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S&P 500 Cash Stock Price Volatilities

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ABSTRACT

S&P 500 stock return volatilities are compared to the volatilities of a matched set of stocks, after controlling for cross-sectional differences in firm attributes known to affect volatility. No significant difference in volatility is observed between 1975 and 1983—before the start of trade in index futures and index options. Since then, S&P 500 stocks have been relatively more volatile. The difference is statistically, but not economically, significant. The relative increase occurs primarily in daily returns and only to a lesser extent in longer interval returns. Other factors besides the start of derivative trade could be responsible for the small increase in volatility.

STOCK PRICE VOLATILITY HAS received much attention in the popular press over the last few years, especially since the October 19, 1987 stock market crash. The rise in volatility has alarmed investors, regulators, and the public in general. Some suggest that the start of trade in stock index futures and index options increased speculative activity that in turn destabilized cash markets, causing higher volatility.

Large trading activity in the derivative contracts makes the suggestion plausible. Volume in index futures and index options increased dramatically since their introductions in 1982 and 1983. By 1987, the average daily dollar volume in the S&P 500 futures contracts alone exceeded the dollar volume of cash S&P 500 trade by a factor of about two, while the dollar value of the daily net change in total open interest is about 8% of S&P 500 stock dollar volume.

Speculative trade in futures and options frequently is accused of destabilizing underlying cash markets. The charge has been made for more than a century in the agricultural, precious metal, and currency markets. Recent evidence by French and Roll (1986) showing stock variance to be strongly related to trading session hours heightens these concerns. Unfortunately, theoretical analyses of whether speculative trade destabilizes cash markets lead to conflicting conclusions, depending on what assumptions are made.[1]

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[1] An increase in well informed speculative trade has two opposite effects on measured volatility. It decreases volatility due to order flow imbalances caused by uninformed traders because informed traders provide liquidity in such events, and it increases volatility due to new fundamental information since the information (which is assumed to be generated at discrete time intervals) is impounded into prices more quickly.

Empirical analyses of the question must compare observed cash volatilities to some estimate of what cash price volatilities would be in the absence of trade in derivative contracts. One common approach compares cash price volatilities before and after the introduction of derivative trade. To be reliable, this approach must reasonably account for all other determinants of volatility that also could have changed.[2] Alternatively, a cross-sectional analysis can compare volatility in an underlying asset to volatilities in similar assets for which no derivative trade exists. This approach is reliable when determinants of volatility are properly modeled in cross-section.

This study employs both approaches to determine whether S&P 500 stock price volatilities have changed relative to non-S&P 500 stock price volatilities. The method uses a cross-sectional analysis of covariance regression model to estimate the mean difference in return standard deviations for S&P 500 stocks and a comparable set of non-S&P 500 stocks. The model adjusts for cross-sectional differences in beta, price level, market value, and trade frequency. Differences are estimated for every year between 1975 and 1987 and tested to see whether they are significantly different from zero. The time series of volatility differences is then analyzed to determine whether S&P 500 stock volatilities have changed relative to control sample volatilities.

Volatility differences between the two groups of stocks are examined for standard deviations measured over daily intervals and over longer intervals. The contrast between the short and long interval results is used to infer differences in short-term return autocorrelations.

The differences in autocorrelation across the two stock samples can be interpreted in terms of two variants of the destabilization hypothesis. The liquidity variant asserts that trade in the derivative contracts causes related transactions in the cash market that are too large to be accommodated in an orderly fashion. Such transactions may be associated with arbitrage activities or with portfolio insurance operations. The increased volatility is transient since prices tend to revert when liquidity arrives. This variant implies that price change standard deviations measured over short intervals (such as daily) will be greater for the S&P 500 stocks than for the control sample but that standard deviations of price changes measured over longer intervals will be the same. The second variant, the populist variant, asserts that speculative trading in futures and options markets

An increase in uninformed speculative trade may increase price volatility by interjecting noise into a market with limited liquidity. Alternatively, it may decrease volatility by increasing the rewards to being well informed, so that their numbers increase, increasing market liquidity and thereby decreasing volatility.

Detailed presentations of these arguments can be found in Kaldor (1939), Stein (1961), Peck (1976, 1977), Kyle (1981), Turnovsky (1983), and Kawai (1983). Weller and Yano (1987), using a general equilibrium analysis, show that spot volatility may decrease when futures are introduced.

