Why the Stock Market May Underweight Bad News?

An Empirical Analysis

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Abstract

Diether, Malloy and Scherbina (2001) document a bias towards optimism in stock prices whenever analysts disagree about the earnings per share forecast. The reason for this upward bias may be that investors do not properly adjust their stock valuations to account for the frictions that hinder the revelation of negative information. In this paper, I focus on two types of relevant frictions: Short-sale costs and analysts' incentives. Short-sale costs impede the revelation of negative opinions through "sell" orders. Incentives prevent analysts from reporting low earnings per share forecasts. I find that the data are consistent with the assumption that investors properly account for short-sale costs but ignore the upward bias in reported earnings-per-share forecasts that is due to analysts' incentives.

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 and try to pinpoint the source of the upward bias in prices. Stock prices reflect valuations, which are based on many inputs. The inputs include among many others analysts' forecasts and "buy" and "sell" order flows. A systematic bias in any of these inputs will induce a biased stock price if investors do not correctly adjust the biased input in their valuations.

Much of the discussion in the literature has been centered on short-sale costs, which impede "sell" orders. If some investors with low valuations are constrained from selling a stock, others may assume wrongly that they agree with the existing price. In this case, the market price will be higher than the average opinion, and future returns will be low. If investors' valuations are made conditional on the possibility that some investors with low valuations did not sell stock, the market price will be unbiased. Short-selling costs are not the only frictions that systematically impede negative information. McNichols and O'Brien(1997) suggest that analysts with bad outlook prefer to stop coverage rather then report their forecasts. If investors do not correctly account for this

[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.

truncation in information, prices will be upwardly biased. Analysts' incentives and sort-sale costs are the two impediments to negative information that I investigate in this paper.[4]

If short-sale costs are responsible for the upward bias in prices, then predictors of short-sale costs should be negatively correlated with future returns. Moreover, when short-sale costs are negligibly low, future returns will not depend on the current level of disagreement. Institutional ownership is an important indicator of how binding the short-sale constraint is for a particular stock, and this is the case for three reasons. First, institutions are among the most informed and sophisticated players in the market, but are often prohibited by regulations from taking short positions (i.e. they have infinite short-selling costs). Institutions can express a negative opinion only if they already own the stock. Second, shares held by institutions are often readily available for lending. D'Avolio (2001) documents that the likelihood that a stock is expensive to short-sell is negatively correlated with the level of institutional ownership. Third, unlike individuals, institutions are rarely concerned about capital gains taxes and sell immediately if they believe the stock is overpriced. All of these considerations mean that the overall impediments to selling a stock are less severe when the institutional ownership is high. Therefore, when opinions diverge, institutional ownership should be positively correlated with future returns. When turnover is high, short-sellers face a higher risk that the owner of the shares they borrowed will want them back and they will be forced to scrap their short position prematurely. Additionally, D'Avolio (2001) shows that high turnover increases the probability that a stock has high short-sale costs; this probability decreases with size. Therefore, when opinions diverge, turnover should be negatively correlated with future returns and institutional ownership and size should be positively correlated with future returns.

I find that none of these predictions are supported in the data. Institutional ownership, turnover and size are insignificant in predicting the cross-section of next month's returns, while dispersion in analysts earnings per share forecasts is reliably negative and significant. Stocks in the S&P 500 index are widely held by institutions and private individuals, as opposed to insiders,

[4]In a similar vein, Hong, Lim and Stein (1999) investigate whether the tendency of firms to hold back bad news is fully accounted for in prices. They present evidence that it is not.

and should have negligibly low costs of short-selling. However, stocks with the high level of earnings forecast dispersion in the S&P 500 index still underperform otherwise similar stocks. This evidence is inconsistent with short-sale costs being responsible for the upward bias in prices.

Analysts' tendency to stop coverage when their outlook is pessimistic creates an upward bias in the mean reported forecast. When the level of disagreement is high, the forecasts that are not reported are likely to be low relative to the mean forecast. The upward bias in the mean of the reported forecasts is then likely to be high. The positive correlation between the upward bias in the mean forecast and the level of forecast dispersion is observed in the data. When the level of forecast dispersion is high, the average error in the mean forecast is more optimistic, and the average future forecast revision is more strongly negative. If investors do not discount their valuations for the bias induced by self-selection in analyst coverage, prices will be high and future returns will be low when dispersion in analysts' forecasts is high.

The mean forecast tends to be revised down gradually over the fiscal year, as the uncertainty about annual earnings is steadily resolved. Hence, the magnitude of the past forecast revision will capture the future downward trend, and the longer the time span used to measure the forecast revision the more reliably it will capture the future downward tendency. When the forecast revision variable is used alongside dispersion to forecast the cross-section of future returns, dispersion slowly loses significance as the time period over which the forecast revision is measured increases. When the past revision has been positive, dispersion is always negative and significant in predicting future returns because it captures the likelihood that the mean forecast will still have to be revised down. This evidence supports the conjecture that the upward bias in prices occurs because investors do not correctly discount the reported earnings forecasts for the bias induced by self-selection in analysts' coverage, and do not anticipate the forecasts to be revised downward.

The rest of the paper is organized as follows. Section II further verifies that dispersion in analysts' forecasts captures disagreement by documenting that low returns on high-dispersion stocks are associated with the resolution of uncertainty. Section III investigates the impact of short-sale costs on the future stock returns. Section IV shows that the upward bias in reported earnings per share forecasts is positively correlated with dispersion. It also demonstrates that dispersion captures the likelihood of mean earnings forecasts to be revised down in the future. Section V 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 VI 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.[5] 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

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

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.

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[6] 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.

[6] Ciccone (2001).

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 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. Resolution of Uncertainty

Miller (1977) states that when opinions diverge, short-sale constraint binds, and investors are dogmatic about their beliefs, the market price will be upwardly biased. The magnitude of the bias will be increasing in the level of the underlying disagreement. Morris (1996) and Viswanathan (2001) offer an additional insight that the convergence of prices down to the fundamentals will be associated with the resolution of uncertainty. These papers assume that short-sale constraints serve as the impediment of negative information. However, their results should be independent of the nature of the impediment to negative opinions. Therefore, when prices are upwardly biased because of the disagreement, they should lose value as the uncertainty that causes this disagreement is diminished. This is what I demonstrate in this section.

Table I, replicated from Diether, Malloy and Scherbina (2001), illustrates that high-dispersion stocks on average earn lower returns than otherwise similar stocks. Over the time period of 1983-2000, high-dispersion stocks on average underperformed the low-dispersion stocks by 0.79 percent per month. The return difference is more pronounced for smaller stocks, but these are also the stocks with the higher average level of forecast dispersion. As can be seen from the bottom plot of Figure 1, dispersion in analysts' earnings per share forecasts is persistent throughout the forecast horizon. Stocks which were in the highest dispersion quintile in the beginning of a fiscal year, tend to remain in the highest-dispersion group by the end of the year. However, dispersion decreases gradually throughout the fiscal year. If dispersion in analysts' forecast was simply caused by some analysts' responding to news with a lag, if would have been less persistent and would not steadily decline over the fiscal year. This seems to indicate that dispersion in analysts' earnings per share forecasts on average captures the genuine disagreement.

Since dispersion in analysts' earnings per share forecasts captures disagreement about annual earnings, high-dispersion stocks should earn significantly negative returns when the uncertainty about annual earnings is resolved. I test this prediction directly, by looking at returns around the quarterly earnings announcement dates. I find that high-dispersion stocks earn significantly negative returns in the three-day window around the quarterly earnings announcement dates. This indicates that the degree of over-pricing decreases as the level of disagreement diminishes.

A. Relative returns around earnings announcement days

For stocks with a fiscal-year end in December, only first quarter earnings are known at the end of June. June annual earnings-forecast dispersions indicate the uncertainty that will be resolved as second, third, and fourth quarter earnings become known. The fourth quarter earnings are often not announced until February of the following year. Therefore, comparison of average daily returns for the time period of July of a given year to the end of February of the following year to the average daily returns for the three-day window around the 2nd, 3rd and 4th quarter earnings announcement days should reveal whether abnormally low returns on high-dispersion stocks occur predominantly around the announcement dates.

