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BIPIN B. AJINKYA and MICHAEL J. GIFT*

ABSTRACT

This study examines whether the information implied by simultaneous levels of option and stock prices (specifically, the implied standard deviation of returns) reflects other *contemporaneously* available information. The independent contemporaneous measure considered is the observed dispersion (across several financial analysts), at a point in time, in the forecasts of earnings per share for a given firm. The results indicate that implied standard deviations clearly reflect the contemporaneous dispersion in analysts' forecasts *incrementally*, i.e., beyond the information contained in the historical time series of returns.

VARIOUS TESTS OF THE Black-Scholes option pricing model have appeared in the literature. The basic formulation posits the price of a call option to be a function of the simultaneous market price of the underlying stock, the instantaneous variance of the stock's rate of return, the exercise price and time to maturity of the option, and the risk-free interest rate. Studies by Black and Scholes [2], Galai [8], Chiras and Manaster [4], and Macbeth and Merville [12] used the formula to explain the observed prices of options to a successful degree. In these tests, all the information needed by the formula was directly observable, except the instantaneous stock return variance, which was measured as the time series variance of historical stock returns. Manaster and Rendleman [14] inverted the procedure to calculate implied stock prices (and implied standard deviations of stock returns simultaneously) and showed that such "implied prices contain information regarding equilibrium (future) stock prices that is not fully reflected in observed stock prices."

Another set of studies (see Latane and Rendleman [11], Chiras and Manaster [4], Schmalensee and Trippi [16], among others) examined the properties of the implied instantaneous variance (or standard deviation) of stock returns that falls out of the formula when the values of all remaining variables are supplied. In a test of the predictive ability of such implied standard deviations (ISD's), Chiras and Manaster [4] found that for predicting *future* actual time series standard deviations (FSD's) of stock returns, the ISD's were superior predictors relative to using historic (past) time series standard deviations (HSD's).

This empirically demonstrated superiority of implied prices and standard

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deviations for predictive purposes suggests that these implied measures apparently capture information not contained in past time series of returns. Hence, the additional information captured must be of a more recent vintage. By incorporating an important *contemporaneous* (but independent) measure of variability, this study proposes an explanation of why ISD's are superior to HSD's in predicting FSD's. However, since a truly *ex ante* or contemporaneous measure of stock return variability (but one determined independently of ISD) is not available, a surrogate variability measure based on the most important practical determinant of stock prices and returns—namely, reported (accounting) earnings—is substituted.

While stock prices and returns are theoretically a function of the cash flow (dividend) stream of the firm, they are empirically more highly correlated with the historical earnings stream. Relatedly, the Modigliani-Miller "dividend irrelevance" proposition asserts that asset valuation is a function of expectations of earnings (in addition to dividends). Changes in estimates of *mean* earnings (even for a short 1-year period) have been shown to be significantly related to changes in the price (return) of the firm's stock. Correspondingly, *ex ante* estimates of the *variance* in earnings should be an important indicator of the perceived *ex ante* (implied) variance of the related stock's rate of return. The particular measure of contemporaneous earnings variance used in this study is the cross-sectional dispersion in financial analysts' forecasts of annual earnings per share (e.p.s.) for a firm.

The rationale for selecting dispersion (or disagreement) among analysts as the desirable measure of earnings riskiness is that financial analysts, on average, are competent searchers and evaluators of the most current information bearing on a firm's prospects and analysts' earnings forecasts as well as forecast revisions have been shown to be significantly associated with the equilibrium values of firms' shares (see, e.g., Brown and Rozeff [3], Givoly and Lakonishok [9], Fried and Givoly [7], and Abdel-khalik and Ajinkya [1]). In fact, Malkiel [3] concluded that "the best single risk proxy is not the traditional beta calculation but rather the dispersion of analysts' forecasts" (see Givoly and Lakonishok [10] for an excellent review of the properties of financial analysts' forecasts of earnings). It should be noted that while the conceptual risk surrogate should be the variability associated with the *entire* future e.p.s. stream, the measured dispersion in this study is restricted to the current fiscal year's e.p.s. mainly because data on periodic (monthly) measurement of the dispersion in e.p.s. estimates are available in a systematic and comprehensive fashion for one fiscal year (ahead).

