Analyst Forecast Dispersion and Future Stock Return Volatility

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In this paper, we examine the relationship between analysts' forecast dispersion and future stock return volatility using monthly data for a cross section of 160 U.S. firms from 1981 to 1996. We find that there is a strong and positive relationship between analysts' forecast dispersion and future return volatility. The dispersion measure has incremental information content even after accounting for market volatility. These results are robust across subsample periods and subsamples based on the number of analysts following a firm, forecast dispersion, and market capitalization. There is also a strong seasonal relationship between the dispersion measure and future volatility. The importance of dispersion on future return volatility is high in January and the first few months of the year and declines thereafter. Such information content of analysts' earnings forecast dispersion is of great importance for active portfolio management, option pricing, and arbitrage trading strategies.

Introduction

Analysts' forecast dispersion refers to the disagreement among analysts with regard to the expected earnings per share (EPS) of a given firm. It is a forward-looking variable that embeds analysts' expectations about the firm's future profitability. It is also used as a proxy variable for differences in investor-opinion for a given firm. Previous research has shown the usefulness and importance of forecast dispersion in forming profitable trading strategies. Ackert and Athanassakos (1997) report that a strategy of buying (selling) low (high) dispersion stocks at the beginning of the year produces positive abnormal returns. Dische (2002) shows that positive

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abnormal returns can be achieved by applying earnings momentum strategies to stocks with low analysts' forecast dispersion. Ang and Cicone (2002) find that buying low dispersion stocks and selling high dispersion stocks on June 30 of each year and holding the portfolio over the next twelve months generates significantly positive returns that are not related to size or book-to-market. Diether, Malloy, and Scherbina (2002) find that high dispersion stocks earn relatively lower future returns.

In this paper, we examine the relationship between analysts' forecast dispersion and future stock return volatility, using monthly data for a cross section of 160 U.S. firms over the period 1981-1996. Such a relationship, if it exists, would be of great importance for active portfolio management, option pricing, and arbitrage trading strategies. For example, mutual fund managers can use volatility forecasts based on analyst dispersions to perform efficient volatility-timing strategies. Similarly, option investors can buy (sell) straddles whenever volatility forecasts based on analysts' forecast dispersion generate straddle prices that are higher (lower) than corresponding market prices. While much of previous work on analysts' forecast dispersion and stock return volatility has studied periods of earnings announcements, we look at such a relationship on an on-going basis, without reference to formal accounting events and disclosures.

Earlier research has also examined the relationship between stock return volatility and forecast dispersion. Abarbanell, Lanen, and Verrechia (1995) present a rational expectations model, which predicts that analysts' forecast dispersion and the ex-ante variance of price changes should be positively related during earnings announcement periods. They indicate that high forecast dispersion implies low forecast precision, which in turn suggests reduced public information and greater uncertainty in the market at the time of the earnings announcement. Early empirical studies by Ajinkya and Gift (1985) and Daley, Senkow, and Vigeland (1988) find that the ex-ante variability of stock returns around earnings announcements (obtained as implied volatility from option prices) is positively related to analysts' forecast dispersion. Daley et al. (1988), in particular, find a positive relationship between dispersions and average implied volatilities of options maturing after the earnings announcement dates. More recently, Lobo and Tung (2002) also find a strong and positive relationship between future stock price volatility and analyst forecast dispersion in periods surrounding quarterly earnings announcements for the sample period 1987-1990. They find that firms with high forecast dispersion experience high price variability over a longer time window surrounding earnings announcements compared to firms with low dispersion. Their findings support the theoretical predictions of Abarbanell et al. (1995).

At the same time, a large body of literature has examined the properties of financial analysts' EPS forecasts and the analysts' incentives to issue optimistic forecasts (Ali, Klein, and Rosenfeld, 1992; De Bondt and Thaler, 1990; and Diether et al., 2002). Ackert and Athanassakos (1997, 2003) show that analyst optimism and uncertainty are positively related. When there is a greater uncertainty about a firm's environment, analysts have fewer reputational concerns in issuing optimistic forecasts; analysts' forecasts tend to vary widely in this case. On the other hand, when the environment is quite certain, analysts are concerned about standing out of the crowd, and, hence, resist issuing optimistic forecasts.[1]

Extant research also shows that analysts' forecast bias is subject to seasonality, i.e., their forecast optimism is largest in January of the forecast year and declines throughout the year as the forecast horizon shortens. (See Ackert and Hunter, 1994; Ackert and Athanassakos, 1997; and Richardson, Teoh, and Wysocki, 1999.) Two forces are found to be behind this phenomenon. First, as more information becomes available (with the quarterly earnings releases), analysts cannot afford to continue being optimistic without hurting their reputation. Second, analysts have an incentive to be more optimistic in the early months of the year irrespective of the information available. Ackert and Athanassakos (1997) show that as portfolio managers rebalance their portfolios at the turn of the year, analysts have a greater incentive to be optimistic early in the year in order to attract new institutional business.

In this paper, we argue that, as analysts tend to be more optimistic when forecast dispersion is high (Ackert and Athanassakos, 1997, 2003), they tend to revise downward their forecasts of EPS of such companies throughout the year and significantly in many cases. The larger the current optimism of analysts (that is induced by the higher forecast dispersion in a stock) at time t, the more analysts will be forced to revise their forecast downward in the next period, i.e., at time t + 1 and, hence, the higher the stock return volatility at time t + 1. As a result, there should be a high correlation between current analysts' forecast dispersion and future stock return volatility. We further argue that such a relationship between optimism and future volatility may exhibit seasonal behavior as analyst optimism tends to be high in January and the first few months of the year, but less so toward year-end.

While much of previous work on dispersion and return volatility has studied periods of earnings announcements, this paper looks at such a relationship on a more on-going basis, namely when analysts revise their forecasts (that are reported) on a monthly basis. Assuming that there are monthly forecast revisions and that analysts' monthly forecasts have a corresponding effect on market prices, we examine the relationship between analysts' forecast dispersion and future stock return volatility on a monthly basis throughout the year, without reference to formal accounting events and disclosures.[2] Furthermore, we employ a much longer time period than any

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[1] Analysts have an incentive to issue optimistic forecasts not only in order to appease corporate managers, but also to attract business for their investment banking operations.

[2] Ajinkya et al. (1991) use analysts' earnings dispersion as a proxy for investors' disagreement about a firm's prospects and examine its relationship to trading volume. They also look at the relationship between variables on a continuous basis independent of any formal accounting events.

of the earlier studies that looked at the dispersion-volatility relationship. Our final sample consists of a time series-cross sectional set of data for 160 U.S. firms over a period from 1981-1996.

