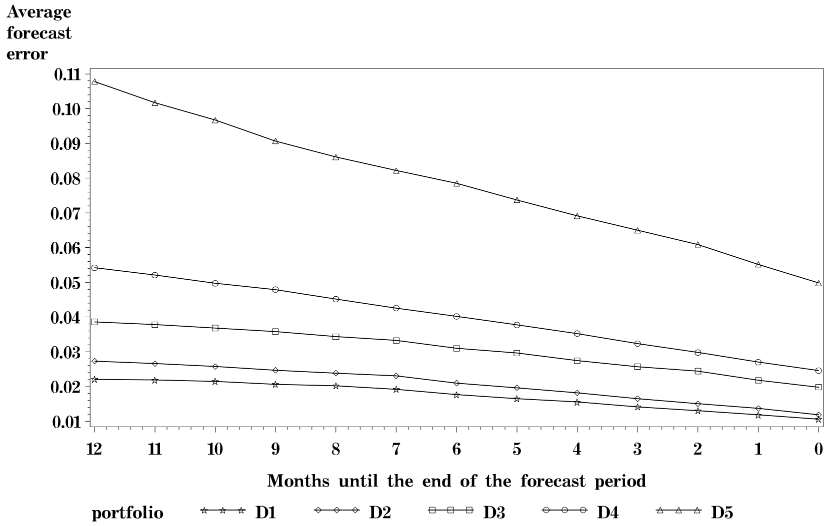


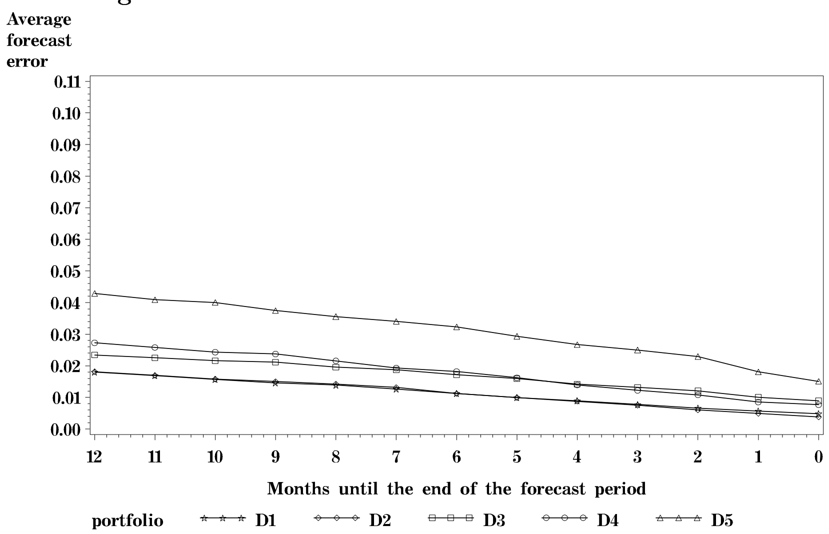
Figure 2
Properties of the Earnings Per Share Forecasts

At the end of the previous fiscal year, stocks are sorted into five portfolios based on dispersion in analysts' earnings earnings per share forecasts for the current fiscal year. Forecast error is defined as the forecast minus the realized earnings, scaled by the stock price at the time of portfolio assignment. Dispersion in the earnings forecasts is calculated as the standard deviation in forecasts scaled by the stock prices at the time of portfolio assignment. End of the forecast period is defined as the current fiscal year end. Forecast errors and the fraction of analysts making revisions are averaged over portfolios and by the number of months remaining until the end of the current fiscal year.