To summarize, the objective of this study is to explain the superiority of ISD's by examining if ISD's reflect *contemporaneously* available information pertaining to earnings (and hence stock return) variability *after controlling for* the historical variability of the stock return series (HSD). Since it is known that ISD's and HSD's are significantly correlated, an alternative way of viewing the above question would be to examine if ISD's are more highly correlated with the dispersion of analysts' forecasts than HSD's are correlated with such dispersion.

For a sample of 624 observations (10 monthly observations on an average 63 calendar fiscal year firms per month), the results indicate that the standard deviation of stock returns implied jointly from option and stock prices clearly reflects the contemporaneous dispersion of financial analysts' e.p.s. forecasts in an incremental sense (i.e., *beyond* the information contained in the historical time series of returns). Also, as posited in a subsidiary hypothesis (explained later), the results reveal that the strength of the relationship between implied standard deviations and analysts' forecast dispersion weakens as the forecast horizon (the period from the month of e.p.s. forecasts to the month of actual e.p.s. announcement) shortens.

The rest of the paper is organized as follows. Section I defines average ISD's and specifies the other variables used in the study. The operationalization of the hypotheses and description of the data are presented in Section II. Results are discussed in Section III, and Section IV provides a summary.

I. Average ISD's and Dispersion of Analysts' Forecasts

The Black-Scholes option pricing formula, as modified by Merton [15] for dividends, is used to estimate the implied variance (and standard deviation). The formula states:

$$W = Se^{-yt}N(Z_1) - Ee^{-rt}N(Z_2) \tag{1}$$

with

$$Z_1 = \frac{\ln(S/E) + (r - y + \frac{1}{2}V^2)t}{V\sqrt{t}}$$

and

$$Z_2 = Z_1 - V\sqrt{t}$$

where W is the current option price, S is the current stock price, E and t are the exercise price and time to maturity of the option, r and y are the continuous risk-free interest rate and dividend yield, $N(\cdot)$ is the cumulative normal density function, and V is the standard deviation of the stock's rate of return.

If information on all the variables, except V, is entered into Equation (1), then the implied value of V can be determined (iteratively). This is the ISD value for each pair of simultaneously observed option and stock prices. The timing of the contemporaneous information variable used in this study (the dispersion of analysts' e.p.s. forecasts) cannot be pinpointed as precisely as the quotations for option and stock prices. As a result, it is necessary to *average* out the several ISD observations associated with the imprecise timing/period of the dispersion measurement (see Section II for details). Since this study deals with the ability of ISD to reflect the dispersion in analysts' e.p.s. forecasts in addition to the historical variability (HSD) of stock returns, these latter two variables are discussed next.

Information on e.p.s. forecasts (for the current fiscal year) for a single firm by several analysts at approximately the same point in time is needed to operationize the cross-sectional dispersion variable defined in this study. Such information on most NYSE and AMEX firms is systematically collected and disseminated by the Institutional Brokers Estimate System (IBES), a service of Lynch, Jones and Ryan. Updated means, medians, and standard deviations of e.p.s. estimates contributed by several analysts for each firm are computed by IBES once a week. The measure of dispersion (D) used in this study is the standard deviation of e.p.s. estimates available from the IBES History Tape, which is updated monthly.[1] Note that for a cross-sectional test *within* each month, the dispersion measure, D, is essentially noncomparable across firms because the related mean forecasted e.p.s. value is noncomparable. Hence, the measure, D, is scaled by the mean e.p.s. value (for each month) to yield a standardized dispersion measure (DISP) for each firm.[2] This latter measure, really a coefficient of variation (standard deviation divided by the mean) is used in the tests. The remaining variable, HSD, is measured simply as the time series standard deviation of stock returns over a suitable period *prior* to the date of ISD determination.

The following linear model is estimated separately for each of 10 monthly cross-sectional periods and forms the basis for evaluating the primary hypothesis of the study.

$$\text{AISD} = a + b_1\text{DISP} + b_2\text{HSD} + e \tag{2}$$

where AISD stands for *average* ISD (based on a variable number of days, as explained later).