We find that a strong positive relationship exists between forecast dispersion and future stock return volatility. Analysts' forecast dispersion has incremental information content for future return volatility after accounting for (future) return volatility of the market-index. These results are robust across subsamples based on different time periods and groupings. There is also a strong seasonal relationship between future stock return volatility and the dispersion measure.

The importance of dispersion on future stock return volatility is high in January and the first few months of the year and declines thereafter. Finally, forecast dispersions in 1987, the crash year, seem to have had an added effect on future stock return volatility. Our results are consistent with the empirical findings of Lobo and Tung (2002) and the theoretical predictions of Abarbanell et al. (1995). Our results are also consistent with the Diether, Malloy, and Scherbina (2002) finding of negative relation between dispersion and future expected returns.

Theoretical Development: Testable Hypotheses

Suppose that analyst j revises his or her annual earnings forecast for firm i at time t. This forecast revision is assumed to affect stock prices[3] and returns according to the following ex-post model (Daley et al., 1988):

$$R_{i,t} = a_i + b_i R_{m,t} + c_i FR_{i,t} + e_{i,t} \tag{1}$$

where $R_{i,t}$ is the return of stock i at time t, $R_{m,t}$ is the return of the market portfolio in period t and $FR_{i,t}$ is the forecast revision of analysts' forecasts of firm i's annual EPS at time t.

Equation (1) is the generalized form of the market model with an additional term to allow for the effect of earnings revisions at time t. The residual term captures any firm-specific shocks and systematic factors not captured by the market index and forecast revisions. The ex-post variance of stock returns during the earnings revision period can be derived from equation (1) as follows:

$$\sigma^2(R_{i,t}) = b_i^2\sigma^2(R_{m,t}) + c_i^2\sigma^2(FR_{i,t}) + \sigma^2(e_{i,t}) \tag{2}$$

In equation (2), we assume that the variance of market returns (and the variance of forecast revisions) and other unaccounted shocks, are orthogonal to each other. Equation (2) posits a positive relationship between the ex-post variance of stock returns and the variance of the earnings forecast revisions.

[3] There is substantial evidence suggesting that analysts' forecast revisions affect stock prices (Imhoff and Lobo, 1984; Lys and Sohn, 1990).

Ackert and Athanassakos (1997), however, show that analyst forecast dispersion and optimism are directly related to uncertainty surrounding a firm. When there is little uncertainty, dispersion in analysts' forecasts is likely to be low and analysts may wish to avoid standing out from the crowd by reporting optimistic forecasts. On the other hand, when uncertainty is high, dispersion in analysts' forecasts is likely to be high and analysts have fewer reputational concerns when they act on their incentives to issue optimistic forecasts.[4] Therefore, the optimism in analysts' forecasts is positively related to analysts' forecast dispersion.[5] Ackert and Athanassakos (2003) confirm and quantify this positive relationship using a simultaneous equations model to examine the relationship between analysts' optimism and dispersion in analysts' forecasts, among other variables.

There are two conclusions that can be drawn from the above discussion. First, there is a positive contemporaneous relationship between optimism and analyst forecast dispersion.

Second, high analyst optimism at time t should lead to large forecast revisions and hence variability in forecast revisions at time t + 1. Hence, one can infer that analysts' forecast dispersion at time t should capture information about the variance of forecast revisions at time t + 1. From equation (2), however, we see that there is a positive relationship between the variance of forecast revisions and the variance of stock returns. As a result, we can expect a positive relationship between analysts' forecast dispersion at time t (i.e., the variance of analysts' forecasts (σ^2 ($AF_{i,t}$)) and future variance of stock returns at time t + 1. Thus, the cross-sectional time-series model, with the residual $u_{i,t}$ capturing the effect of all unaccounted variables on the next period's variance, is as follows:

$$\sigma^2(R_{i,t+1}) = a_0 + a_1\sigma^2(R_{m,t+1}) + a_2\sigma^2(AF_{i,t}) + u_{i,t+1} \tag{3}$$

In this paper then, we argue that as analysts tend to be more optimistic for companies with high forecast dispersion; they tend to revise downward their forecasts of EPS of such companies throughout the year. The larger the optimism of analysts, the larger is the downward revision in the analyst forecasts and the higher is the future stock volatility. As a result, we expect a positive relationship between analysts' forecast dispersion and future stock return volatility, even after controlling for (future) market volatility.

This leads to our first testable hypothesis:

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[4] If there is uncertainty about the future, analysts know there will be high variability in earnings forecasts and hence they can be optimistic without hurting their reputation.

[5] This relationship has been confirmed with the data used in this paper. The coefficient of the regression of optimism on analysts' forecast dispersion is positive and statistically significant (t-stat = 6.86).

H_1: There is no relationship between analysts' forecast dispersion and future stock return volatility, after controlling for market volatility.

As high analysts' forecast dispersion (i.e., companies with high analysts' optimism) should lead to large future forecast revisions and high volatility, we expect to reject H_1.

We further argue in this paper that, if dispersion and future return volatility are related, such optimism-induced future volatility may also exhibit seasonal behavior as analyst optimism tends to be high in January, but decreases toward year-end. Analysts' forecast accuracy improves as the length of the forecast horizon declines (Ackert and Hunter, 1994; Ackert and Athanassakos, 1997; and Richardson, Teoh, and Wysocki, 1999). Over time, information relating to the firm's performance is revealed and, as a result, there is less uncertainty about earnings as the forecast date approaches. Seasonality in the level of analysts' forecast optimism (and forecast dispersion) may also arise from the relationships between analysts, the firms that employ them, and their clients. Because portfolio managers rebalance their portfolios as a New Year begins (Haugen and Lakonishok, 1988), large amounts of funds are available to be reallocated among various investments at the beginning of the year. As a result, analysts may be more willing to err on the upside at the beginning of the year in order to attract transactions business (and at the same time please management of client firms). With a long forecast horizon, analysts have plenty of time to revise their forecasts. As the year progresses and the forecast horizon diminishes, analysts may be more concerned about accuracy.

This leads to our second hypothesis:

H_2: There is no difference in the relationship between analysts' forecast dispersion and future stock return volatility depending on the month of the year, after controlling for market volatility.