To see how the average daily return in a three-day window around the earnings announcement dates is related to the average daily return over the July-February period, I run the following regression, pooled over years and cross-sections:

$$\bar{r}_{it}^{Jul_t - Feb_{t+1}} - \bar{r}_{it}^{Qtr2,3,4} = \beta_0 + \beta_1 \ln(ME)_{it} + \beta_2 \ln(BE/ME)_{it} + \beta_3 disp_{it} \tag{1}$$

where $\ln(ME)_{it}$ is the logarithm of stock i's market-capitalization level as of the end of June of year t, $\ln(BE/ME)_{it}$ is the logarithm of stock i's book-to-market ratio as of the end of fiscal year preceding year t if more than three months have passed since the fiscal-year end, otherwise, the data from the year before is used; and $disp_{it}$ is the dispersion in analyst earnings forecasts for stock i as of June of year t, defined as the ratio of the standard deviation in the forecasts to the absolute value of the mean forecast. Observations for which the mean forecast is zero are removed from the sample. The time period under consideration is 1979-2000.

When mean arithmetic daily returns are used in the calculations, the regression coefficients are as follows (with t-statistics in parentheses): $\beta_0 = -0.300$ (-3.78), $\beta_1 = 0.023$ (3.73), $\beta_2 = 0.0358$ (2.48), and $\beta_3 = -0.019$ (-2.71). Using mean geometric daily returns and mean log-returns produces similar results, and the adjusted R^2 of the regressions ranges from 1.1% to 1.9%. As can be seen from the results of the regressions, dispersion is a strong predictor of the difference between average returns and returns around earnings announcement days. The higher the dispersion, the lower the announcement-day returns. On the other hand, the larger the size, the smaller the difference between average returns and returns around announcement days. This is because for larger firms, information gets revealed more steadily throughout the course of the year, via earnings pre-announcements and perhaps better news coverage. This observation is consistent with Chari, Jagannathan and Ofer (1988), who state: "The hypothesis that information is available more continuously [rather than just being revealed during the dividend and earnings announcements] for large firms is made more plausible by our results."[7] The positive and significant coefficient on

[7] *Journal of Financial Economics* 21 (1988), page 103.

the book-to-market ratio indicates that the price correction is more pronounced by growth than for value stocks.

B. How much return difference comes on earnings announcement dates?

To illustrate that much of the return differential between the low- and high-dispersion stocks is due to returns around announcement dates, I employ the following strategy. In June of each year from 1983 to 2000, I assign stocks with a December fiscal-year end to one of five groups based on size, and then further subdivide each group into three dispersion groups. Size is the level of market capitalization as of the end of June. Dispersion is defined as the standard deviation in the earnings-per-share forecasts scaled by the absolute value of the mean forecast. Observations with mean earnings per share forecast is zero are assigned to the highest dispersion portfolio. This produces a total of 15 portfolios. Stocks in the portfolios are equally weighted.

The portfolio strategy is to short-sell stocks in the high-dispersion portfolios and buy stocks in the low-dispersion portfolios in each size quintile. The position is maintained from the beginning of July until the end of February of the following year. For stocks in the lowest size quintile, this strategy has on average earned 10.54 percent of cumulative return each year over the 1983-2000 time period. However, on average 1.15 percent, or 10.94 percent of the July-February cumulative return, was earned in the three-day window around the earnings announcement dates for the second, third and fourth quarters. Stocks in the second lowest size quintile have on average earned a cumulative return of 2.64 percent over the July-February period, and 0.88 percent, or 33.19 percent of that return, was earned around earnings announcement dates. In the three largest size quintiles, the portion of returns of the strategy that occur around earnings announcement dates are much lower or even negative. Again, this evidence is consistent with the observation of Chari, Jagannathan and Ofer (1988) that information about larger firms is available more continuously.

C. Cumulative abnormal returns around earnings announcement days

If diminished disagreement causes the price decline in the high-dispersion stocks, they should earn a negative return around earnings announcement dates. Moreover, this return should be lower than for otherwise similar stocks with low levels of disagreement.

I use the portfolio assignment described earlier (5 x 3 sorting) for June of each year. I compute the abnormal return for each stock for the second, third, and fourth quarters of that year for a three-day window around the earnings announcement date. In order to minimize the time-series and cross-sectional correlation in cumulative abnormal returns with closely spaced earnings announcement dates, I group together stocks in the same June-based portfolios with identical earnings announcement dates, assigning equal weights to each stock in the group.[8]

In order to calculate the cumulative abnormal returns around earnings announcement dates, I assume that all returns can be described by the market model with $\beta = 1$:

$$r_{it} = r_{mt} + \epsilon_{it} \tag{2}$$

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, I estimate the standard deviation σ_{it} of ϵ_{it} as the sample standard deviation from day -61 to -2, and denote it by s_{it}. The cumulative abnormal return (CAR) is estimated as:

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

The scaled cumulative abnormal return $SCAR_{it} = \frac{CAR_{it}}{s_{it}}$ normalizes the cumulative abnormal returns by the volatility of stock returns, thus assigning a lower weight to more volatile stocks.[10]

[8] There will still be some correlation between cumulative abnormal returns on stocks with the earnings announcement dates less than two days apart. I assume that this effect is negligible.

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

[10] The methodology is described in Chari, Jagannathan, and Ofer (1988) and Campbell, Lo, and MacKinlay (1997).

After constructing a time series of scaled cumulative abnormal returns, I calculate their averages and standard deviations by portfolio over quarters and years.

A problem with this methodology is that the high-dispersion stocks also tend to have more volatile returns. But assigning lower weights to more volatile stocks, I am also underweighting the higher-dispersion stocks. Possibly as a result of this, the average portfolio returns do not decline smoothly with increasing dispersion rankings.[11]

The resulting mean $SCAR$s and t-statistics of the difference in abnormal returns between the lowest and highest dispersion categories are reported in Table II. For the 5 x 3 sorting on size and dispersion, stocks in the high-dispersion portfolios have on average earned significantly negative returns for all except the largest size quintile. The return difference between the low- and high-dispersion stocks is highly significant for the two smallest size groups and significant for the second largest size group.[12]

The evidence in this section supports the claim that low returns on high-dispersion stocks are associated with the resolution of uncertainty. These stocks appear to be initially overpriced, and the price comes down to the fundamentals as the disagreement about their value is resolved.[13]

In the next two sections, I will try to answer whether the optimistic bias in prices arises because investors do not properly account for the impact of short-sale constraints and for analysts' incentives, or both.

[11] When abnormal returns are not scaled by volatility, they show a similar pattern, but decline more smoothly with the dispersion ranking.

[12] None of the differences in $SCAR$s between the low- and high-dispersion portfolios have been on average significant during any other three-day window besides the earnings announcement day window. I tested this using the mean individual stock returns and the standard deviations of these returns over the July-February period of each year.

[13] Scherbina (2001) finds that dispersion of long-term earnings growth forecasts does not predict future returns. She conjectures that one of the reasons is that the uncertainty about long term growth rates takes a long time to resolve, and so the optimists see not reason to revise their opinions.

IV. Tests of Relationship Between Returns and Predictors of Short-Sale Costs

The costs of selling short are notoriously difficult to measure. They include not only the fee for borrowing a stock, but also the risk that the short-seller will be forced to liquidate his position early. The market for lending shares is not well-developed, and different short-sellers pay different fees and face different risks that they will be forced to scrap their positions early.

The data on lending fees are very difficult to obtain, and are probably not available far enough in history. However, institutional ownership may serve as good indicator of how binding the short-sale constraint is for a particular stock. Taking a broader view of the costs of selling a stock, an investor with a pessimistic outlook may be unwilling to sell because he may want to avoid realizing capital gains at that particular point in time. Mutual funds are generally unconcerned about capital gains taxes, but they are almost always prohibited by regulations from taking short positions in a stock (in other words, they have an infinite cost of short-selling). Mutual funds are among the most sophisticated investors in the market, and therefore, their desire to sell may be more informative to the market than a sale by a private individual. If a mutual fund already owns a stock, it can sell it easily and thereby disseminate the negative information to the market. In addition, high mutual fund ownership should ease short-selling restrictions for other investors. Shares held by mutual funds are often available for lending, and the high the supply of shares, the lower will be the lending costs.