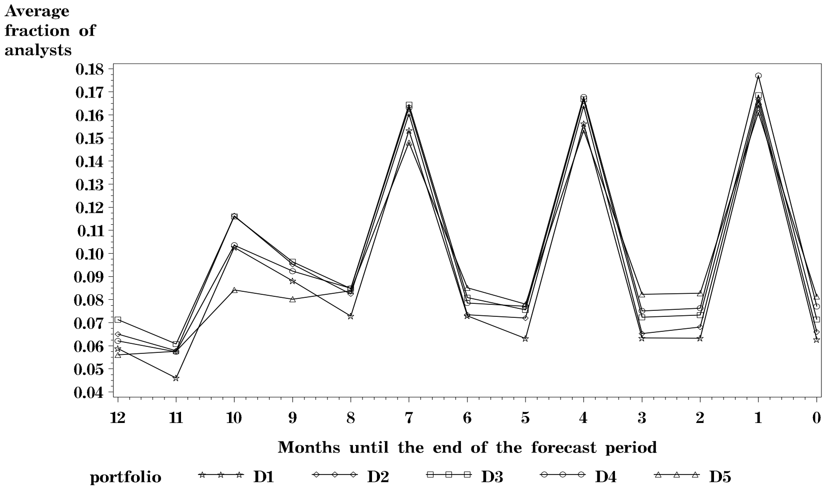
Average Forecast Error of the Most Optimistic Forecast



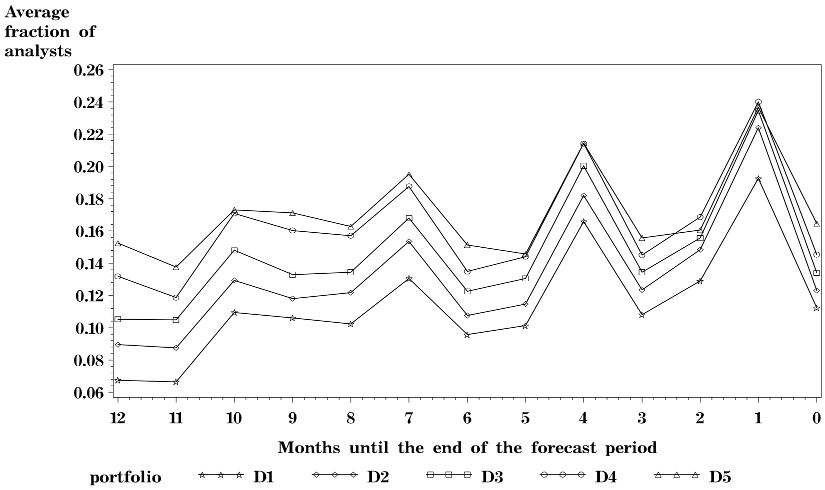
Average Forecast Error of the Most Pessimistic Forecast



Average Fraction of the Upward Revisions



Average Fraction of the Downward Revisions



Average Fraction of No Revisions

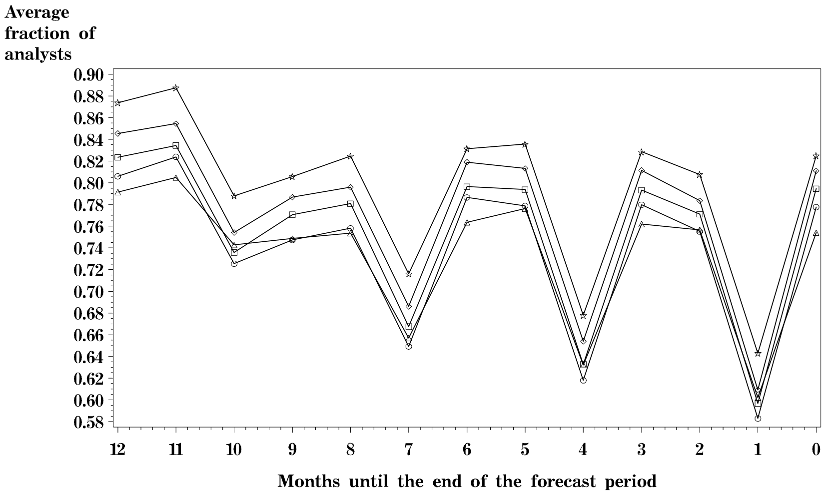
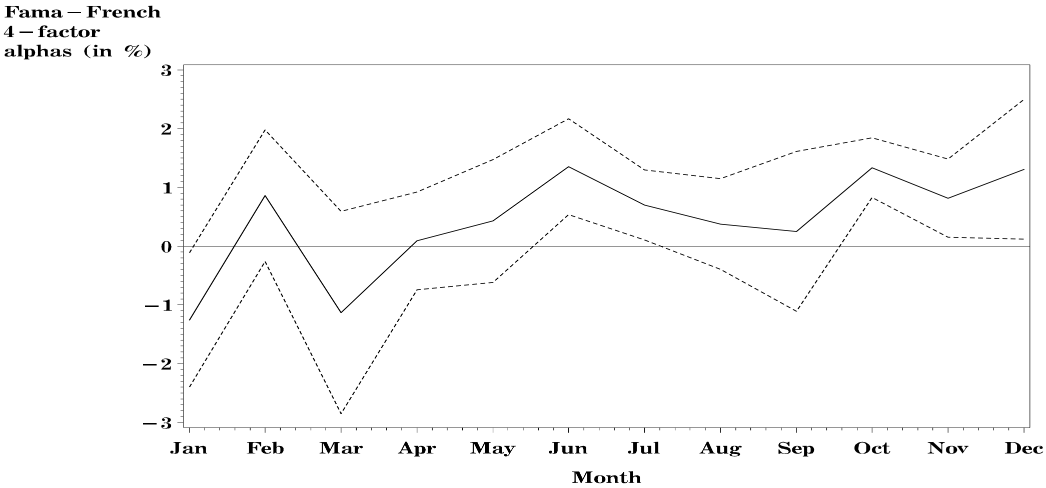