II. Data, Operational Procedures, and Hypotheses

The data for option model-related information is taken from the Berkeley Options Data Base, which provides intra-day observations on option and stock price pairs for all Chicago Board Options Exchange (CBOE) firms, as well as all other information needed to calculate ISD's from Equation (1).[3] The ISD computation is an iterative procedure accomplished through a computer algorithm. The particular data base available to us had information from November 1977 to August 1978, a period of 10 months. This 10-month limitation on the available machine-readable option model-related data is the reason for limiting the tests to this particular 10-month period. Also, the sample is restricted to calendar fiscal year firms in order to maximize the comparability of the forecast dispersion

[1] The IBES service provides information on analysts' e.p.s. estimates for the current fiscal year (up to 12 months ahead) as well as for the next fiscal year. In this study, the standard deviation pertaining to only the current period's e.p.s. forecasts is used as the dispersion measure. The reason for this choice is that fewer analysts' forecasts are available for the second year to estimate a stable dispersion measure. Also, the Pearson correlation between the current and the second years' standard deviations (across all firm months in the sample) is a high 0.69 (with a Spearman correlation of 0.82). Thus, the current year's standard deviation appears to be a sufficient descriptor of expected earnings variance.

[2] The various filters applied to the data set—primarily the December 31 fiscal year and the deletion of negative e.p.s. observations for scaling the independent variables—reduced the sample size from the available 93 firms on the Berkeley tape to an average of 63 firms for each of the 10 months in the analysis.

[3] While the primary information pertaining to the option price, the exercise price, the time to maturity of the option, and the stock price is taken from the intra-day records of the Berkeley Options Data Base (Consolidated Format), the information on dividends and treasury bill rates is taken from the accompanying supplemental data tape.

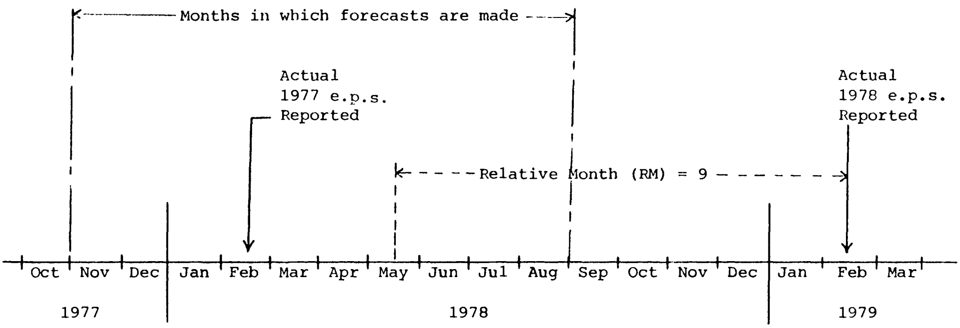

Figure 1. The data on the dispersion of monthly e.p.s. forecasts pertains to *each* of the 10 calendar months (November 1977 to August 1978). The corresponding forecast horizon (see example of relative month, RM = 9) extends from the month in which forecasts are made (say, May 1978) to the month in which the related fiscal year's actual e.p.s. are reported during February of the next year (1979).

variable across firms, since the linear model in Equation (2) is estimated cross-sectionally for each calendar month.

As stated previously, the IBES History Tape provides more-or-less concurrent e.p.s. forecasts by several analysts for each firm. These are updated each month and pertain to annual e.p.s. estimates for the current year. The monthly updates for each firm provide information on the mean, median, standard deviation, number of forecasters, etc. Figure 1, for calendar fiscal year firms, illustrates the nature of the e.p.s. forecast information used in this study. Note that actual e.p.s. for a given year (say, 1977) are typically reported during February of the following year (1978). Also, the forecasts made during January 1978 really pertain to fiscal 1977 reported e.p.s., which become available generally in February 1978. (These are, therefore, the shortest duration forecasts, just 1 month ahead.) Forecasts made in February 1978 and onwards pertain to fiscal 1978 e.p.s., which become available in February 1979. Thus, the February 1978 forecasts are the longest duration forecasts, 12-months ahead. To summarize, the February 1978 to August 1978 forecasts (for fiscal year 1978) are the 12-month to 6-month ahead forecasts, respectively, while the November 1977 to January 1978 forecasts (for fiscal year 1977) are the 3-month, 2-month, and 1-month ahead forecasts.