[2] A partial list of studies employing this method includes Froewiss (1978), Figlewski (1981), and Simpson and Ireland (1982) for the GNMA market, Taylor and Leuthold (1974), Powers (1970), Simpson and Ireland (1985), and Ely (1988) for the treasury bill market, and Bortz (1984) for the treasury bond market.

fundamentally destabilizes the value formation process in cash markets. This variant implies that both short and long interval price change standard deviations should be larger for the S&P 500 sample than for the control sample.

The results show that volatility in S&P 500 stocks increased relative to that observed for a comparable sample of non-S&P 500 stocks. The increase became significant starting in 1985 and is largest in volatilities measured from short interval returns. In 1986, the average difference in daily return standard deviations between the two groups was 14 basis points in daily data and about half that in longer difference interval data. Although the differences are statistically significant, they are probably too small to be of much economic significance unless the additional volatility occurs only on a few days such as the triple witching days.

Stoll and Whaley (1987) study volatility surrounding expiration days which include the triple witching days. They find that S&P 500 index volatility increased on expiration days. The increase has a transient component since the index tends to revert toward former levels on the day following the expiration day. It is shown below that the increase in variance that they measure can only partially explain the results found here.

This study differs from Stoll and Whaley (1987) in four respects. First, the methods used here allow for the possibility that volatility may increase on non-expiration days. Second, this analysis examines individual stock volatilities rather than index volatilities. This focus is important because order flow from index strategies can have both a systematic and a nonsystematic effect on individual stocks. A systematic effect may result because index strategies operate on all (or most) index stocks at the same time. A nonsystematic effect may result because index-related order flow is not separately identified to market-makers. They may therefore mistake it for order flow related to firm-specific information. As a result, index-related order flow may affect firm-specific return component volatilities as well as the systematic return component volatility. Third, the S&P 500 stock volatilities are compared to a carefully matched sample of non-S&P 500 stocks. The results are therefore less likely due to differences in the composition of the index used to control for non-S&P 500-related changes in volatility. Finally, independent results are obtained for each year so that trend can be studied. The increase in expiration day volatility found by Stoll and Whaley explains only a small fraction of the increase volatility documented in this paper.

This study is also related to the Pruitt and Wei (1989) event study of volatility surrounding changes in institutional ownership when a stock is added to the S&P 500 list. The methods do not directly compare before and after inclusion volatilities, but there appears to be little difference.

Neal (1988) presents contrasts between the return volatilities of the S&P 500 index and those of a small firm index. Although his results suggest that the S&P 500 index recently became more volatile, his methods do not control for cross-sectional differences and time-series changes in firm characteristics that affect volatilities.

Conrad (1989), Damodaran and Lim (1988), Detemple and Jorion (1988), and Nabar and Park (1988) all find that individual stock daily volatilities decrease after the introduction of equity options. Damodaran and Lim attribute the decrease to a decline in the bid/ask spread as measured by first-order serial correlation. However, they also show that longer measures of volatility decrease, which may indicate that option trading stabilizes prices.

The remainder of the paper is organized in four sections. Section I presents the analysis of covariance methodology and a description of the experimental design. The empirical results are then described in Section II. Section III discusses some related implications and empirical results for the serial correlations of stock price changes. Finally, a summary, an interpretation of the results, and an important discussion of their limitations are offered in Section IV.

I. Empirical Methods

Many factors besides inclusion on the S&P 500 List may cause volatilities of S&P 500 and non-S&P 500 stocks to differ. Among other causes, differences may be due to cross-sectional variation in beta, price level, firm size, and trade frequency. Two methods are used to control for variation due to these factors. The first, analysis of covariance, controls for the variation by modeling its effects. The second, careful selection of the non-S&P 500 firm sample, controls for the variation by making the two stock samples as comparable as possible. If the analysis of covariance model is well specified and well estimated and if the two samples are closely matched, both methods should yield identical and reliable results. Since, in practice, regression models are never perfectly specified and since it is never possible to perfectly match two samples, this study uses both methods to ensure to the greatest extent possible that the results do not depend on differences in easily identified cross-sectional determinants of volatility.