Figure 3
Fama-French Four-Factor Alphas

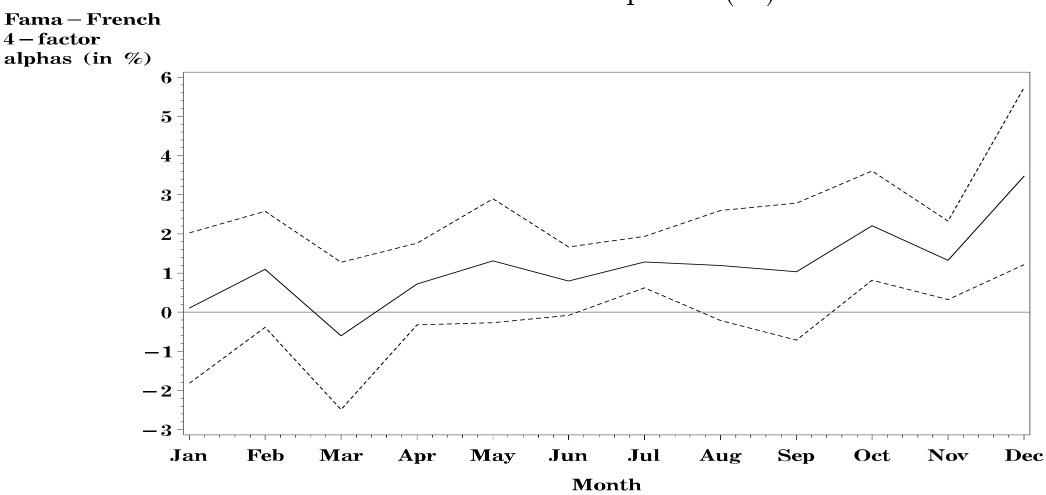
All stocks in the specified groups are sorted into portfolios based on dispersion in analysts' earnings per share forecasts (defined as the standard deviation in reported forecasts scaled by the mean forecast; if the mean forecast is zero, stocks are assigned to the highest dispersion-based portfolio) as of the previous month. Portfolio returns are equally-weighted, and the return differential between low- and high-dispersion stocks is computed monthly. This return differential is then regressed on size, book-to-market, market, and momentum factors and a constant term. The coefficients on a constant term are averaged by calendar month. Since the time period under consideration is 1983-2000, each monthly average coefficient is computed from 18 observations. Coefficients on the constant term of the regressions, with broken lines indicating the 90% confidence interval corresponding to 18 observations, are reported in the graphs by calendar month.