The IBES service has a date indicator associated with each month which specifies the *last* day on which some forecast information could have been added to the set for that month. The monthly updates are obviously not supplied by the various analysts to IBES on a single day, but rather over an undetermined period prior to the date specified on the IBES tape. In order to capture the period when this information was presumably "available" to market participants (analysts' clients) to be reflected in the option-stock price pair, four different horizons are used to average out the ISD's. If "t" is the "last" information date specified for the month, then the four periods used are: one day (t); five days (t to $t - 4$); 10 days (t to $t - 9$); and the period extending from day t of the current month to day t for the previous month. It is felt that the 5-day and the 10-day periods are the most appropriate, hence results are reported only for these two accumulations of the ISD's.[4] However, all four periods give results that are qualitatively very similar.

Data for computing the historical time series standard deviations of returns (HSD) is taken from the CRSP Daily Returns File. The standard deviation is calculated over three alternative time periods (all ending on the date of determination of a particular month's AISD). Weekly returns are used in this computation, with the alternate time period lengths being 13 weeks, 50 weeks, or 100 weeks ending with the date of the related AISD determination. These values for each firm are tagged HSD_{13}, HSD_{50}, and HSD_{100}, respectively. Since these standard deviations over the alternative horizons are very highly correlated (the correlation coefficient is 0.87 between HSD_{13} and HSD_{50} and 0.92 between H_{50} and HSD_{100} on the basis of the entire sample of 624 firm-month observations), the results are invariant of horizon choice and hence only the results using HSD_{50} are reported.

The primary hypothesis examines whether, and the degree to which, ISD reflects contemporaneously available variability information (specifically, the dispersion in financial analysts' earnings forecasts). This hypothesis is tested in two ways. One, by estimating the linear model in Equation (2), a determination can be made whether DISP is reflected *incrementally* in AISD (i.e., beyond the effect of historical returns variability, HSD). Linear regression is used to estimate Equation (2), and it is expected that the coefficient, b_1, for DISP will be positive. The coefficient, b_2, for the "control" variable HSD is also expected to be positive. Another way of looking at the hypothesis is to directly compare the correlation between AISD and DISP with the correlation between HSD and DISP. The expectation here is that the former correlation would be higher than the latter (which is consistent with the statement that AISD reflects the contemporaneous DISP more than HSD does). Both procedures are applied separately to each of the 10 sample months. Finally, as a matter of *practical* interest, three alternative statistics (detailed later) are provided to give the reader a feel for the amount of *reduction* in estimation error when DISP is added to HSD for the purpose of estimating AISD.

A subsidiary hypothesis is suggested when one considers the nature of the dispersion measure used. Since the forecasts are continuous monthly updates of e.p.s. for the same (current) fiscal year, the accuracy of the forecasts should improve as the forecast horizon shortens (and as the first, second, and third quarter earnings are progressively revealed). Due to this, the dispersion across analysts should diminish as the fiscal year-end approaches (see Crichfield,

[4] Because of the vast number (over 1 million intra-day option-stock price pairs for the approximate 10-month period) of records available, every seventh record is (arbitrarily) selected for analysis and inclusion in the averaging process for ISD's. Of the 156,379 intra-day records selected, 147,410 (94%) resulted in a solution for the ISD. When a firm has multiple-calculated ISD values for a single day, an arithmetic average ISD is computed as the representative measure for that day. Daily *weighted* average ISD's are also calculated using the elasticity of the option price with respect to the stock price, as per Chiras and Manaster [4]. However, the relationship between the arithmetic and the weighted ISD's, by firm, indicates that the correlation coefficient is greater than 0.90 for all firms and greater than 0.98 for 60% of the firms. Hence, only the arithmetic average ISD's are used in the analysis.