Data

Analyst following, earnings forecasts, and dispersion of earnings estimates are obtained from the Institutional Brokers Estimate System (I/B/E/S) for each month in the 1981 through 1996 sample period.[6] Daily stock return and index data are obtained from the CRSP database for the same period. The firms included in the final sample passed through several filters, described below:

- At least three individual forecasts determine the consensus forecast of earnings per share.
- The company's fiscal year ends in December.
- The I/B/E/S database includes analysts' consensus forecasts for twelve consecutive months from January to December of the forecast year and

[6] The study period covers 1981-1996 as our IBES database ended in 1996.

firms have data for the whole sample period, namely, starting in 1981 and ending in 1996.

- Matching daily stock and index (CRSP value-weighted S & P 500 index) return data are available from CRSP for the period 1981-1996.

The first criterion helps enhance the statistical stability of the standard deviation of analysts forecast. The second criterion ensures that the forecast horizon is the same for all firms. Similar criteria have been employed by other researchers (Ajinkya et al., 1991; Ackert and Athanassakos, 1997, 2003). The third criterion ensures data continuity and availability of successive monthly observations that help us overcome data-overlapping problems. Successive observations are needed to construct time series of volatility estimates. The fourth criterion ensures that we have daily data necessary for the construction of monthly stock and market volatilities. The first three filters reduce the original sample to 165 firms, while the fourth filter brings the final sample down to 160 firms.

While I/B/E/S makes available to investors EPS forecasts and other information on weekly basis, it also compiles for each firm a monthly summary of, among other statistics, the number of analysts forecasting, the mean and median of EPS forecasts made in the current month, and the standard deviation (dispersion) of analysts' forecasts during the current month. Starting from about June of a given year, say year t, and ending in January of year t + 2, I/B/E/S reports monthly analyst forecasts and forecast dispersions for a given firm for calendar year t + 1. We truncate the monthly observations from June-December of year t and January of year t + 2. This gives us twelve monthly non-overlapping observations for the above variables in every year of the sample for a given firm. Given that we have 192 monthly observations for each firm during 1981-1996, we have a total of 30,720 cross sectional-time series observations for our final sample of 160 firms.

Methodology and Implementation

We perform time series-cross sectional estimations using future return volatility as the dependent variable and future market volatility and analysts' forecast dispersion as the independent variables.

The dispersion measure for firm i and month t refers to the standard deviation of analysts' forecasts at the end of month t (i.e., $\sigma(AF_{i,t})$ in equation (3)). This is reported by I/B/E/S. We standardize the above dispersion measure by the firm i stock price at the end of month t ($DISP_{i,t}$).[7] The standardization renders our dispersion measure scale free across firms for the cross sectional analysis conducted in each month. As Ajinkya et al. (1991) explain, $DISP_{i,t}$ could reflect something more than

[7] We also standardized by the absolute mean of EPS forecast and obtained qualitatively similar results. Moreover, dividing by EPS tends to produce many more outliers that dividing by price due to the fact that extremely small EPS tend to inflate the standardized measure. As a result, we only report the results based on stock price standardization.

the contemporaneous disagreement among analysts when analysts do not have access to the same information sets and do not issue and transmit their EPS updates to I/B/E/S on the same day. Any differential lag-induced bias in dispersion only adds noise to the $DISP_{i,t}$ measure and works against our hypothesis of positive relation between $DISP_{i,t}$ and future return volatility.

Stock return volatility for firm i at time t ($SVOL_{i,t}$) is calculated as the annualized standard deviation of daily CRSP stock returns from the month t - 1 to month t. For example, for the month of April, $SVOL_{i,t}$ is calculated by annualizing (i.e., multiplying by $\sqrt{252}$) the standard deviation of daily percentage CRSP stock returns from April 1 to April 30. Similarly, market volatility for time t ($MVOL_t$) is calculated as the annualized standard deviation of daily CRSP index (value weighted S&P 500) returns from the month t - 1 to month t. $SVOL_{i,t+1}$ refers to next month's stock volatility and $MVOL_{t+1}$ refers to next month's market volatility. Both $SVOL_{i,t+1}$ and $MVOL_{t+1}$ represent the future return volatilities because each of them is based on the non over-lapping information set that covers the period t to t + 1.[8]

The following pooled cross sectional-time series models are estimated with individual stock return volatility as the dependent variable:[9]

Model (1) $$LSVOL_{i,t+1} = c_0 + c_1 LMVOL_{t+1} + c_2 LDISP_{i,t} + c_3 YEAR87_{i,t} + u_{i,t+1} \tag{4}$$

for i = 1 to I firms and t = 1 to T periods

$$YEAR\ 87_{i,t} = \begin{cases} 1 \text{ if firm i, period t observations belongs to the 1987 crash period} \\ 0 \text{ otherwise} \end{cases}$$

Model (2) $$LSVOL_{i,t+1} = c_0 + c_1 LMVOL_{t+1} + c_2 LDISP_{i,t} + c_3 YEAR87_{i,t} + \sum_{m=2}^{12} c_{2,m} d_{i,t}^{m}\, LDISP_{i,t} + u_{i,t+1} \tag{5}$$

for i = 1 to I firms and t = 1 to T periods m = 2 to 12 months

$$d_{i,t}^{m} = \begin{cases} 1 \text{ if firm i, period t observation belongs to month m} \\ 0 \text{ otherwise} \end{cases}$$

[8] Since our forecast dispersion measures are reported monthly, we have used one-month ahead periods to proxy for future stock and market return volatilities. We could have alternatively chosen two, three or multiple month ahead periods for such volatilities. These alternatives, however, would lead to overlapping data problems in the regressions.

[9] Furthermore, we also employed analysts' forecast dispersion for forecasts made from June to December of year t for forecast year t+1. This dispersion variable was highly correlated with our DISP variable (i.e., the forecast dispersion for forecasts made from January to December of year t for forecast year t) and its inclusion in our models discussed below added nothing to the explanatory power of these models. Hence, we did not pursue further the use of such additional variable of forecast dispersion.

where $LSVOL_{i,t+1}$ refers to the natural logarithm of annualized volatility of daily CRSP returns for firm i for the month t to t + 1 and $LMVOL_{t+1}$ is the natural logarithm of annualized volatility of daily CRSP index returns (i.e., the CRSP value-weighted S & P 500 index) for the month t to t + 1. $LDISP_{i,t}$ refers to the natural logarithm of one plus the standardized dispersion for firm i at time t, i.e., Ln(1 + $DISP_{i,t}$) (Falkenstein, 1996). The variable $YEAR87_{i,t}$ is a dummy variable that takes the value of 1 for firm i, if the current month/year is 9/1987 to 12/1987 (i.e., the months surrounding the 1987 stock market crash) and zero otherwise, whereas $d^{m}_{i,t}$ is a dummy variable that takes the value of 1 for firm i, if the current month is m and zero otherwise. The variable $d^{m}_{i,t}$ multiplied by $LDISP_{i,t}$ captures the interaction between months of the year and the $LDISP_{i,t}$ variable.