D'Avolio (2001) and Reed (2001) study the data on short-selling fees for 1998-1999 and find that only about 6 to 10 percent of all stocks were expensive to short-sell at any given point of time. These stocks are said to be "on special." The other stocks had low fees, around 10 basis point, and are referred to as "general collateral." Reed (2001) finds that specialness is most often triggered by episodic corporate events, such as IPOs, mergers and dividend reinvestment discount programs. D'Avolio (2001) finds that the probability of being on special is negatively correlated with institutional ownership and size, and positively with turnover. High turnover should also have an adverse impact on the willingness to sell short because stocks which are actively traded have a higher chance of being called back prematurely. Given these considerations, if short-sale constraints are responsible for the upward bias in stock prices, institutional ownership and size should be positively correlated and turnover negatively correlated with future returns when there is disagreement about the value of a stock.

A. Institutional ownership, size and turnover as predictors of returns

I test whether institutional ownership, size and turnover predict the cross-section of next month's returns. Institutional ownership is defined as the fraction of all shares outstanding held by institutions. I calculate total institutional ownership by summing up individual holdings from the Spectrum dataset, which reports holdings of institutions that file the 13F reports with the Securities Exchange Commission (SEC). Total number of shares outstanding is taken out of CRSP. The Spectrum data are quarterly and the CRSP data are monthly. Turnover is defined as the ratio of the monthly trading volume to the total number of shares outstanding. I also introduce a new measure of turnover. Adjusted turnover is defined as the ratio of monthly trading volume to the total number of shares held by 13F SEC report filers. The idea is that the total number of shares outstanding is a misleading measure for the supply of shares because the shares owned by insiders are rarely traded. The number of shares available for trade is better measured by the total holdings of outsiders, which are approximated by total institutional holdings. The importance of using free float (approximated here by institutional holdings) in place of the total number of shares outstanding has been illustrated by a recent trend to value-weight stock indexes by free-float-adjusted market capitalization, which is a product of share price and free float.[14]

I run Fama and MacBeth (1973) cross-sectional regressions of monthly month's returns on the previous month's predictive variables:

$$r_{t+1} = \beta_0 + \beta_1 \ln(ME)_{it} + \beta_2 \ln(BE/ME)_{it} + \beta_3 disp_{it} + \beta_4 instit_{it} + \beta_5 turn_{it} + \beta_6 cov_{it} + \epsilon_{it} \quad (4)$$

[14]The Dow Jones Indexes September 2000 newsletter discusses using free float in the future. Morgan Stanley Capital International has already devised the guidelines for the free float adjustments of their stock indexes.

where $\ln(ME)$ is the natural logarithm of the firm's market-capitalization value for the previous month; $\ln(BE/ME)$ is the natural logarithm of the ratio of book value to the previous month's market value of equity (book value of equity as of the end of the most recent fiscal year is used unless less than less than three months have elapsed since the last fiscal year end; in that case, the book equity value from the fiscal year before last is used); *disp* is the ratio of dispersion in analyst earnings per share forecasts to the absolute mean value of the forecast (observations with a mean forecast of zero are removed from the sample); *instit* is the ratio of the number of shares held by institutions to the total number of shares outstanding; *turn* is either the adjusted or the unadjusted turnover variable; [15] and *cov* is analyst coverage in excess of what is average for stocks in the same size and book-to-market category (residual analyst coverage); Hong, Lim and Stein (1999) claim that it captures the speed with which information reaches the market.

Since *instit* is expected to be highly correlated with the firm's market-capitalization level and book-to-market ratio (mutual funds tend to hold large growth stocks), I orthogonalize it with respect to these variables. (When it is not orthogonalized, results are still similar.) Orthogonalized *instit* can be interpreted as institutional ownership, which is in excess of what is the norm for a stock of a given size and book-to-market ratio.

I test different variations of model (4). Neither *instit* nor *turnover* or $ln(ME)$ turn out significant in predicting the cross-section of next month's stock returns. Contrary to the expectation, *adjusted turnover* turns out positive and significant.[16] While residual analyst coverage is positive, it is not significant. In order to appear significant it needs to be used in conjunction with an indicator of negative momentum. Dispersion is always negative and significant, with the t-statistics ranging from -1.85 to -2.11, depending on the regression specification. Since these regressions make use of the Spectrum data, the sample is smaller and the average firm size is higher than

[15] Chen, Hong and Stein (2001) suggest demeaning trading volume and turnover by the average volume and turnover of the firm's exchange, where NYSE and AMEX are treated as one exchange, and Nasdaq as another. This definition of turnover and trading volume does not significantly affect the results.

[16] Lee and Swaminathan (2000) hypothesize that high trading volume helps attract attention to a firm and broaden the investors base. They show that high trading volume is negatively related to stock returns over the next 12 months. Consistently, *adjusted turnover* may help capture the initial price appreciation, but this question needs to be investigated further.

for the sample used for the cross-sectional regressions in Diether, Malloy and Scherbina (2001). Consequently, the dispersion variable is less significant than significant in their regressions, since it tends to be better at forecasting returns for smaller stocks.

B. S&P 500 stocks

The Standard and Poor's Composite (S&P 500) includes 500 of the largest stocks in the United States. The performance of the S&P 500 index is considered a benchmark of the overall U.S. stock market. Numerous mutual funds have been created to replicate S&P 500 returns by holding the stocks in the index. Mutual funds earn profits by lending their shares to short-sellers. Therefore, stocks included in the S&P 500 listing are widely available for borrowing from mutual funds. It is then natural to conclude that costs of short-selling these stocks should be very low. Since pessimists would be able to express their opinions at low cost, it is expected that the return differential between low- and high-dispersion stocks would be low or even insignificant for the stocks in the S&P 500 index.

I have obtained the composition of the S&P 500 index from Standard and Poor's Corporation up to July of 1997. On average, 451 of these stocks are covered by I/B/E/S analysts. The number of the S&P 500 stocks in the I/B/E/S universe grew from 419 stocks in January of 1983 to 462 stocks in July of 1997. I assigned each of these stocks to one of five portfolios based on the dispersion in the analyst earnings-per-share forecasts. Average monthly portfolio returns are reported in Table 11. As can be seen from the table, the low-dispersion stocks on average have earned a return of 0.48 percent higher than the low-dispersion stocks. This difference is significant with at the 10 percent level with the t-statistic of 1.69. This is strong evidence against the short-sale-constraints explanation.

The evidence presented in this section is inconsistent with short-sale costs being the cause of the upward bias in stock prices. As per Diamond and Verrecchia (1987) logic, if investors correctly adjust their valuations for the possibility that a group of traders that is constrained from selling short may have low valuations, the prices will be unbiased. Given that only a small fraction of stocks have high short-sale costs, possibly because they are mispriced in the first place, it is likely that investors adjust their valuations down based on this knowledge. Short-sale constraints have been around for a long time, and it is not unreasonable to expect that investors have learned to account for their impact.

V. Information Flow From Analysts to Investors

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 that this truncation causes a positive correlation between the level of analyst disagreement and the upward bias in the mean reported forecast. If investors do not account for this property of analysts' forecasts in their valuations, prices will be more optimistic, the higher the level of disagreement among analysts.

A. Analysts' incentives and the 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.[17] Therefore, negative forecast revisions will be associated with low returns. As hypothesized, the initial upward forecast bias and the magnitude of the future downward forecast revisions are positively related to the initial dispersion in analysts' forecasts. Scherbina (2001) found that analysts on average tend to have the more optimistic forecast errors for the quarterly earnings just before the earnings are announced, the higher the dispersion in the underlying forecasts. The time series of analysts' annual earnings forecasts also reveals that analysts tend to be more optimistic in the beginning of the forecast period. The mean forecast tends to get revised downward over the forecasting period. The magnitude of the optimistic bias, but also the speed of the downward revision is highest for the stocks which initially have the highest forecast dispersion.

[17] 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).

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 V 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. In the rest of this section, I explains this phenomenon with self-selection in analysts coverage.

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 to analysts more precise. Analysts once again receive private signals with the same precision relative to the common information, 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:

$$s_0 = AEPS + \epsilon_0 \tag{5}$$

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}:

$$s_{i1} = AEPS + \epsilon_{i1} \tag{6}$$

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.