Dyckman and Lakonishok [5] and Elton, Gruber, and Gultekin [6] for empirical evidence). Hence, the dispersion measure (DISP) will lose its ability to affect the implicit variability of the underlying stock's rate of return as the forecast horizon shortens. Such a weakening in the relationship would not be expected if continuous (moving-window) 12-month ahead e.p.s. forecasts were available each month (such forecasts, however, are not available). The subsidiary hypothesis therefore posits a *weakening* of the relationship between implied stock return variability (AISD) and the dispersion in analysts' e.p.s. forecasts (DISP) as the forecast horizon *shortens.* That is, the coefficient for DISP will remain positive, but the strength of the relationship (the statistical significance of b_1) is expected to taper off as the forecast horizon gets very short (say, less than 3 months).

Note, however, that the historical returns variability measure (HSD) is not susceptible to the above argument since it captures long-run (inherent) returns variability. As a result, referring again to Equation (2), coefficient b_2 (for HSD) is expected to maintain a significant and constant level irrespective of the length of the forecast horizon.

III. Results

Descriptive statistics relating to the "dependent" and "independent" variables of the model specified in Equation (2) are presented in Table I. The table provides the minimum, maximum, mean, standard deviation, and various percentiles of the distributions of the variables for the *entire* 10-month sample of 624 observations. The two alternate measures of the dependent variable (average implied standard deviation of stock returns) are denoted $AISD_5$ and $AISD_{10}$, where the subscripts refer to the 5-day or 10-day averaging period. N_5 and N_{10} indicate the *number* of option-stock price pairs *per day* used in calculating the AISD values for the two respective averaging periods. A mean of approximately 8 ISD values *per day* (and a median of about 5) enters the AISD computation for both periods. The entire distributions for $AISD_5$ and $AISD_{10}$ are highly similar.

Table I

Distribution of Dependent and Independent Variables

Percentile, Mean & Std. Dev.	$AISD_5$	N_5	$AISD_{10}$	N_{10}	NAF	D	DISP	HSD_{50}
Minimum	0.092	1.0	0.094	1.0	4.0	0.01	0.003	0.011
0.10	0.169	1.8	0.172	1.8	7.0	0.03	0.011	0.021
0.25	0.210	3.0	0.210	2.9	11.0	0.06	0.017	0.027
0.50	0.256	5.4	0.252	5.1	15.0	0.11	0.034	0.032
0.75	0.311	9.2	0.307	8.8	20.0	0.23	0.061	0.037
0.90	0.366	15.0	0.357	14.5	23.0	0.37	0.098	0.042
Maximum	0.569	66.4	0.546	72.0	28.0	1.84	0.655	0.056
Mean	0.265	7.9	0.262	7.8	15.3	0.18	0.047	0.032
Std. Dev.	0.076	9.2	0.073	9.3	6.2	0.22	0.049	0.008

Note: The table gives the distributions for the entire sample of 624 observatons over the 10-month test period. The percentile values across the rows are unrelated.

NAF denotes the number of concurrent financial analysts' forecasts of e.p.s. for a firm during a given month, with a mean (and median) of approximately 15. The next two columns show values of the raw standard deviations of e.p.s. forecasts (D) and the scaled standard deviations (DISP) used as the dispersion measure in the monthly cross-sectional regressions. The last column gives the distribution of the historic standard deviation of returns (HSD_{50}) based on a 50-week period.

Table II provides information on the means of the variables and certain correlation coefficients for each of the 10 months in the test period. The columns are arranged (left to right) according to a decreasing forecast horizon. RM stands for *relative month*, i.e., month of the e.p.s. forecasts relative to the month (February of next fiscal year) in which the actual current year's e.p.s. number is reported. Given the earlier discussion on data availability constraints, the following correspondence exists between *relative months* and the underlying calendar months. RM = 12 signifies forecasts made in February 1978 for fiscal year 1978, where actual 1978 e.p.s. are reported in February 1979, thus the February 1978 forecasts are 12-month-ahead forecasts. Similar meanings apply to RM = 11, 10, 9, 8, 7, and 6, where RM = 6 stands for forecasts made in August 1978 (where the related actual 1978 earnings are reported in February 1979). Given our data base, there are no RM = 5 and RM = 4 observations. RM = 3, 2, and 1 signify forecasts made in November 1977, December 1977, and January 1978 for the 1977 fiscal year, with related actual e.p.s. figures becoming available in February 1978. Henceforth, references to the months are restricted to their shorthand RM designation.