Model (1) examines the incremental effect of dispersion in analysts' forecasts on future stock return volatility after accounting for future market volatility. It also controls for the month/year of market crash (9/1987-12/1987) and examines whether the month/year of market crash had any effect on future stock return volatility.[10] Model (1) will help us test hypothesis H_1. We expect the forecast dispersion coefficient to be positive and significant.

Model (2) uses monthly slope dummies to examine seasonal effects of analysts' earnings forecast dispersion on future stock return volatility. While model (1) captures the average effect of LDISP on future volatility, Model (2) captures the differential effect of LDISP on future stock return volatility for different months of the year. Model (2) will help us test the hypothesis H_2. In order to reject H_2 based on this model, we would expect the January LDISP coefficient (c_2) to be large and positive and the remaining slope coefficients to record small changes from January in the first few months of the year and decline thereafter. This is because analysts' optimism and forecast dispersion tend to be high at the beginning of the year, giving scope for large downward revisions and increased stock price volatility. Analysts' optimism and forecast dispersion decline significantly later in the year as more information is available for firms and as analysts have a lower incentive to be optimistic toward year-end (Ackert and Athanassakos, 1997).

Time series-cross sectional data on 160 firms, over 192 months covering the period 1981-1996 are used to estimate models (1) and (2). We use the single equation maximum likelihood procedure in order to correct for autocorrelation (Judge et al., 1985, pp. 289-290), as diagnostic tests indicated the presence of significant autocorrelation in the uncorrected residuals.[11] Additional diagnostic tests indicate that the

[10] We also tested alternative specifications of the dummy variable by defining the crash period as 01/1987-12/1987 and 06/1987-12/1987, without much difference in estimates.

[11] Ackert and Athanassakos (2003) employ a similar approach. The data are stacked into a pooled regression model, which is estimated using MLE by iteration to correct for autocorrelation (Greene, 1993, p. 453). The data are treated as a single time series and the parameter vector is assumed to be the same for all firms. The panel data approach is an

maximum likelihood procedure adequately corrects for autocorrelation.[12] Moreover, the logarithmic transformations in models (1) and (2) help account for possible non-linear relationships between the variables and for the presence of heteroskedasticity in the data. We employ the SPEC option in the REG SAS procedure to test for heteroskedasticity. We can not reject the null hypothesis of no heteroscedasticity.

We first estimate the two models using the entire sample. Then, we check the robustness of our results by re-estimating the same models for subsamples. Subsamples are constructed based on time periods and three other variables viz., the number of analysts, dispersion of analysts' forecasts, and market capitalization.

Results

Summary Statistics

Table 1 presents summary statistics for four variables of interest, namely, the number of analysts, analysts' forecast dispersion, and market capitalization, for the whole sample period and sub-periods. These variables are subsequently used to form subsamples. Generally, the number of analysts following the firms has slightly increased over time, as have market capitalization and stock price. Analysts' forecast dispersion standardized by the stock price has decreased over the same period, though the decrease has not been steady. Table 2 reports summary statistics for the key variables used in models (1) and (2), namely, future stock volatility, analysts' forecast dispersion, and future market volatility, for the whole sample and sub-periods. Table 3 shows mean and median values of the above variables on a monthly basis for the whole sample. From these tables, we observe that the mean analysts' forecast dispersion declines over time and as we progress from January to December, consistent with findings in Ackert and Athanassakos (1997). Future volatility both for stocks and the market index has also declined in recent years and, in general, trends down from January to December, although such a decline has not been monotonic. The departure from monotonicity is possibly due to the fact that both the 1987-1988 sub-period (Table 2) and the months of October-November (Table 3) contain the months of the 1987 stock market crash and are thus marked by increased volatility. The correlation coefficient between analysts' forecast dispersion and future stock return volatility is 0.22 and future market and stock return volatility is 0.35. Both correlations are statistically significant at the 1 percent level.

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alternative to the pooled time series cross section. Greene (1993, p. 464) suggests, "... in practical terms the pooled regressions provide a good way to address the issue of time series cross-sectional data".

[12] We used the AUTOREG SAS procedure for these tests.

Table 1—Summary Statistics of (Raw) Variables of Interest Based for the Full Sample (1981–1996) and Subsamples, Based on Time Periods

	Maximum	Minimum	Mean	Median	Standard Deviation
Whole Sample					
Number of Analysts	52	3	19.6307	19	7.4830
Dispersion	0.7648	0	0.0080	0.0042	0.0181
Stock Price	341	1.16	24.6586	21	22.8264
Market Value (mil of $)	129636.0000	6.0934	2981.4470	1309.9594	5847.3716
1981-82					
Number of Analysts	34	3	15.5742	15	5.48532
Dispersion	0.19068	0	0.010882	0.0066	0.0161
Stock Price	121.87	1.16	12.4700	10.06	10.6843
Market Value (mil of $)	11367.0734	6.0934	757.9562	301.1496	1300.0698
1983-84					
Number of Analysts	38	5	17.4820	17	6.2876
Dispersion	0.20118	0	0.0088	0.0052	0.0130
Stock Price	200	1.83	15.9562	13	15.7023
Market Value (mil of $)	12447.3429	12.2459	1049.1286	433.8480	1584.7494
1985-86					
Number of Analysts	52	4	20.3841	19	7.2533
Dispersion	0.7648	0	0.0101	0.0047	0.0288
Stock Price	317.5	2.25	20.6640	16.47	22.3397
Market Value (mil of $)	13406.0504	20.4989	1464.9818	778.4300	1878.1549
1987-88					
Number of analysts	47	5	21.1138	21	7.4323
Dispersion	0.6480	0	0.0086	0.0045	0.0211
Stock price	314.38	3.59	25.0527	20.57	27.3969
Market value (mil of $)	33604.6646	23.0011	2229.5651	1367.2634	3048.2998
1989-90					
Number of Analysts	50	6	22.0681	21	7.9809
Dispersion	0.2146	0	0.0078	0.0046	0.0128
Stock Price	291.75	2	25.824	22.13	23.1771
Market Value (mil of $)	32500	28.6565	2941.034	1540.94	4301.427
1991-92					
Number of Analysts	48	5	20.4711	20	7.6574
Dispersion	0.5089	0	0.0088	0.0036	0.0249
Stock Price	245	2.75	27.8607	24.68	19.7175
Market Value (mil of $)	59694.1930	42.7572	3780.5022	1808.6309	5639.7915
1993-94					
Number of Analysts	51	4	20.7281	20	7.7133
Dispersion	0.3140	0	0.0048	0.0027	0.0091
Stock Price	263.88	4.5	32.1348	28.63	21.5777
Market Value (mil of $)	49756.8166	122.13	4793.7389	2535.0645	6676.4054
1995-96					
Number of Analysts	43	3	19.2471	19	7.5260
Dispersion	0.0756	0	0.0041	0.0024	0.0058
Stock Price	341	4	37.1426	32.72	26.3416
Market Value (mil of $)	129636.0	165.47	6847.4810	3016.5513	11453.1221