The mean difference between the volatilities of S&P 500 stocks and non-S&P 500 stocks is measured within the following cross-sectional analysis of covariance regression model:

$$\begin{aligned} STD_i = b_0 &+ b_1\, InS\&P_i + b_2\, (AbsBeta_i \times MkSTD) + b_3\, InvPrice_i \\ &+ b_4\, LogMkVal_i + b_5\, NoTradeFreq_i + e_i, \end{aligned} \tag{1}$$

where STD_i is the return (log price relative) standard deviation of stock i, $InS\&P_i$ is a dummy classification variable that takes the value of one if the stock is on the S&P 500 List and zero otherwise, and *AbsBeta*, *MkSTD*, *InvPrice*, *LogMkVal*, and *NoTradeFreq* are independent variables described below.[3] The parameter estimate of b_1 is of primary interest. It is the average difference between the S&P 500 stock standard deviations and those of the control sample, after accounting for cross-sectional variation due to the independent variables.

[3] If prices follow a random walk, price change variances measured at various differencing intervals will be proportional to the measurement interval length in large samples. To ensure that this property is preserved for returns as well, this study analyzes price returns computed as log differences of dividend- and split-adjusted prices. The method is necessary because, as Blume and Stambaugh (1983) point out, returns do not possess additive properties. For example, a 100 percent increase followed by a 50 percent decrease yields a total arithmetic average return of −25 percent.

A specification in which variances are modeled instead of standard deviations yields similar results. The standard deviation specification is presented because its residual distribution is much more symmetric than that of the variance model.

The model is estimated for each year in 1975–1987 and separately for return standard deviations measured over daily, 2-day, 3-day, 5-day, 10-day, and 20-day intervals. The multiday standard deviations are computed from overlapping data to maximize their information content and are expressed as daily rates so that cross-equation comparisons easily can be made.[4] The liquidity variant of the destabilization hypothesis predicts that b_1 is large for the short interval data but near zero for the long interval data. The populist variant predicts that b_1 is large at all intervals. Both versions predict that b_1 is zero before derivative trade started in 1982. The pre-1982 data therefore allow a test of whether the independent variables capture most of the differences in cross-sectional volatility determinants between the S&P 500 and the non-S&P 500 firms. In particular, this test shows whether omitted variables might influence the results.

The inclusion of the absolute beta times the market standard deviation ($AbsBeta_i \times MkSTD$) is suggested by the market model. The constant market standard deviation multiplies the absolute stock betas so that the b_2 estimates can be compared across years. The stock beta also helps model volatility due to nonsystematic fundamental firm risk since beta contains information about the firm's leverage ratio. The betas are computed with respect to the CRSP equally weighted market index from overlapping 5-day returns within the sample. The market standard deviation is the standard deviation of the CRSP equally weighted market index, computed from overlapping 5-day returns.

Inverse price level (*InvPrice*) models volatility that may be related to bid/ask spreads and/or to stock price discreteness. These processes add nearly identical constant components to the price change variances of all stocks, regardless of price level.[5] This causes return variances to be inversely correlated with price levels in cross-section. Since information-induced volatility is probably proportional to measurement interval length, the inverse price level should not be a significant determinant of return volatility for long differencing intervals.[6]

Log market value (*LogMkVal*) models nonsystematic components of return variation. Large firms are generally better diversified and less subject to catastrophic events than are small firms. Nonsystematic variation therefore should be smaller for large firms. The market value variable also helps model cross-sectional variation due to bid/ask spreads. Larger firms usually trade in more liquid markets with smaller bid/ask spreads than do smaller firms. (See Benston

[4] The usual unbiased estimator of no-overlapping return variance is biased when applied to overlapping returns in small samples. Assuming that price changes are independent, this estimator can be made unbiased by multiplying by $(N - 1)/(N - k + (k^2 - 1)/3N)$, where N is the number of k-period price changes. All variances computed in this study are so adjusted. A derivation of this factor can be found in Appendix B of Fama and French (1988).

[5] The rounding of stock prices to the nearest trade unit adds a constant component to the variance of price changes. It is approximately equal to $d^2/6$, where d, the "tick," is the minimum price change, usually an eighth of a dollar. (See Harris (1988).)

Bid/ask bounce adds a constant component to the total price change variance if bid/ask spreads are fixed in absolute terms for most price levels. Although average spreads do increase for higher price level stocks, the increase is not proportional to the price level so that higher price stocks have lower proportional spreads. (See Stoll and Whaley (1983).)