Panel A of Table II gives the means of the variables of interest while Panel B provides correlation coefficients between appropriate pairs. Since the correlation between $AISD_5$ and $AISD_{10}$ is extremely high in every month during the test period, only the $AISD_5$ results are reported from this point on to economize the presentation. The means for the raw standard deviation of analysts' e.p.s. forecasts (D) show a gradual reduction in this dispersion measure as the forecast horizon shortens (especially for 3 months and less). Note that this raw dispersion measure is the more relevant one for a time series comparison, while the standardized dispersion measure (DISP) is more appropriate for the monthly cross-sectional regression across firms. As posited in the subsidiary hypothesis, the positive correlation between $AISD_5$ and DISP tapers off as the forecast horizon becomes shorter. Also, as posited, the correlations between HSD_{50} and $AISD_5$ remain high and relatively constant during the entire 10-month period, since the argument for a progressively weakening relationship is not relevant in this case.

Recollect that the primary hypothesis is tested using two different methods. The first method relates to estimating Equation (2) to assess the incremental (rather than the raw or gross) effect of DISP, while the second method directly compares the correlation between AISD and DISP with the correlation between HSD and DISP. Table III presents the regression results for Equation (2), where the dependent variable is $AISD_5$, the 5-day average ISD of stock returns (results for $AISD_{10}$ are virtually identical and hence not reported). The independent

Table II

Variable Means and Correlation Coefficients by Month

Relative Month (RM):	12	11	10	9	8	7	6	3	2	1
Sample Size:	(48)	(62)	(61)	(64)	(65)	(65)	(64)	(65)	(65)	(65)
Panel A: Variable Means										
$AISD_5$	0.234	0.231	0.222	0.274	0.323	0.288	0.299	0.223	0.272	0.274
$AISD_{10}$	0.232	0.235	0.221	0.271	0.311	0.290	0.290	0.222	0.269	0.269
D	0.215	0.233	0.229	0.181	0.170	0.168	0.199	0.172	0.146	0.130
DISP	0.050	0.057	0.055	0.045	0.044	0.042	0.059	0.050	0.041	0.034
HSD_{50}	0.031	0.032	0.031	0.032	0.032	0.033	0.034	0.030	0.031	0.031
Panel B: Pairwise Correlation Coefficients*										
$AISD_5$, $AISD_{10}$	0.986	0.983	0.987	0.980	0.984	0.980	0.986	0.978	0.970	0.990
$AISD_5$, DISP	0.442	0.435	0.525	0.402	0.505	0.570	0.371	0.252	0.187	0.230
$AISD_5$, HSD_{50}	0.673	0.723	0.767	0.768	0.822	0.792	0.743	0.664	0.720	0.786
HSD_{50}, DISP	0.348	0.245	0.300	0.343	0.416	0.405	0.441	−0.051	−0.070	0.252

* Correlation coefficient values of approximately 0.250 and greater are statistically significant at the 0.05 level for $n = 60$ (two-tailed test).

Table III

Regression Coefficients for Equation (2)[a] (For 5-Day Average Implied Standard Deviations of Stock Returns)[b]

Month[c]	DISP	HSD_{50}	R^2
RM = 12	0.354	4.080	0.502
	(0.041)	(0.001)	
RM = 11	0.285	4.791	0.571
	(0.012)	(0.001)	
RM = 10	0.454	5.016	0.684
	(0.001)	(0.001)	
RM = 9	0.360	6.653	0.612
	(0.010)	(0.001)	
RM = 8	0.451	6.862	0.708
	(0.011)	(0.001)	
RM = 7	0.700	5.774	0.701
	(0.001)	(0.001)	
RM = 6	0.050	6.637	0.555
	(0.577)	(0.001)	
RM = 3	0.297	5.676	0.523
	(0.002)	(0.001)	
RM = 2	0.295	6.090	0.574
	(0.060)	(0.001)	
RM = 1	0.227	6.648	0.628
	(0.194)	(0.001)	

[a] The table shows values of coefficients b_1 and b_2 (for DISP and HSD_{50}) in Equation (2). The numbers in parentheses are the related significance levels of the coefficient t-values.