Notes: Dispersion is the standardized analysts' forecast dispersion. Total observations: 30720

Table 2—Summary Statistics of (Raw) Variables of Interest Based on Full Sample (1981-1996) and Subsamples, Based on Time Periods

	Maximum	Minimum	Mean	Median	Std. Deviation
Whole Sample					
SVOL	2.6220	0.0433	0.2552	0.2297	0.1277
DISP	0.7648	0	0.0080	0.0042	0.0181
MVOL	0.8727	0.0492	0.1293	0.1166	0.0715
1981-82					
SVOL	1.0768	0.0733	0.2845	0.2634	0.1186
DISP	0.1907	0	0.0109	0.0066	0.0161
MVOL	0.2672	0.0990	0.1531	0.1423	0.0487
1983-84					
SVOL	1.0295	0.0433	0.2669	0.2421	0.1090
DISP	0.2012	0	0.0088	0.0055	0.0130
MVOL	0.1997	0.0787	0.1270	0.1208	0.0274
1985-86					
SVOL	2.1813	0.0581	0.2531	0.2342	0.1137
DISP	0.7648	0	0.0101	0.0058	0.0288
MVOL	0.2186	0.0762	0.1200	0.1092	0.0323
1987-88					
SVOL	1.8997	0.0571	0.2999	0.2570	0.1896
DISP	0.648	0	0.0086	0.0045	0.0211
MVOL	0.8727	0.0857	0.1981	0.1546	0.5380
1989-90					
SVOL	1.4467	0.0513	0.2402	0.2144	0.1171
DISP	0.2146	0	0.0078	0.0046	0.0125
MVOL	0.2573	0.0854	0.1347	0.1205	0.0478
1991-92					
SVOL	2.6220	0.0523	0.2566	0.2323	0.1367
DISP	0.5090	0	0.0088	0.0036	0.0248
MVOL	0.1919	0.0667	0.1167	0.1098	0.0336
1993-94					
SVOL	1.3285	0.0450	0.2300	0.2116	0.0975
DISP	0.314	0	0.0048	0.0027	0.0091
MVOL	0.1370	0.0528	0.0898	0.0937	0.0225
1995-96					
SVOL	0.9453	0.0495	0.2169	0.1979	0.0923
DISP	0.0756	0	0.0041	0.0023	0.0058
MVOL	0.1648	0.0492	0.0953	0.1873	0.0305

Notes: SVOL is the annualized future volatility, DISP is the standardized analysts' forecast dispersion, and MVOL is the annualized future volatility of the value weighted S & P 500 index returns. Total observations: 30720

Full Sample Regression Results

Table 4 presents the whole sample time series-cross sectional estimates for model (1) (both in its full and restricted versions) and model (2). The future market volatility variable is positively related to future stock return volatility. The relationship is highly significant in all cases. Analysts' forecast dispersion is positively and statistically significantly related to uture stock return volatility, thus increasing the

Table 3—Mean (Raw) Values of variables of Interest by Each Month of the Year for the Full Sample, 1981-1996

	SVOL		DISP		MVOL	
	Mean	Median	Mean	Median	Mean	Median
January	0.2742	0.2481	0.0095	0.0054	0.1426	0.1346
February	0.2592	0.2383	0.0091	0.0052	0.1310	0.1275
March	0.2474	0.2288	0.0087	0.0048	0.1201	0.1254
April	0.2601	0.2401	0.0082	0.0046	0.1298	0.1199
May	0.2388	0.2221	0.0081	0.0044	0.1170	0.1081
June	0.2370	0.2211	0.0079	0.0043	0.1139	0.1144
July	0.2467	0.2264	0.0078	0.0041	0.1144	0.1057
August	0.2466	0.2229	0.0077	0.0040	0.1288	0.1218
September	0.2419	0.2224	0.0074	0.0038	0.1211	0.1092
October	0.3092	0.2489	0.0072	0.0037	0.1820	0.1178
November	0.2562	0.2282	0.0072	0.0034	0.1331	0.1069
December	0.2452	0.2206	0.0070	0.0031	0.1182	0.1048

Notes: SVOL is the annualized future volatility, DISP is the standardized analysts' forecast dispersion, and MVOL is the annualized future volatility of the value weighted S & P 500 index returns. Total observations: 30720

Table 4—Maximum Likelihood Time Series-Cross-Sectional Estimates with Future Volatility as Dependent Variable for Full Sample, 1981-1996, for Models (1) and (2)

	Model 1 (restricted version)	Model 1 (restricted version)	Model 1 (full version)	Model 2
Constant	-0.5626***	-0.5891***	-0.5684***	-0.5719***
LMVOL	0.4213***	0.4207***	0.4269***	0.4244***
LDISP		3.0631***	1.8020***	2.3134***
YEAR87			0.0139***	0.0132***
D_{Feb}*LDISP				-0.4647
D_{Mar}*LDISP				-0.3291
D_{Apl}*LDISP				0.3337
D_{May}*LDISP				-1.8990***
D_{Jun}*LDISP				-1.7342***
D_{Jul}*LDISP				0.2360
D_{Aug}*LDISP				0.7341
D_{Sep}*LDISP				-1.7094***
D_{Oct}*LDISP				0.3418
D_{Nov}*LDISP				-1.0185**
D_{Dec}*LDISP				-0.8853**
R-Square	0.114	0.119	0.131	0.132

Notes: LDISP is the natural logarithm of one plus the standardized analysts' forecast dispersion. LSVOL is the natural logarithm of future volatility. LMVOL is the natural logarithm of future volatility of the value weighted S & P 500 index returns. YEAR87 is a dummy variable and is 1 for 1987 crash months (09/1987-12/1987) and 0 otherwise. D_{Feb} to D_{Dec} are slope dummy variables for February to December. D_{Feb} is 1 if February and zero otherwise. Likewise for the other slope dummy variables. *, **, and *** stand for significance at 10 percent, 5 percent, and 1 percent levels, respectively. Total number of observations is 30720