[6] Since return standard deviation is the square root of the average squared return, the inverse price level is computed as the square root of the average inverse squared price.

and Hagerman (1974), Branch and Freed (1977), Roll (1984), Glosten and Harris (1988), Stoll and Whaley (1983), and Amihud and Mendelson (1986).) Bid/ask bounce variation should therefore be smaller for large firms. Firm capitalization for a given year is computed as the average of the total market common stock market value at the beginning and end of the year.

The no-trade frequency variable (*NoTradeFreq*) models differences in measured variation that may be due to infrequent trading. Infrequently traded stocks tend to have larger bid/ask spreads so that variance due to bid/ask bounce is greater.[7] *NoTradeFreq* is computed as the percentage of trading days during the year for which no trade took place. The effect is not expected to be significant since most stocks in the sample traded every day.

Deliberately omitted from the model is annual average stock trading volume. Inclusion of this variable might be suggested by the well known time-series correlation between daily absolute returns and volume.[8] This time-series correlation, however, does not imply a cross-sectional correlation in annual data. The variable is left out because derivative trading market strategies that might affect cash volatilities would also tend to increase stock volume. Including volume would make it difficult or impossible to identify volatility that might be associated with derivative trade.

For each year, the cross-sectional sample includes a set of S&P 500 firms and a matching control set. The S&P 500 set includes all firms traded on the New York Stock Exchange that were included on the S&P 500 List for the entire year and that could also be found on the CRSP tape.[9] The control set consists of an equal number of firms chosen from the set of all NYSE stocks that were not included at any time on the S&P 500 List and that traded during the entire year. To minimize the difference between the control set and the S&P 500 set and thereby increase the reliability of the test, the control set was chosen to ensure that, for each security in the S&P 500 set, there would be a security in the control set with similar values of the independent variables.[10] Several alternative methods

[7] A second minor effect may reduce the size of the volatility effect due to infrequent trade. When a stock is not traded, CRSP uses the average of the closing bid and ask quotes to compute a "closing price." This removes bid/ask bounce variation that otherwise would be present, causing infrequently traded stocks to have lower volatilities, all other variables held constant.

[8] See, for example, the mixture of distribution results presented in Westerfield (1977) or Harris (1986).

[9] This eliminates approximately 50 S&P 500 stocks traded over the counter and about four listed on the American Stock Exchange that otherwise might have qualified and approximately 20 stocks each year that entered or exited the S&P 500 List in midyear.

[10] The control set was chosen using the following method. A distance measure, described below, was used to compute the distance between each qualifying security in the S&P 500 set and each qualifying security in the non-S&P 500 set. The sample was then constructed starting first with the closest pair of securities. The next closest pair among the remaining pairs was then added, and the process was continued until all S&P 500 firms were exhausted. This algorithm is very similar to the Assignment Algorithm from Operations Research that minimizes total distance. The latter algorithm was not used because it is computationally intractable given the large sample size. The algorithm used in this paper, however, yields a nearly optimal solution to the total distance minimization problem.

The distance between security i and security j with attribute vectors X_i and X_j is defined by

$$\text{Distance} = (X_i - X_j)'A(X_i - X_j).$$

Table I

CRSP Equally Weighted Stock Index Return Standard Deviations

Log price relatives are used for returns. The multi-day standard deviations are computed from overlapping data and are expressed in daily percentage rates. The pre-crash period is January 2, 1987 to October 16, 1987. The post-crash period starts with October 19, 1987 and extends through December 31, 1987. The long differencing interval standard deviations for the post-crash period are not very reliable because of the small sample size relative to the differencing interval.

	N	Differencing Interval					
Year	(days)	Daily	2-day	3-day	5-day	10-day	20-day
75	253	0.91%	1.07%	1.14%	1.24%	1.34%	1.53%
76	253	0.67	0.80	0.86	0.94	1.07	1.28
77	252	0.46	0.53	0.55	0.58	0.63	0.63
78	252	0.85	1.02	1.11	1.20	1.39	1.57
79	253	0.73	0.85	0.89	0.91	0.99	1.12
80	253	0.96	1.05	1.11	1.18	1.33	1.53
81	253	0.76	0.86	0.89	0.91	1.00	1.09
82	253	0.84	0.96	1.03	1.16	1.31	1.41
83	253	0.67	0.75	0.80	0.84	0.87	0.95
84	253	0.61	0.71	0.77	0.84	0.91	0.92
85	252	0.46	0.52	0.55	0.60	0.71	0.82
86	253	0.63	0.71	0.73	0.76	0.80	0.87
87	253	1.65	1.82	1.85	1.87	2.12	2.16
Pre-Crash 87	201	0.71	0.78	0.81	0.84	0.80	0.78
Post-Crash	52	3.36	3.24	2.70	2.58	2.00	1.62