[b] The dependent variable used here is $AISD_5$. Results for $AISD_{10}$ are very similar, and hence, not reported.

[c] RM stands for relative month, or length of e.p.s. forecast horizon in months.

variables are: (i) DISP, the forecast dispersion (at a point in time, for a single firm) across financial analysts, and (ii) HSD_{50}, the historical time series standard deviation based on a 50-week period (again, the results for alternate HSD horizons are very similar and hence not reported). The results are arranged by relative month, with RM = 12 representing the longest horizon (12-month-ahead) and RM = 1 the shortest (1-month-ahead).

The coefficients, b_1, for DISP are all positive and significant at the conventional 0.05 level except for months RM = 6, 2, and 1. Thus, as posited in the primary hypothesis, the implied standard deviations of returns (or equivalently, the option-stock-price pairs) clearly reflect contemporaneously available information pertaining to riskiness. Also, in consonance with the subsidiary hypothesis, the relationship captured by b_1 weakens (as evidenced by the significance level of the coefficient) as the forecast horizon gets shorter. The weakening, however, does not appear to be a smooth function. Note that the expected multicollinearity between the two independent variables (DISP and HSD_{50}) biases the coefficients downward and makes comparisons of coefficient levels *across* months (as needed for the subsidiary hypothesis) somewhat suspect. The focus of the primary hypothesis, however, is to examine the *incremental* contribution of DISP *given* that HSD_{50} is in the model. The coefficient of DISP in the multiple regression (*within* any month) captures precisely the marginal effect sought. Thus, the fact that b_1 shows up positive and significant (in the longer horizon months) in spite of the multicollinearity bias attests to the ability of $AISD_5$ to capture any independent (orthogonal) information in DISP beyond that associated with HSD_{50}. The coefficient b_2 for HSD_{50} is highly significant in each of the 10 months, corroborating the results of previous studies.

The alternative test of the primary hypothesis simply compares the raw correlation coefficient between $AISD_5$ and DISP with that between HSD_{50} and DISP. The related coefficient data for each of the 10 months is shown in Panel B of Table II. The values indicate that for 8 of 10 months, corr ($AISD_5$, DISP) > corr (HSD_{50}, DISP), as posited. The expected direction does not obtain in months RM = 6 and RM = 1. Since these 2 months represent "shorter" horizons, the explanation probably is related to the decreasing relevance and discriminability of the information in DISP as the forecast horizon shortens. To gauge whether corr ($AISD_5$, DISP) is *significantly* greater than corr (HSD_{50}, DISP), the matched pairs t-test and the Wilcoxon-signed rank test are performed on the 10 pairs of correlation coefficients. Based on one-sided tests, the alpha levels achieved are 0.0484 for the t-test and 0.0652 for the Wilcoxon test, indicating reasonable significance levels given the small sample size of only 10 observations for each set of correlations. Thus, the results again indicate that $AISD_5$ reflects DISP better than HSD_{50} reflects DISP.

A final evaluation is undertaken to gauge the practical import of the findings of this study. For example, from a usefulness standpoint, one may wish to know a sort of bottom line: if one uses DISP in conjunction with HSD, how much *closer* can one expect to get? That is, by how much would estimation *error* be *reduced* when DISP is added to HSD.[5] The relevant errors to be compared are those from the "full" model (consisting of both DISP and HSD) with those from the "reduced" model (consisting only of HSD):

$$\text{AISD} = a + b_1\text{DISP} + b_2\text{HSD} + e \qquad \cdots \text{ (Full Model)}$$