Model (1) $LSVOL_{i,t+1} = c_0 + c_1 LMVOL_{t+1} + c_2 LDISP_{i,t} + c_3 YEAR87_{i,t} + u_{i,t+1}$

Model (2) $LSVOL_{i,t+1} = c_0 + c_1 LMVOL_{t+1} + c_2 LDISP_{i,t} + c_3 YEAR87_{i,t} + \sum_{m=2}^{12} c_{2,m} d_{i,t}^{m} LDISP_{i,t} + u_{i,t+1}$

explanatory power (R^2) of the expanded models. The month/year of the 1987 market crash has a positive and statistically significantly effect on future volatility.[13] Finally, there is also evidence of strong seasonality in the relationship between dispersion and future stock return volatility. The month-forecast dispersion interaction term coefficients (slope dummies) of model (2) are high in January; they are (incrementally) stable for the first few months of the year following January and decline in importance thereafter.[14]

The results from Table 4 imply that analysts' forecast dispersion has information in explaining future volatility, after conditioning for future market volatility. These findings help us reject the hypothesis H_1. They are also consistent with Lobo and Tung (2002) who also report a positive and significant relation between future stock price variability and earnings forecast dispersion surrounding earnings announcements. Further, the documented seasonal effect of forecast dispersions on future stock return volatility in Table 4 helps us reject the hypothesis H_2.

Subsample Regression Results By Time Period

We next examine the robustness of earlier results by running model (1) for each of the sixteen annual Subsample periods of the total sample. The results are reported in Table 5. All the sixteen sub-period dispersion and future market volatility coefficients are positive and significant at the 1 percent level. The coefficient for YEAR87 is positive and significant at the 5 percent level (not reported here), suggesting high volatility in the crash year. Moreover, the crash year 1987 is characterized by a very high R-square value, which could suggest a possible unit root consistent with a regime break in the regression variables. Finally, the slope coefficient for dispersion has significantly increased since 1992, suggesting that future volatility has become more sensitive to analyst dispersion in recent years.

Lack of serial correlation and homoskedasticity are not rejected in our time-series/cross-sectional tests for the whole sample, but the possibility of cross-sectional

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[13] Model (1) was expanded to include other variables that the volatility literature has examined, such as market value, optimism, number of analysts, and trading volume, in natural log form. All the coefficients were statistically significant and had expected signs (i.e., positive sign for optimism and trading volume and negative sign for market value and number of analysts). The R^2s were 0.13 and 0.17 respectively for model (1) and the expanded model. The corresponding t-statistics of forecast dispersion were 6.12 and 5.29. In other words, the relationship between future stock return volatility and forecast dispersion is robust to the inclusion of other explanatory variables in model (1). The detailed results are not reported here, but are available from the authors upon request.

[14] The insignificant interaction term coefficients for April, July, and October, the months in which quarterly earnings are released, strengthen our seasonality findings. This provides sufficient evidence that out results in model (2) are not driven by quarterly earnings releases.

Table 5—Maximum Likelihood Time-Series/Cross-Sectional Estimates for Model (1): Annual Subsample Periods 1981 to 1996

	Constant***	LMVOL***	LDISP***	R-square
1981	-0.970	0.217	5.531	0.190
1982	-0.450	0.487	3.451	0.257
1983	-0.870	0.279	4.905	0.180
1984	-0.644	0.395	5.490	0.279
1985	-0.717	0.376	4.425	0.313
1986	-0.621	0.389	3.127	0.381
1987	-0.153	0.647	3.684	0.650
1988	-0.596	0.495	6.285	0.371
1989	-0.753	0.423	5.432	0.421
1990	-0.609	0.455	9.198	0.478
1991	-0.700	0.380	4.620	0.528
1992	-0.547	0.443	10.613	0.528
1993	-1.070	0.219	12.699	0.451
1994	-1.122	0.210	21.260	0.264
1995	-1.231	0.184	16.786	0.379
1996	-1.094	0.241	15.024	0.370
pooled t-statistic	-10.669***	11.235***	6.048***	

Notes: LDISP is the natural logarithm of one plus the standardized analysts' forecast dispersion. LSVOL is the natural logarithm of future volatility. LMVOL is the natural logarithm of future volatility of the value weighted S & P 500 index returns. YEAR87 is a dummy variable that takes on the value of 1 if 09/87 to 12/87 and zero otherwise. For consistency of presentation, the coefficient of YEAR87 (which is positive and significant) is not reported here. Model (1) (see below) is run successively for each of the annual subsample periods. All the annual coefficients are significant at 1 percent level. Total number of observations for each year is 1920. The pooled t-statistic is computed for the variable *j* as $\overline{b}_{jt}/(\sigma_j/\sqrt{T})$, where the numerator $\overline{b}_{jt}$ is the average of the yearly coefficient estimates of *j*, σ_j is the standard deviation of the coefficient estimates of *j* and T is the number of sample years. *** stands for significance at the 1 percent level of significance

Model (1) $LSVOL_{i,t+1} = c_0 + c_1 LMVOL_{t+1} + c_2 LDISP_{i,t} + c_3 YEAR87_{i,t} + u_{i,t+1}$

correlation in the residuals does exist. To avoid the possibility of consequent bias in the estimated standard errors, we used an approach employed by Alford and Berger (1999). We initially run model (1) for every year in our sample between 1981and 1996. Then, we aggregate our estimates by averaging the coefficients across years. Significance levels are based on pooled t-statistics, computed for the variable *j* as $\overline{b}_{jt}/(\sigma_j/\sqrt{T})$, where the numerator $\overline{b}_{jt}$ is the average of the yearly coefficient estimates of j, σ_j is the standard deviation of the coefficient estimates of j, and T is the number of sample years. The pooled t-statistics for model (1) coefficients are reported in Table 5 below the annual coefficient estimates. They are significant at the 1 percent level of significance. Overall, the findings in Table 5 suggest that the time-series/cross-sectional model (1) results are robust.