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:

$$\begin{aligned} E_0[C_1] &= E_0\left[F | F \geq -k\sigma_0\right] \\ &= E_0\left[\frac{s_{i1}\sigma_0^2}{\sigma_0^2 + \sigma_{An,1}^2} \middle| s_{i1} \geq -k\sigma_0 \frac{\sigma_0^2 + \sigma_{An,1}^2}{\sigma_0^2}\right] \end{aligned} \tag{7}$$

Substituting $\nu \equiv \frac{\sigma_{An,1}}{\sigma_0}$, since this ratio will be constant over time, the solution to equation 7 can be expressed as:

$$E_0[C_1] = \sigma_0 \frac{\nu}{1 + \nu^2} \frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})} \tag{8}$$

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 8, the bias disappear in case that the private signal is certain ($\sigma_s = 0$), 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 commonly-known mean. 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 degree of uncertainty in common information.

The function of 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 private information is less precise than the common signal, the bias in the mean forecast increases in the relative precision of the common signal.*

Proof In the Appendix.

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

$$\begin{aligned} E_0[\mathrm{VAR}(C_1)] &= E_0\left[F^2|F \geq -k\sigma_0\right] - \left[E_0\left(F|F \geq -k\sigma_0\right)\right]^2 \\ &= \sigma_0^2\left(\frac{\nu}{1+\nu^2}\right)^2\left[k\frac{\nu}{1+\nu^2}\frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})} + 1 - \frac{f^2(k\frac{1+\nu^2}{\nu})}{\Phi^2(k\frac{1+\nu^2}{\nu})}\right] \end{aligned} \tag{9}$$

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 private information is less precise than the common signal, dispersion in reported analysts' forecasts increases in the relative precision of the 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:

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

$$
\begin{aligned}
&= \sigma_0 \frac{\nu}{\sqrt{K+\nu^2}} \frac{\nu}{1+\nu^2} \frac{f(k\frac{1+\nu^2}{\nu})}{\Phi(k\frac{1+\nu^2}{\nu})} \\
&= \frac{\nu}{\sqrt{K+\nu^2}} E_0[C_1] \qquad (10)
\end{aligned}
$$

$E_0[\mu_1] = 0$ 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 private information 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 private information.*

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. 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 seriously, she 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, planning to gradually reduce it over the year.[18] 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 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, meaning that they revise a little at a time, whereas the upward revisions are less gradual. This is consistent with the incentive not to appear too pessimistic relative to others and waiting for others to revise their forecasts down before further downward revisions. 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. They are forced to revise their forecasts down in grater numbers towards the end of the fiscal year, when the uncertainty gets resolved rapidly.

D. 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

[18] This has been suggested by Richardson, Teoh, and Wysocki (2001)

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.

Table VI 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, though not always significant. But 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 is likely to lower the future returns.

Table VII 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.

E. 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. 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 are not known to earn 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 VIII, 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 indicates 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. This indicates that the practice of earnings management leads to higher, not lower level of agreement.

VII. Conclusion

There are numerous obstacles that prevent negative information from reaching the market. This paper focuses on two such obstacles in asking why dispersion in analysts' forecasts predicts future returns: Short-sale constraints and analysts' incentives.

The "sell" order flow from informed pessimistic investors is impeded by short-sale constraints. If investors are rational, they would correctly account for these costs in their valuations, and market prices will be unbiased. Proxies for short-sale costs turn out to be insignificant in predicting the cross-section next month's returns. High-dispersion stocks in the S&P 500 index earn significantly lower returns than the low-dispersion stocks in the index, even though the costs of short-selling these stocks should be negligible. This evidence is consistent with investors correctly accounting for short-sale costs in their valuations.

Analysts prefer not to report their forecasts when they are sufficiently pessimistic relative to their peers. This produces an upward bias in the mean reported forecast, which is increasing in the level of disagreement. The data indicate that investors do not properly discount the reported forecasts for this bias. Disprison in reported forecasts captures the likelihood that the mean forecast will be revised down. This likelihood is even better captured by the past forecast revisions. Dispersion and the past forecast revision are highly negatively correlated. This correlation increases when the time horizon over which the forecast revision is measured increases. When the revision in the mean forecast over the past six months is used alongside dispersion in predicting the cross-section of next month's returns, dispersion becomes insignificant. It's predictive power is subsumed by the predictive power of the forecast revision.

If investors are always surprised by the downward revisions in the mean forecast, and it declines gradually over the fiscal year, low-dispersion stocks should consistently outperform the low-dispersion stocks throughout year. However, this is not the case in the data. High-dispersion stocks underperform the low-dispersion stocks on average over the year, but 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. 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.

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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 9 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

Portfolio Returns by Size and Dispersion in Analysts' Earnings Per Share Forecasts

Every month, stocks are sorted into quintiles based on the level of market capitalization as of the end of the previous month. Within each size quintiles, the stocks are sorted into quintiles based on dispersion in analyst earnings per share forecasts for 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 mean forecast, as reported in the I/B/E/S Summary History file. Stocks with a mean forecast of zero are assigned to the highest dispersion groups, and stocks with a price less than 5$ are excluded from the sample. Stocks are held for one month, and portfolio returns are equal-weighted. The time period considered is February 1983 through December 2000. The table reports average monthly portfolio returns; t-statistics in parentheses are adjusted for autocorrelation.

Returns

Dispersion Quintiles	Size Quintiles small *S1*	*S2*	*S3*	*S4*	large *S5*	All Stocks
D1 (low)	1.52	1.45	1.50	1.51	1.48	1.48
D2	1.12	1.40	1.41	1.18	1.35	1.36
D3	0.99	1.20	1.32	1.11	1.36	1.23
D4	0.76	1.07	1.18	1.33	1.33	1.12
D5 (high)	0.14	0.56	0.83	1.03	1.20	0.69
D1-D5	1.37[a]	0.89[a]	0.67[b]	0.48	0.29	0.79[a]
t-statistic	(5.98)	(3.12)	(2.41)	(1.55)	(0.94)	(2.88)

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

Average Dispersion

Dispersion Quintiles	Size Quintiles *S1*	*S2*	*S3*	*S4*	*S5*	All Stocks
D1 (low)	0.010	0.011	0.012	0.014	0.014	0.012
D2	0.039	0.033	0.030	0.028	0.025	0.030
D3	0.081	0.062	0.053	0.047	0.039	0.053
D4	0.172	0.125	0.103	0.086	0.067	0.105
D5 (high)	1.256	0.963	0.813	0.722	0.462	0.852

Table II
Scaled Abnormal Returns Around Earnings Announcement Dates

In June of each year, stocks with December fiscal year end are sorted into size quintiles. Within each size quintiles, the stocks are sorted into three groups based on dispersion in current-fiscal-year analysts' earnings per share forecasts. Scaled abnormal returns for the second, third, and fourth quarters of each year are then calculated for the stocks in each portfolio. Scaled abnormal return is defined as the ratio of cumulative abnormal return to its standard deviation. Cumulative abnormal return is calculated as the three-day cumulative market model prediction error from one day before the announcement date to one day after the announcement date. Standard deviation is calculated as the standard deviation of the market model prediction error from 60 days to two days before the announcement date. If earnings announcement dates coincide for several stocks in a portfolio then the scaled abnormal return on the portfolio on that date is calculated using average daily returns on the stocks. The numbers in the table are the scaled cumulative abnormal returns around earnings announcement dates, averaged over the time period of 1979 to 2000 and over stocks in a portfolio; t-statistics are adjusted for autocorrelation.