All stocks

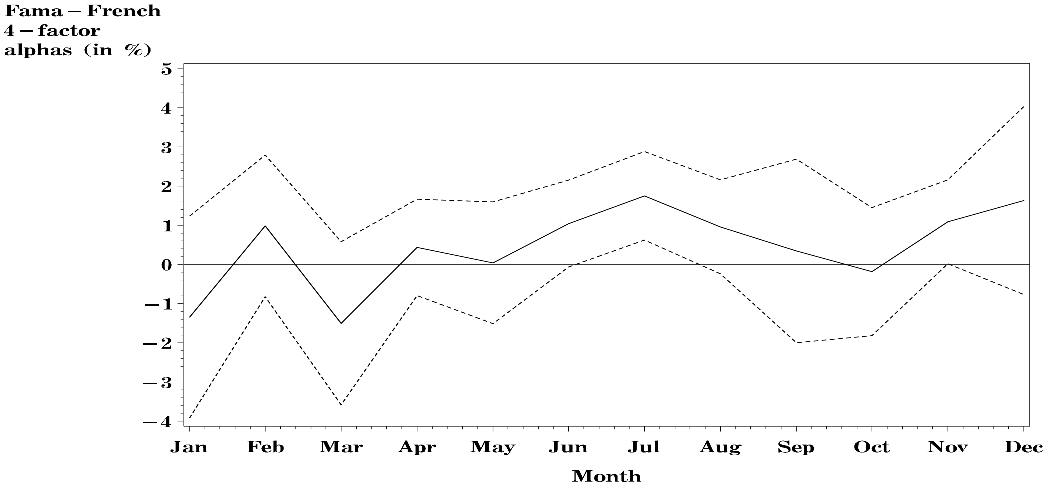


Size Groupings

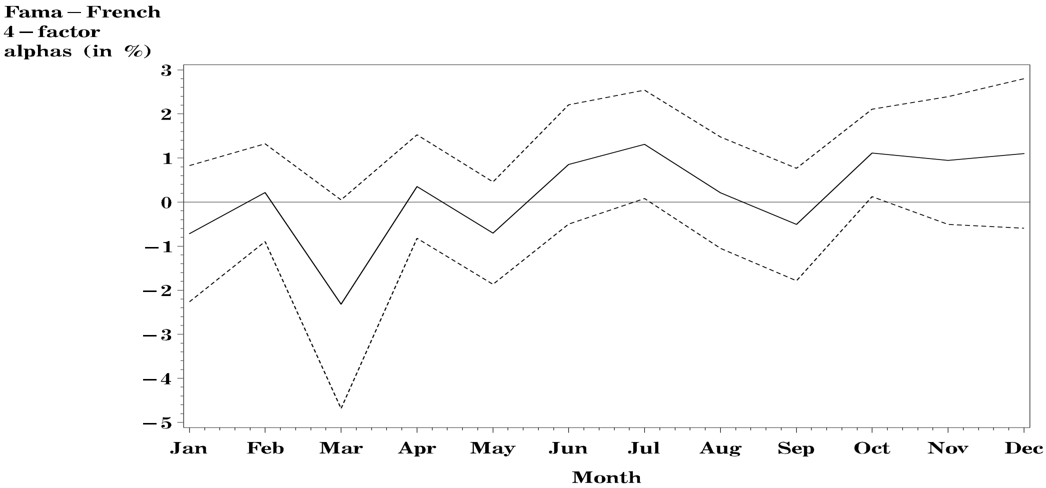
Stocks in the smallest size quintile (S1)