Table 6—Summary Statistics and Regression Results, Based on Number of Analysts Following a Firm

Panel A: Summary Statistics of Variables of Interest for Subsamples Based on the Number of Analysts Following a Firm for 1981-1996

	Maximum	Minimum	Mean	Median***	Std. deviation
Quartile 1 (Small number of analysts group)					
SVOL	2.6220	0.0433	0.2756	0.2458	0.1427
DISP	0.7648	0	0.0099	0.0044	0.0265
Quartile 2					
SVOL	1.5015	0.0523	0.2580	0.2340	0.1274
DISP	0.448	0	0.0084	0.0042	0.0166
Quartile 3					
SVOL	2.1813	0.0495	0.2383	0.2118	0.1237
DISP	0.4029	0	0.0073	0.0042	0.0152
Quartile 4 (Large number of analysts group)					
SVOL	1.3966	0.0549	0.2355	0.2256	0.1083
DISP	0.16	0	0.0058	0.0039	0.0068

Notes: SVOL is the annualized future volatility and DISP is the standardized analysts' forecast dispersion. Total observations: 30720. Each quartile has 40 firms. *** Median one-way analysis shows that median SVOL and DISP are statistically different at the 1 percent level across quartiles

Panel B: Maximum Likelihood Time-Series Cross Sectional Estimates with Future Volatility (Regression 1) and Standardized Analysts' Forecast Dispersion (Regression 2) as Dependent Variables for Full Sample, 1981-1996, based on Number of Analysts Following a Firm

Regression	Dep. Variable	Constant	QUARTILE	R^2	Observations
1	LSVOL	-1.373	-0.035	0.01	30720
		(87.59)***	(6.04)***		
2	LDISP	-0.011	-0.0013	0.01	30720
		(16.97)***	(5.25)***		

Notes: LDISP is the natural log of one plus the standardized analysts' forecast dispersion. LSVOL is the natural logarithm of future volatility. QUARTILE is a dummy variable that takes on the values 1 to 4 for low to high number of analysts following a firm, respectively. *** stands for significance at the 1 percent level

Subsample Summary Statistics and Regression Results By Number of Analysts Following a Firm

Table 6, Panel A presents summary statistics of the two key variables, future stock volatility and analysts' forecast dispersion for subsamples constructed based on the number of analysts following a firm.[15] According to O'Brien and Bushan (1990), analysts have more to gain from following a firm when there is little competition from other analysts. When few analysts follow a firm, an analyst has little competition and more opportunity to generate transactions business by issuing an optimistic report. On the other hand, when many analysts follow a firm, the quality

[15] We rank all firms in a given year by number of analysts from low to high, and then divide the sample into four groups. We do this for every year, and then we aggregate all data into the four groups from low to high. This is a more efficient way to group the data as membership in each group changes every year depending on whether the number of analysts changes from year to year. We follow a similar approach in other sections.

of analysts reports increases because the collective expenditure on private information acquisition is higher (Alford and Berger, 1999). At the same time, forecast optimism should decline and observed forecasts should be closer to actual earnings. Alford and Berger (1999) confirm a negative relationship between forecast optimism and analyst following. Because optimism and analysts' forecast dispersion are directly related, based on our earlier discussion, a negative relationship should be expected between forecast dispersion and analyst following. Moreover, because future stock volatility is positively related to forecast dispersion, a negative relationship should also be expected between future volatility and analyst following. In other words, the higher the number of analysts following a firm, the higher is the forecast accuracy (i.e., lower optimism) and the lower the future stock volatility (as there will be less optimism and less scope for forecast revisions).

The above expectations are substantiated by the results reported in Table 6, Panel A. For example, as we go from a small number of analysts following a firm to a large number, the median forecast dispersion declines from 0.0044 to 0.0039 and so does future volatility, which declines from 0.2458 to 0.2256. A test for median differences shows that median future volatility and dispersion are statistically different across quartiles at the 1 percent level of significance.[16]

Table 6, Panel B reports two regression results: regression 1 with future volatility as the dependent variable and regression 2 with forecast dispersion as the dependent variable. The explanatory variable is a dummy variable (QUARTILE) that takes values from 1 to 4; quartile 1 firms (QUARTILE = 1) have the smallest number of analysts following them while quartile 4 firms (QUARTILE = 4) have the largest number of analysts following them. The coefficient of QUARTILE should be negative in both regressions in order for the results to be consistent with the findings reported in Panel A of Table 6. As expected, the coefficient of the variable QUARTILE is negative and significant for both regressions. Our previously stated hypotheses and regression results reported in Table 4 seem to be robust.

Subsample Summary Statistics and Regression Results By Analysts' Forecast Dispersion

Table 7, Panel A presents summary statistics for subsamples constructed based on analysts' forecast dispersion. Consistent with this paper's main hypothesis, if part of what drives future volatility is analysts' forecast dispersion, then dividing our total sample into groups based on analysts' forecast dispersion, future volatility should increase for groups with high analysts' forecast dispersion. The group with the high-

[16] Because the distributions of our measures are skewed, we use a nonparametric Brown-Mood (median) test, which provides an approximate χ^2 test. This test does not rely on normality. The only assumptions are that the samples are independent and population distributions have similar shapes.

Table 7—Summary Statistics and Regression Results, Based on Standardized Analysts' Forecast Dispersion

Panel A: Summary Statistics of Variables of Interest for Subsamples Based on the Standardized Analysts' Forecast Dispersion for 1981-1996

	Maximum	Minimum	Mean	Median***	Std. Deviation
Quartile 1 (Low forecast dispersion group)					
SVOL	1.4764	0.0450	0.2397	0.2076	0.1104
DISP	0.0043	0.0001	0.0015	0.0013	0.0008
Quartile 2					
SVOL	1.8997	0.0495	0.2290	0.2080	0.1133
DISP	0.0074	0.0012	0.0033	0.0031	0.0012
Quartile 3					
SVOL	1.6484	0.0571	0.2463	0.2218	0.1186
DISP	0.0140	0.0021	0.0059	0.0058	0.0021
Quartile 4 (High forecast dispersion group)					
SVOL	2.6220	0.0433	0.3057	0.2811	0.1501
DISP	0.7648	0.0040	0.0212	0.0132	0.0326

Notes: SVOL is the annualized future volatility and DISP is the standardized analysts' forecast dispersion. Total observations: 30720. Each quartile has 40 firms. *** Median one-way analysis shows that median SVOL and DISP are statistically different at the 1 percent level across quartiles

Panel B: Maximum Likelihood Time-Series Cross Sectional Estimates with Future Volatility (Regression 1) and Standardized Analysts' Forecast Dispersion (Regression 2) as Dependent Variables for Full Sample, 1981-1996, based on the Standardized Analysts' Forecast Dispersion

Regression	Dep. Variable	Constant	QUARTILE	R^2	Obis.
1	LSVOL	-1.669	0.084	0.01	30720
		(108.89)***	(15.08)***		
2	LDISP	-0.0066	0.0058	0.02	30720
		(9.60)***	(22.97)***		

Notes: LDISP is the natural log of one plus the standardized analysts' forecast dispersion. LSVOL is the natural logarithm of future volatility. QUARTILE is a dummy variable that takes on the values 1 to 4 for low to high forecast dispersion, respectively. *** stands for significance 1 percent levels

est dispersion in analyst's forecast should experience the largest downward revisions and, hence, the largest future stock return volatility based on our earlier discussion.