of choosing the control set were tested with qualitatively similar results.[11] This suggests that the analysis of variance model effectively captures most of the systematic cross-sectional variation. No American Stock Exchange firms are used in the analysis because there are fewer than five S&P 500 firms listed on that exchange.

II. Results

Except for 1987, return volatility for the market index tended to decrease over the sample period (Table I). Mean S&P 500 stock return volatilities, however,

In this problem, the attribute vectors contain the independent variables *AbsBeta*, *MkSTD*, *InvPrice*, *LogMkVal*, and *NoTradeFreq*. The matrix A is the diagonal matrix containing the squares of the OLS estimated regression coefficients of

$$STD_i = a_0 + a_1\,(AbsBeta_i \times MkSTD) + a_2\,InvPrice_i + a_3\,LogMkVal_i + a_4\,NoTradeFreq_i + e_i,$$

with the estimation conducted only over the S&P 500 sample using the 5-day measure of security standard deviation. This measure defines distance to be the summed square of the differences in the contributions of each independent variable to predicted standard deviation.

[11] The alternatives included a method that controls for primary industrial classification.

show no apparent trend (Table II). The relative increase of the individual stock volatilities compared to the index volatilities may be due to the introduction of index futures and index options trade. Alternatively, it may be caused by an increase in the average S&P 500 beta over the sample period (Table III). The analysis of covariance results, discussed below, control for this alternative.

The S&P 500 stocks have higher mean market values, price levels, and trade frequencies than do the control sample stocks (Table III). Ignoring S&P 500 inclusion effects, the S&P 500 stocks therefore should have lower standard deviations, which they generally do (Table II). This implies that the effect, if any, that list inclusion has on volatility must be smaller than the cumulative effects predicted by differences in market values, price levels, and trade frequencies. The analysis of covariance methodology separates these effects.

Ordinary least squares estimates of b_1 in equation (1), the average difference in security standard deviations between the set of S&P 500 firms and the matching sample of non-S&P 500 firms, are presented in Table IV. Between 1975 and 1982, there is little evidence that S&P inclusion systematically affects stock volatilities, except perhaps in 1977. After the introduction of index futures in April 1982 and index options trading in March 1983, volatilities in S&P 500 stocks rose relative to the control sample. The effect peaked in 1986 and is largest in returns measured over short intervals.[12] The results are statistically significant in 1985, 1986, and 1987.[13]

[12] The following numbers of CME S&P 500 Stock Index futures contracts and CBOE S&P 100 Stock Index options contracts traded during the sample period. These two contracts are the most important derivative index products.

Year	CME S&P 500 Futures	CBOE S&P 100 Options
82	2.9 million	—
83	8.1	10.6 million
84	12.4	64.3
85	15.0	90.8
86	19.5	113.2
87	19.0	101.8

The growth in these contracts precedes the increase in S&P 500 cash stock price volatilities documented in Table IV by about one year. This suggests that other factors may also account for the results.

During the two and one-third months of trading starting with October 19, 1987, S&P 500 stock volatilities were significantly higher than non-S&P 500 stocks, despite the fact that index futures and index options volume over this period was about half of the pre-Crash volume. If destabilization is due to the trade in derivatives, much of the effect during this period must have accrued on October 19 and 20 when derivative volume was still high.

[13] To ensure that the statistically significant results are not due to some misspecification of the assumptions underlying the standard regression model, two bootstrap analyses were conducted for each of the regressions reported in Table IV. In the first analysis, the predicted value of the dependent variable is obtained for each sample observation from the actual OLS regression. The estimated residuals from that regression are then sampled at random with replacement and added to the predicted values to obtain a bootstrap sample of the dependent variable. It is then regressed on the independent variables of the original experimental design to obtain a Monte Carlo observation from the coefficient estimator distribution. The process is repeated 1000 times and the results used to

The failure to find systematic and significant differences in the first half of the sample suggests that the results obtained in the second half are not due to the omission of some significant independent variable correlated with inclusion in the S&P 500, whose levels or effects did not change over the sample period.