	Size Quintiles				
Dispersion Groups	small *S1*	*S2*	*S3*	*S4*	large *S5*
D1 (low)	0.030	0.011	-0.043	0.034	-0.013
	(0.81)	(0.29)	(-1.07)	(0.71)	(-0.31)
D2	-0.072^b	-0.051	0.048	-0.048	-0.011
	(-2.17)	(-1.22)	(1.20)	(-1.14)	(-0.28)
D3 (high)	-0.149^a	-0.128^a	-0.068^c	-0.134^b	0.048
	(-4.43)	(-3.60)	(-1.66)	(-2.12)	(1.33)
D1-D3	0.179^a	0.139^a	0.026	0.168^b	-0.036
	(3.59)	(2.66)	(0.45)	(2.11)	(-0.65)

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

Table III
Fama-MacBeth Regressions of Monthly Returns on Stock Characteristics and Predictors of Short-Sale Costs

$\ln(ME)$ is the logarithm of firm's market value as of the end of previous month. $\ln(BE/ME)$ is the logarithm of the ratio of the firm's book value of equity to the market value of equity as of the end of the previous month. Book value of equity is taken from the latest fiscal year end report, but if less than three months have passed since the fiscal year end, then the book equity value for the year before that is used. *Residual Coverage* is the residual from monthly regressions of $\ln(1+\textit{analyst coverage})$ on $\ln(ME)$ and $\ln(BE/ME)$. *Dispersion* is the ratio of the standard deviation of the analyst current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast (observations with the mean forecast of zero are deleted from the sample). *Instit.* is the ratio of total shares held by institutions filing 13F reports (measured on the quarterly basis) to the total number of shares outstanding (measured monthly). *Turnover* is the ratio of the trading volume to the end-of-month number of shares outstanding. *Adjusted Turnover* is the fraction of volume to the total number of shares held by institutions filing 13F reports. Since *Instit.* is orthogonalized with respect to $\ln(ME)$, $\ln(BE/ME)$ and *Residual Coverage*. *Turnover* (and *Adjusted Turnover*) are orthogonalized with respect to $ln(ME)$ and $ln(BE/ME)$. When these variables are not orthogonalized, results are similar. Returns are in percent, t-statistics, adjusted for serial autocorrelation, appear in parenthesis. The period of analysis is February 1980 to December 2000.

ln(ME)	ln(BE/ME)	Dispersion	Instit.	Turnover	Adjusted Turnover	Residual Coverage
0.025	0.207	-0.127^b	-0.004	0.000	-	0.096
(0.53)	(1.59)	(-2.11)	(-0.03)	(0.33)	-	(0.92)
0.020	0.205	-0.126^b	-	-	0.147^b	0.136
(0.43)	(1.53)	(-2.08)	-	-	(2.04)	(1.23)
0.023	0.196	-0.118^c	-	-	-	-
(0.49)	(1.44)	(-1.88)	-	-	-	-
0.020	0.204	-0.125^b	-	-	0.154^b	-
(0.42)	(1.52)	(-2.03)	-	-	(2.10)	-
0.024	0.194	-0.117^c	-0.016	-	-	-
(0.50)	(1.42)	(-1.85)	(-0.11)	-	-	-
0.025	0.212^c	-0.126^b	-	0.000	-	-
(0.54)	(1.66)	(-2.07)	-	(0.85)	-	-
0.024	0.195	-0.118^c	-0.017	-	-	0.144
(0.52)	(1.43)	(-1.90)	(-0.12)	-	-	(1.27)
0.025	0.197	-	-	-	0.148^b	-
(0.53)	(1.47)	-	-	-	(2.01)	-
0.031	0.204	-	-	0.000	-	-
(0.65)	(1.60)	-	-	(0.78)	-	-

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

Table IV
Average Monthly Returns on the S&P 500 Stocks Sorted by Dispersion in Analysts' Earnings Per Share Forecasts

Stocks that are in the S&P 500 index at the time of portfolio formation are sorted into quintiles, based on dispersion in analyst earnings-per-share forecasts. Dispersions in analyst forecasts are defined as the ratio of standard deviation in the current year's earnings per share estimates to the absolute value of the mean estimate. If the mean estimate is zero, then the stock is assigned to the highest dispersion portfolio.

Dispersion Quintiles	Average Dispersion	Average Monthly Returns for January 1983 - July 1997
D1	0.019	1.70
(low dispersion)		(4.41)
D2	0.033	1.56
		(4.41)
D3	0.053	1.49
		(4.63)
D4	0.099	1.45
		(4.89)
D5	0.838	1.22
(high dispersion)		(5.52)
D1-D5	-	0.48[c]
		(3.46)
t-statistic		(1.69)

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

Table V
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.

	Size Quintiles					
Dispersion 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 VI

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 $\ln(1+\textit{analyst coverage})$ 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); $Rev1$, $Rev2$, $Rev3$, $Rev4$, $Rev5$, and $Rev6$ – 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 VII
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 $\ln(1 + \textit{analyst coverage})$ 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 VIII

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)	

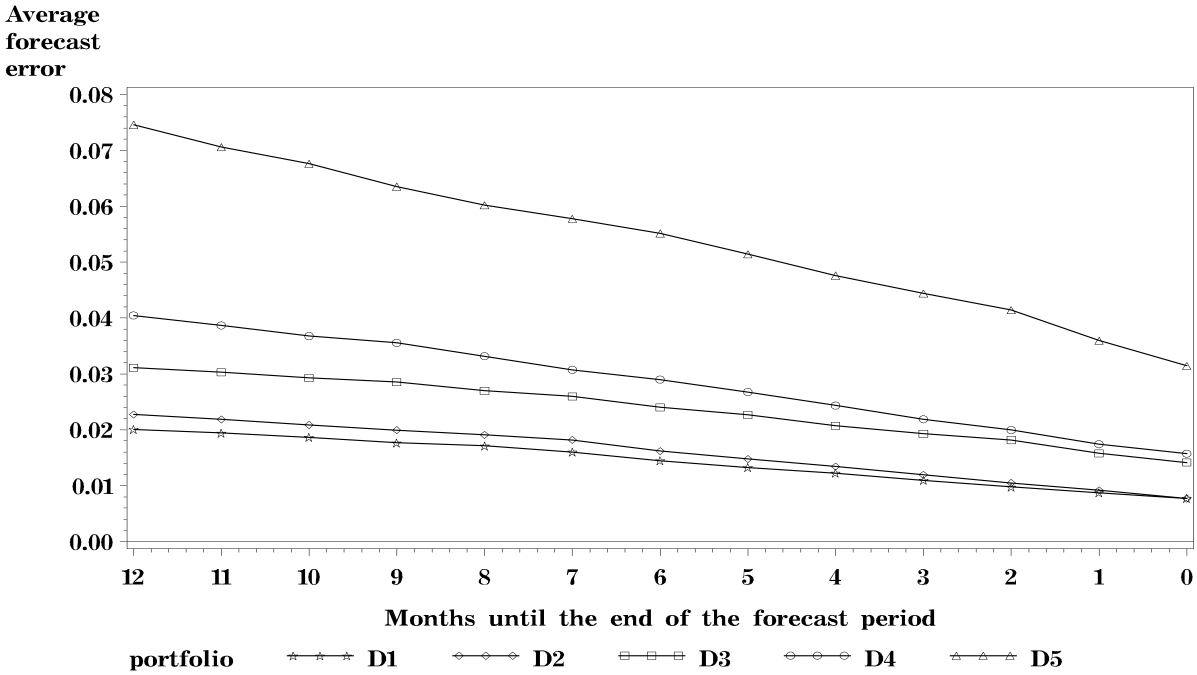
^{a,b,c} Statistically significant at the 1, 5, and 10 percent levels, respectively

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.