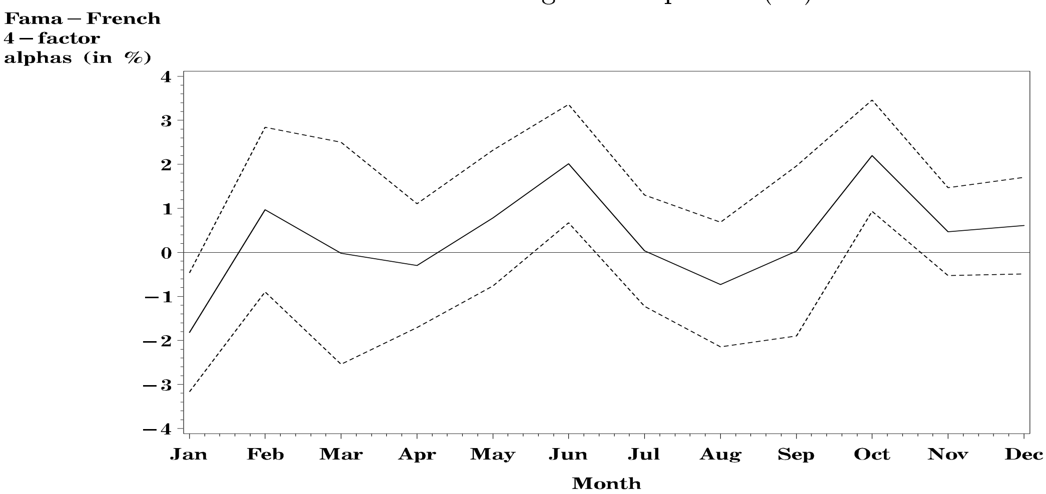
Stocks in the second smallest size quintile (S2)



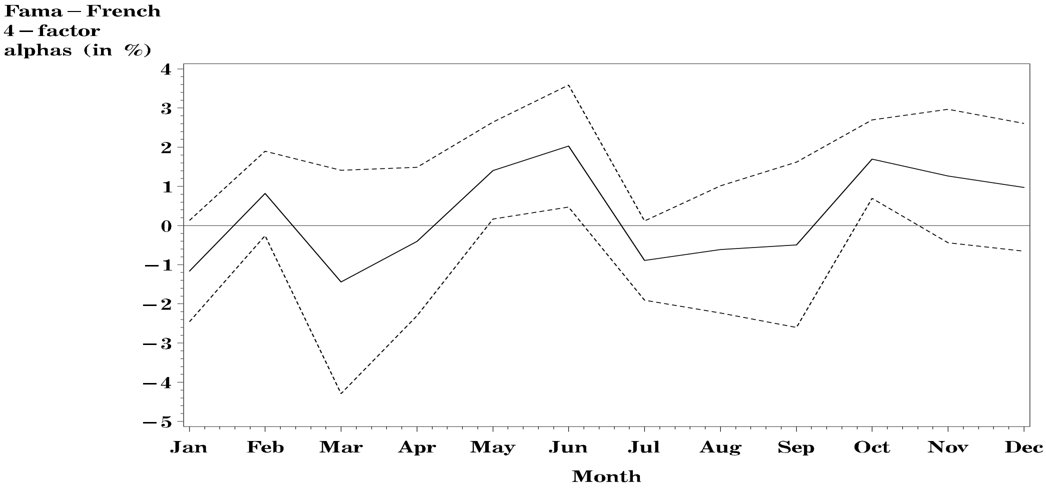
Stocks in the third smallest size quintile (S3)



Stocks in the second largest size quintile (S4)

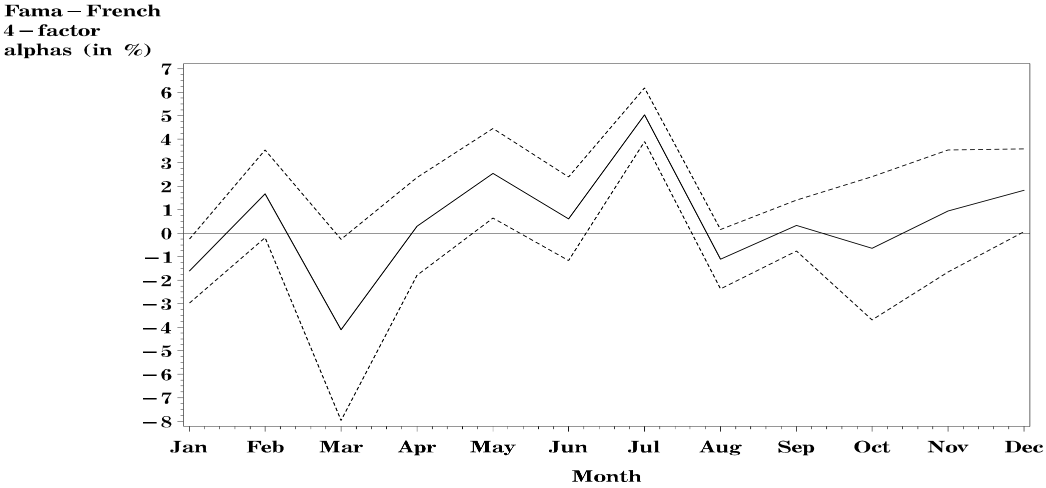


Stocks in the largest size quintile (S5)