The findings in Table 7, Panel A substantiate these expectations. The median analysts' forecast dispersion in the low group is 0.0013 and for the high group is 0.0132. The median future volatility for the corresponding groups is 0.2076 and 0.2811, respectively—that is, future volatility increases along with dispersion. A test for median differences shows that median future volatility and dispersion are statistically different across quartiles at the 1 percent level of significance.

Table 7, Panel B reports regression results for future volatility (regression 1) and forecast dispersion (regression 2). The dummy variable (QUARTILE) now takes the value of 1 for quartile 1 firms (i.e., firms with low analysts' forecast dispersion) and 4 for quartile 4 firms (i.e., firms with high analysts' forecast dispersion). The coefficient of QUARTILE should be positive in both regressions in order for the results to be consistent with the findings reported in Panel A of Table 7. The coefficient of the variable QUARTILE is positive and significant for both regressions and the results are consistent with the findings in Table 7, Panel A. Our hypotheses and regression results again seem to be robust.

Subsample Summary Statistics and Regression Results By Market Capitalization

Table 8, Panel A presents summary statistics for subsamples constructed based on market capitalization.[17] Size is one measure of information availability. More information is available about large firms compared to smaller firms. As a result, we expect the larger the firm size, the smaller is analysts' forecast dispersion. At the same time, if analysts' forecast dispersion drives part of future volatility, we should expect to find that future volatility is smaller for larger firms.

Table 8—Summary Statistics and Regression Results, Based on Market Capitalization

Panel A: Summary Statistics of Variables of Interest for Subsamples Based on Market Capitalization for 1981-1996

	Maximum	Minimum	Mean	Median***	Std. deviation
Quartile 1 (Small Cap group)					
SVOL	2.1813	0.0495	0.2746	0.2443	0.1430
DISP	0.7648	0	0.0109	0.0050	0.0297
Quartile 2					
SVOL	2.6220	0.0450	0.2571	0.2329	0.1332
DISP	0.4433	0	0.0080	0.0040	0.0156
Quartile 3					
SVOL	1.8997	0.0523	0.2437	0.2187	0.1193
DISP	0.2012	0	0.0065	0.0036	0.0112
Quartile 4 (Large Cap group)					
SVOL	1.5597	0.0549	0.2400	0.2265	0.1112
DISP	0.1907	0	0.0066	0.0042	0.0092

Notes: SVOL is the annualized future volatility and DISP is the standardized analysts' forecast dispersion. Total observations: 30720. Each quartile has 40 firms. *** Median one-way analysis shows that median SVOL and DISP are statistically different at the 1 percent level across quartiles

Panel B: Maximum Likelihood Time-Series Cross Sectional Estimates with Future Volatility (Regression 1) and Standardized Analysts' Forecast Dispersion (Regression 2) as Dependent Variables for Full Sample, 1981-1996, Based on Market Capitalization

Regression	Dep. Variable	Constant	QUARTILE	R^2	Observations
1	LSVOL	-1.384	-0.030	0.01	30720
		(82.55)***	(4.91)***		
2	LDISP	0.011	-0.0013	0.01	30720
		(16.27)***	(5.29)***		

Notes: LDISP is the natural log of one plus the standardized analysts' forecast dispersion. LSVOL is the natural logarithm of future volatility. QUARTILE is a dummy variable that takes on the values 1 to 4 for low to high market capitalization, respectively. *** stands for significance at the 1 percent level

[17] Groupings based on market price give results consistent with the results based on market capitalization; hence, findings are not reported based on this criterion.

In Table 8, Panel A, we see that the median dispersion for the small cap group of firms is 0.0050 and for the large group of firms is 0.0042. The corresponding figures for future volatility are 0.2443 and 0.2265, respectively. That is, we document lower volatility for the large market cap group. A test for median differences shows that median future volatility and dispersion are statistically different across quartiles at the 1 percent level of significance.

Table 8, Panel B reports regression results for future volatility and forecast dispersion regressions in regressions 1 and 2, respectively. The dummy variable (QUARTILE) now takes the value of 1 for quartile 1 firms (i.e., firms with low market capitalization) to 4 for quartile 4 firms (i.e., firms with high market capitalization). The coefficient of QUARTILE is expected to be negative in both regressions. As expected, the coefficient of the variable QUARTILE is negative and significant for both regressions, consistent with the findings in Table 8, Panel A. Our hypotheses and regression results once again are robust.

Summary and Conclusions

In this paper, using monthly data for a cross section of 160 U.S. firms for the period 1981-1996, we examine the relationship between analysts' forecast dispersion and future stock return volatility over time and within the year. We argue that because analysts tend to be more optimistic when forecast dispersion is high, they would revise downward their forecasts of earnings per share of such companies throughout the year and significantly in many cases. The larger the optimism of analysts, the more analysts would be revising their forecast down and, hence, the higher is future stock return volatility. As a result, there should be a positive relationship between analysts' forecast dispersion and future stock return volatility. We further argue that such prior optimism-induced future volatility would also exhibit seasonal behavior as analyst optimism tends to be high in January, but less high later in the year.

While previous work on dispersion and return volatility studied periods of earnings announcements, this paper examines such a relationship on a continuous basis. Assuming that there is a continuous flow of information in the market and analyst monthly forecasts have a continual effect on market prices, we test for the relationship between dispersion and future return volatility throughout the year, without reference to formal accounting events and disclosures.

We find that there is strong and positive relationship between dispersion and future return volatility and that dispersion has information content for future return volatility after conditioning for future market volatility. These results are robust across subsamples based on time periods and firm groupings based on number of analysts following a firm, forecast dispersion and market capitalization. The months of the market crash in 1987 seem to have an added effect on future volatility. Our results are consistent with empirical findings of Lobo and Tung (2002) and theoretical predictions of Abarbanell et al. (1995). Our results are also consistent with negative relation between dispersion and future expected returns reported in Diether, Malloy, and Scherbina (2002). There is also strong seasonal relationship between future volatility and the dispersion measure with the importance of dispersion on future stock return volatility being high in January and the first few months of the year and declining thereafter.

The documented information content of the earnings dispersion measure with regards to future volatility can be of great importance for active portfolio management and option pricing and arbitrage trading strategies. Such trading strategies and their potential profitability, however, are the subject of a future study.

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