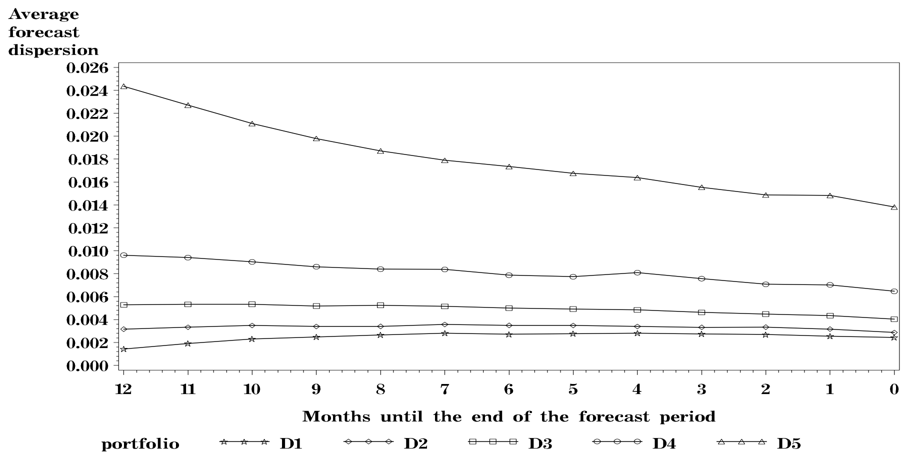
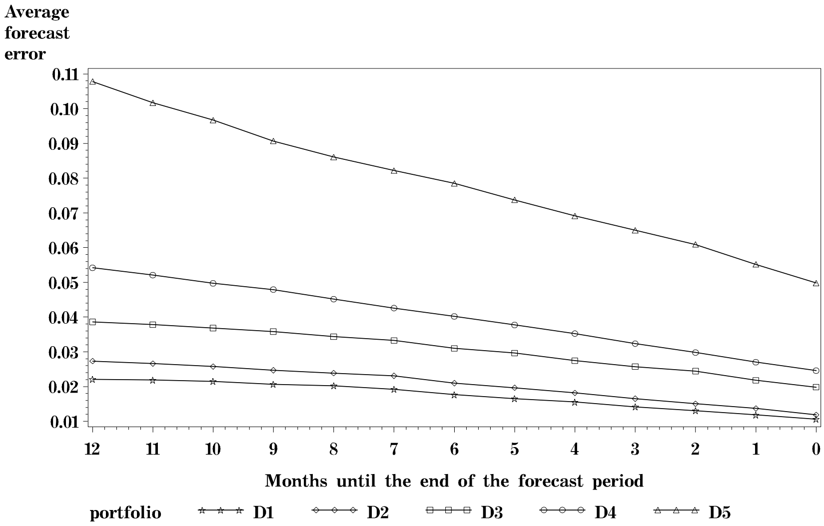


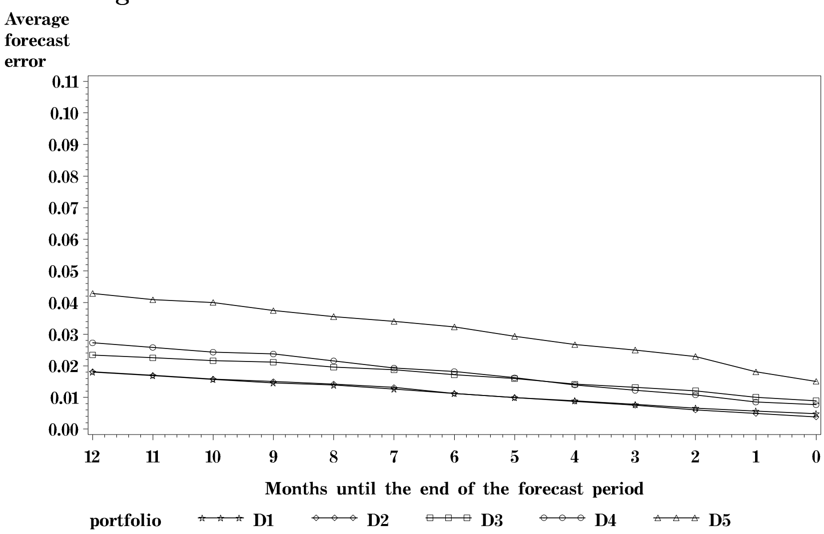
Figure 2
Properties of the Earnings Per Share Forecasts

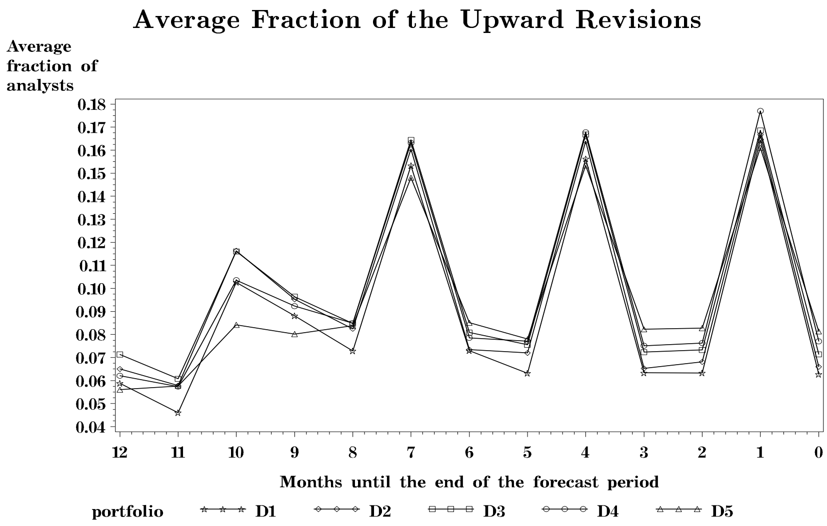
At the end of the previous fiscal year, stocks are sorted into five portfolios based on dispersion in analysts' earnings earnings per share forecasts for the current fiscal year. Forecast error is defined as the forecast minus the realized earnings, scaled by the stock price at the time of portfolio 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.

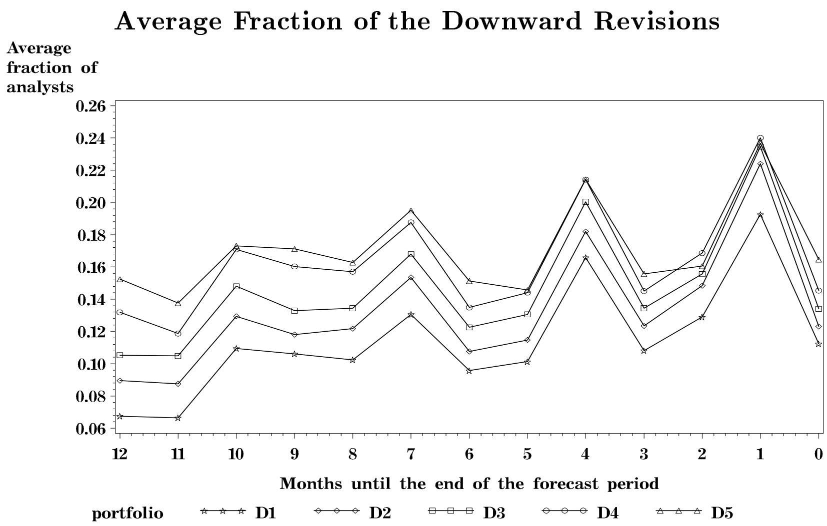
Average Forecast Error of the Most Optimistic Forecast



Average Forecast Error of the Most Pessimistic Forecast




Average Fraction of the Upward Revisions
Average fraction of analysts
0.18 0.17 0.16 0.15 0.14 0.13 0.12 0.11 0.10 0.09 0.08 0.07 0.06 0.05 0.04
12 11 10 9 8 7 6 5 4 3 2 1 0
Months until the end of the forecast period
portfolio D1 D2 D3 D4 D5


Average Fraction of the Downward Revisions
Average fraction of analysts
0.26 0.24 0.22 0.20 0.18 0.16 0.14 0.12 0.10 0.08 0.06
12 11 10 9 8 7 6 5 4 3 2 1 0
Months until the end of the forecast period
portfolio D1 D2 D3 D4 D5