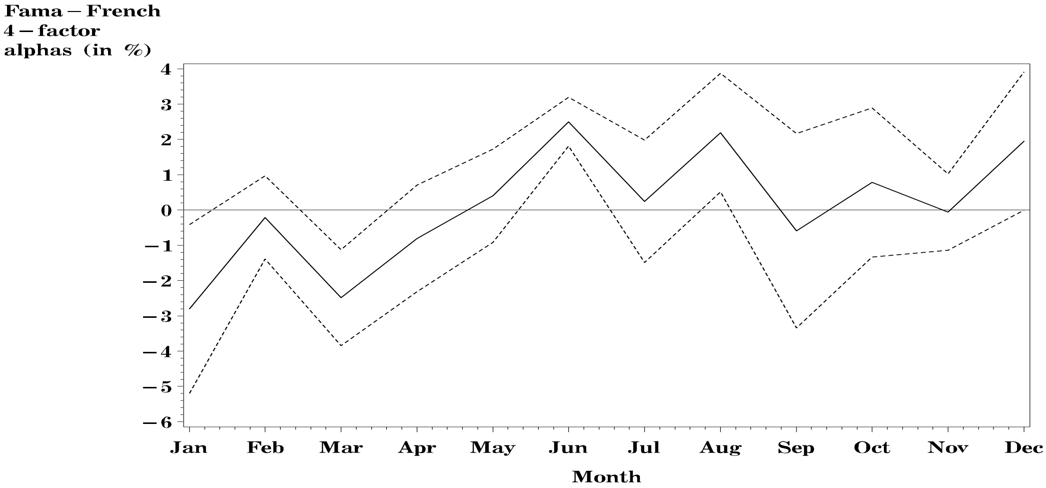


Fiscal-Year-End Groupings

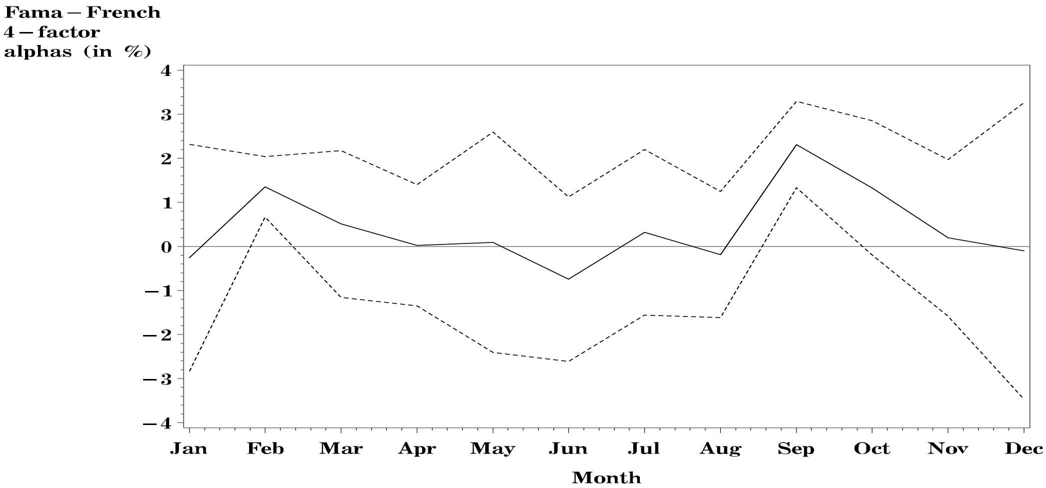
March fiscal year end



June fiscal year end



September fiscal year end



December fiscal year end