and

$$\text{AISD} = a' + b'\text{HSD} + f. \qquad \cdots \text{ (Reduced Model)}$$

Note that e is identical to the error or regression residual estimated from the earlier Equation (2) used in this study, and f is estimated as the residual from regressing only HSD against AISD. Since loss functions and degrees of risk aversion may vary significantly across users, the following three alternative error reduction (ER) statistics are computed:

$$ER1 = (\Sigma_j \mid f_j \mid /n - \Sigma_j \mid e_j \mid /n)/(\Sigma_j \mid f_j \mid /n)$$

$$ER2 = \Sigma_j[(\mid f_j \mid - \mid e_j \mid)/\text{AISD}_j]/n$$

and

$$ER3 = (\Sigma_j f_j^2/n - \Sigma_j e_j^2/n)/(\Sigma_j f_j^2/n),$$

[5] We are grateful to an anonymous referee for this suggestion.

Table IV

Reduction in Estimation Error (When DISP is Added to HSD in a Model for Estimating AISD)

Relative Month	Error Reduction Statistics		
	ER1	ER2	ER3
RM = 12	3%	<1%	9%
RM = 11	9%	1%	13%
RM = 10	12%	2%	25%
RM = 9	7%	1%	10%
RM = 8	14%	2%	19%
RM = 7	11%	2%	20%
RM = 6	<1%	<1%	1%
RM = 3	6%	1%	15%
RM = 2	4%	<1%	9%
RM = 1	<1%	0%	2%

Note: ER1 and ER3 are measures of mean *absolute* and mean *squared* error reduction, respectively. ER2 measures reduction in absolute error relative to the observed AISD value.

where n observations $(j = 1, \cdots, n)$ are used to estimate the full and reduced models. $ER1$ and $ER3$ are the familiar measures of mean *absolute* error reduction and mean *squared* error reduction, respectively; while $ER2$ is the mean absolute error reduction relative to the observed AISD value.

Table IV provides values of all three alternative error reduction measures for the reader's own evaluation. The values shown are percentage error reductions for each of the 10 months. Not including the last 3 months (since the information potency of DISP is limited during the short horizon months RM = 1, 2, and 3), the average percentage error reduction for the first 7 months (RM = 12 through RM = 6) is approximately 8% for $ER1$, 1% for $ER2$, and 14% for $ER3$. The error reductions defined as $ER2$ have smaller magnitudes because the base for comparison is the level of observed AISD rather than the remaining error of the reduced model. The results for the $ER1$ and $ER3$ metrics indicate that the reduction in error due to the addition of DISP to HSD, while not spectacular, is not insignificant from a practical standpoint.

IV. Summary and Concluding Comments

This study examines the degree to which information embedded in simultaneous levels of option and stock prices (and hence, implied standard deviations) reflects an important independently derivable contemporaneous measure of riskiness (the primary hypothesis). The contemporaneous measure considered is the dispersion (at a point in time) in the forecasts of e.p.s. for a given firm across several financial analysts. Monthly updates of the cross-sectional standard deviation of analysts' forecasts of the current year's annual e.p.s. (generated by the IBES service) are used as the primary data source. However, the nature of the dispersion measure makes it susceptible to an aging (irrelevance) argument as the forecast horizon shortens (the subsidiary hypothesis). In order to assess the ability of implied standard deviations to capture the portion of contemporaneous information (DISP) that is *uncorrelated* with historically available information on returns variability (HSD), the latter is included as an additional ("control") independent variable in a multiple regression model.

The sample used in the study has 624 total observations over a 10-month period. Separate regression results for each of the 10 months (differing only on length of forecast horizon) appear to lend reasonable support for both the primary as well as the subsidiary hypotheses examined in the study. The overall model seems well specified in all 10 months. The results suggest that the standard deviations of stock returns implied from a simultaneous observation of option and stock prices clearly reflect an incremental (beyond historical variability) component of the contemporaneously measured dispersion in e.p.s. forecasts across analysts. The results may be viewed as a distinctly different type of external validation of the Black-Scholes-Merton option pricing formulation in that the *ex ante* standard deviation of stock returns is shown to reflect another independent and contemporaneously available *ex ante* fundamental measure of variability.

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