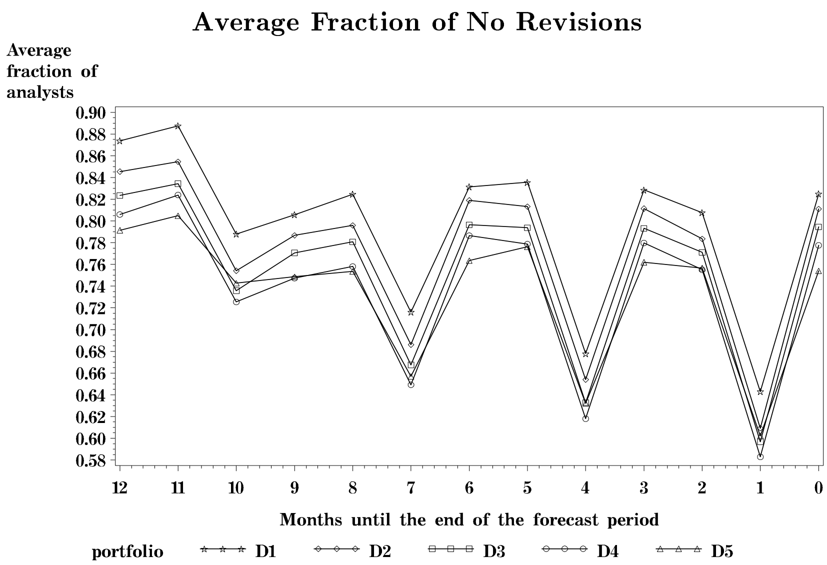
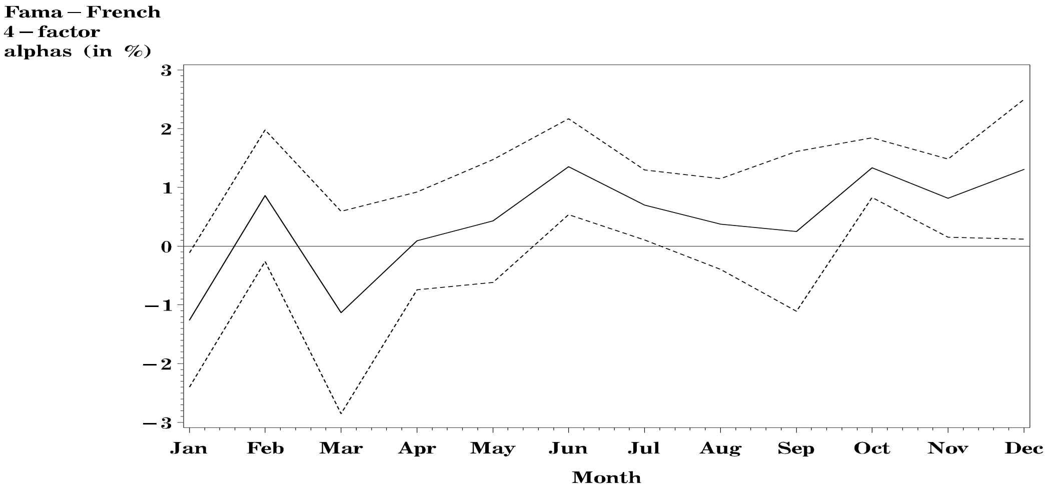

Average Fraction of No Revisions
Average fraction of analysts
0.90 0.88 0.86 0.84 0.82 0.80 0.78 0.76 0.74 0.72 0.70 0.68 0.66 0.64 0.62 0.60 0.58
12 11 10 9 8 7 6 5 4 3 2 1 0
Months until the end of the forecast period
portfolio D1 D2 D3 D4 D5

Figure 3
Fama-French Four-Factor Alphas

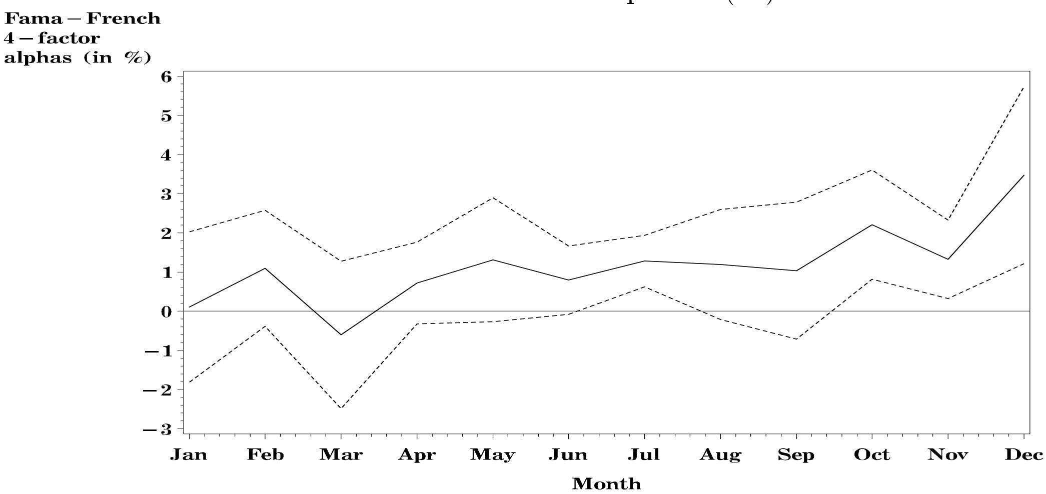
All stocks in the specified groups are sorted into portfolios based on dispersion in analysts' earnings per share forecasts (defined as the standard deviation in reported forecasts scaled by the mean forecast; if the mean forecast is zero, stocks are assigned to the highest dispersion-based portfolio) 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

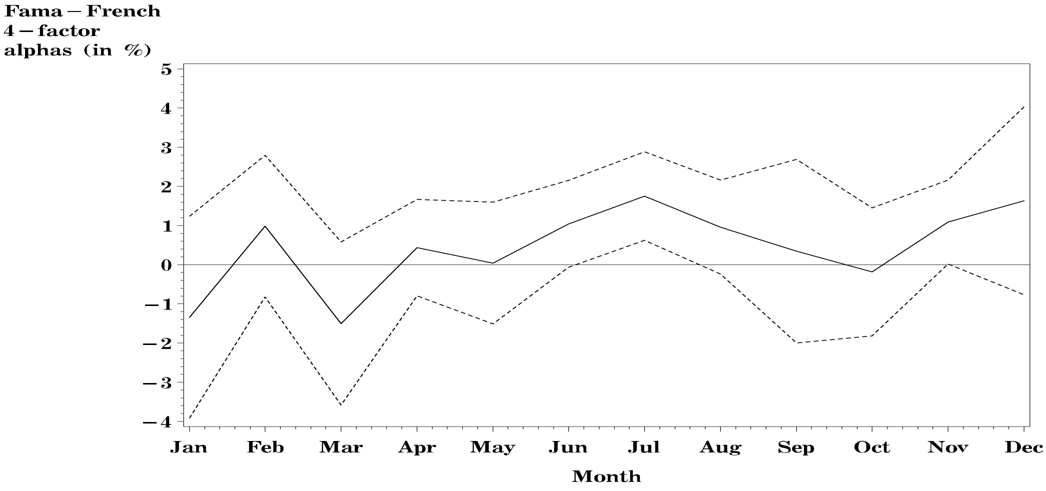


Size Groupings

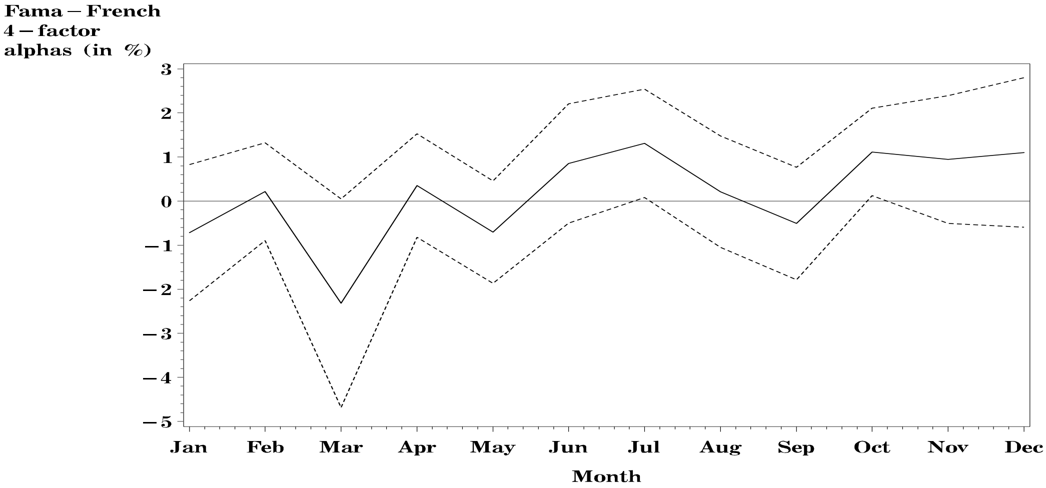
Stocks in the smallest size quintile (S1)



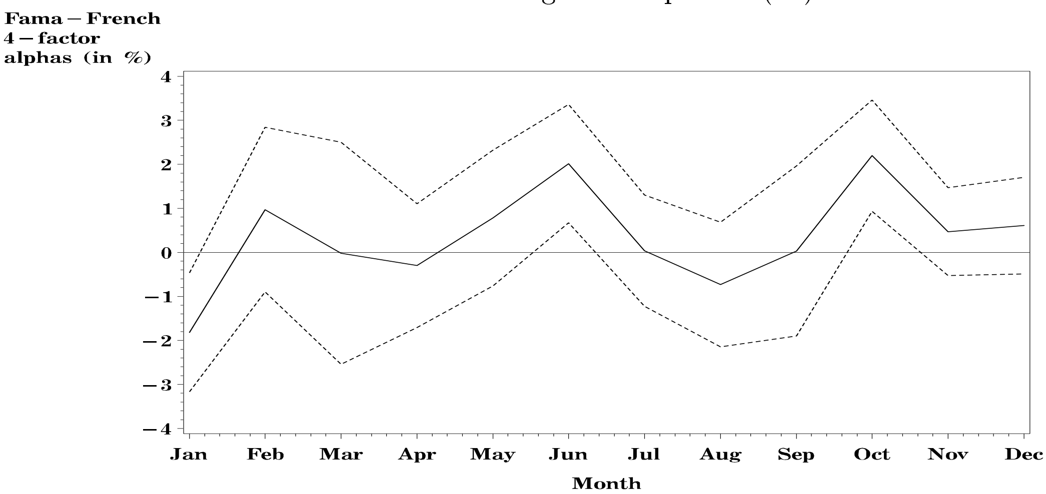
Stocks in the second smallest size quintile (S2)



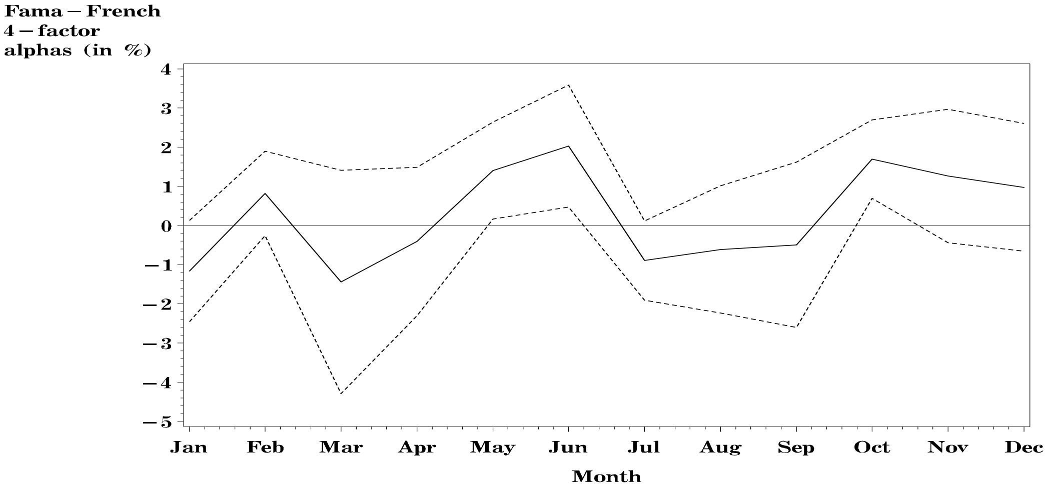
Stocks in the third smallest size quintile (S3)



Stocks in the second largest size quintile (S4)

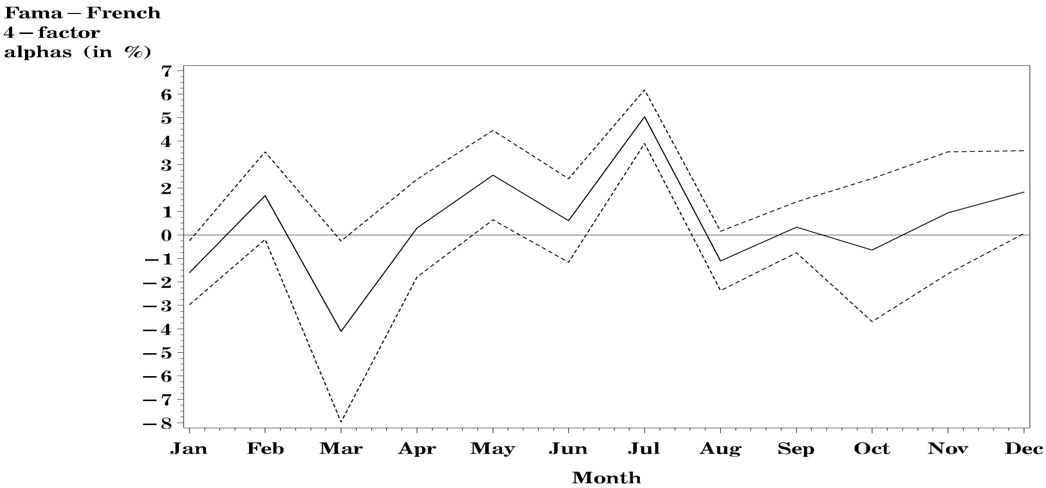


Stocks in the largest size quintile (S5)

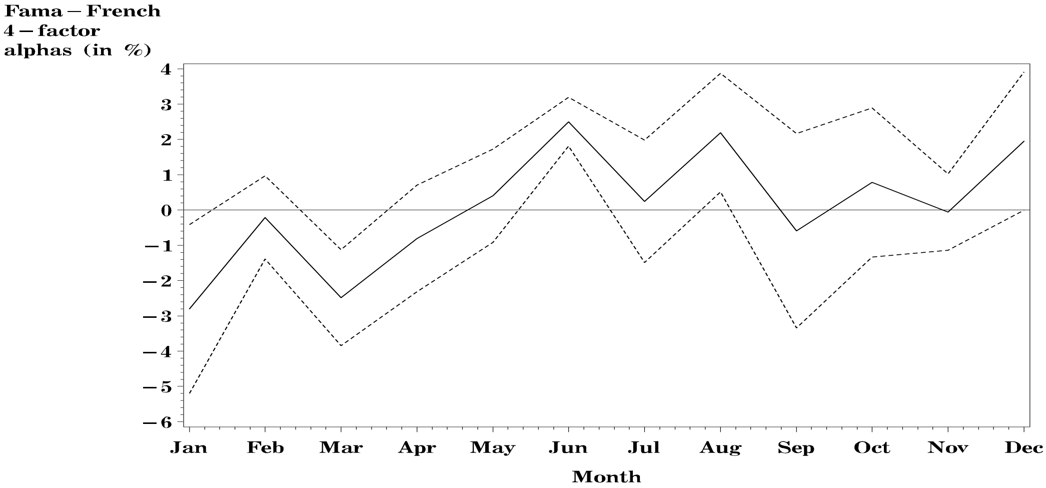


Fiscal-Year-End Groupings

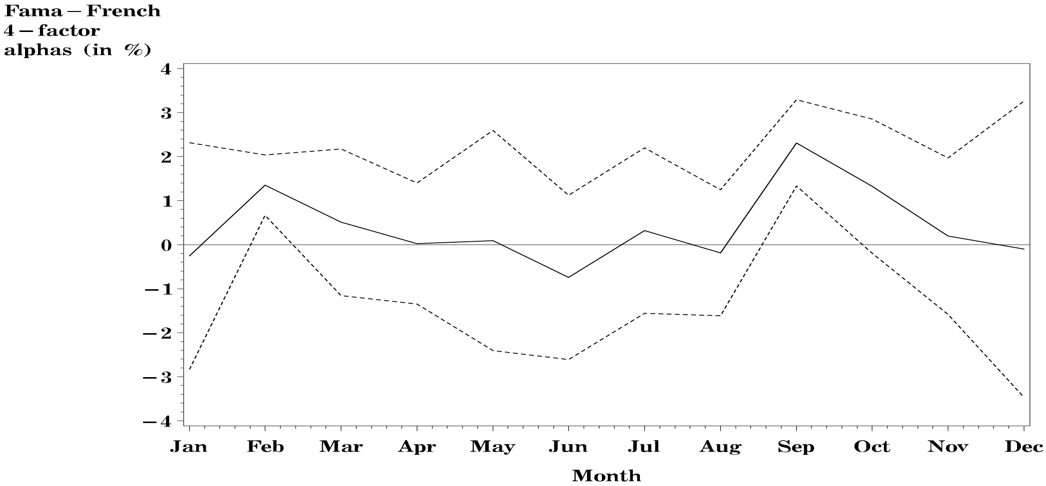
March fiscal year end



June fiscal year end



September fiscal year end



December fiscal year end