The complete regression results summarized in Table V confirm the ancillary predictions of the cross-sectional volatility model. The estimated coefficient on the absolute value of the stock beta is very significant and positive in all cases. The inverse price level estimate is also significant and positive in all cases, with largest values found in the daily data and smallest values found in the analyses of standard deviations measured over longer intervals. Log market value has a negative effect in every year but 1987, with the estimated coefficient almost always significant. (The effect in 1987 is negative when only data from before the crash are analyzed.) As expected, the coefficient for no-trading frequency is generally insignificant with mixed signs. Had the ancillary predictions of the cross-sectional model not been confirmed, the primary results concerning the effect of S&P 500 inclusion would be subject to question.

Although many estimates of b_1 are statistically significant, no estimate for any year or return horizon is particularly large in economic terms. The largest is 0.14 percent for daily returns in 1986. This seems small when compared to a typical daily stock return standard deviation of two percent. Note, however, that if the increase in volatility were associated only with the four triple witching expiration days each year, these results would be economically significant since they would imply an expiration day standard deviation of about seven percent, three and one-half times normal.[14]

Evidence presented in Stoll and Whaley (1987) can be used to suggest that the volatility increase is not confined only to expiration days. They find that the May 1982 to December 1985 standard deviation of non-expiration Friday S&P

compute the bootstrap estimate of the estimated coefficient standard error. This method holds constant the experimental design. The second method constructs the 1000 bootstrap samples by sampling the entire vector of dependent and independent variables. This method assumes that the original experimental design is random.

The results of both methods show that the regression estimated standard errors are close to their true values so that inferences using the t-statistics in Table IV are not flawed. The bootstrap standard errors from the first method are nearly identical to the regression estimated standard errors. The bootstrap standard errors from the second method tend to be larger than the regression standard errors, but not so much so that the conclusions from the statistical analysis are in any way changed or qualified. The larger standard errors are probably due to the fact that the bootstrapped samples typically are not as balanced as the original matched samples that were chosen to maximize the power and reliability of the test.

A description of bootstrap and other resampling methods can be found in Efron and Gong (1983).

[14] Assuming that returns are independent, the implied expiration day standard deviation is obtained by solving the following formula:

$$(std_n + b_1)^2 = (N - N_x)/N\, std_n^2 + N_x/N\, std_x^2,$$

where N is the total number of days in the year, N_x is the number of expiration days, std_n is the normal daily standard deviation, std_x is the implied expiration day standard deviation, and b_1 is the increment in return standard deviation due to inclusion.

Table II

Mean Stock Return Standard Deviations for S&P 500 and Non-S&P 500 Stocks

The S&P 500 samples consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency. Log price relatives are used for returns. The multi-day standard deviations are computed from overlapping data and are expressed in daily percentage rates. The pre-crash period is January 2, 1987 to October 16, 1987. The post-crash period starts with October 19, 1987 and extends through December 31, 1987.

	N	Differencing Interval					
Year	(firms)	Daily	2-day	3-day	5-day	10-day	20-day
Panel A: S&P 500 Stocks							
75	370	2.35%	2.40%	2.38%	2.35%	2.27%	2.24%
76	346	1.77	1.81	1.80	1.79	1.74	1.70
77	376	1.53	1.55	1.55	1.53	1.49	1.41
78	397	1.77	1.80	1.82	1.83	1.82	1.83
79	407	1.71	1.73	1.73	1.71	1.69	1.69
80	414	2.10	2.15	2.17	2.15	2.13	2.14
81	409	1.91	1.96	1.97	1.95	1.92	1.88
82	410	2.18	2.25	2.28	2.30	2.26	2.18
83	423	1.92	1.98	2.00	1.98	1.89	1.81
84	414	1.84	1.90	1.91	1.90	1.86	1.81
85	420	1.67	1.70	1.70	1.68	1.64	1.62
86	436	1.99	2.04	2.03	2.01	1.95	1.92
87	408	2.85	2.93	2.91	2.82	2.86	2.78
Pre-Crash 87	408	2.03	2.07	2.06	2.01	1.90	1.80
Post-Crash	408	4.81	4.37	3.92	3.53	2.95	2.55
Panel B: Control Sample Stocks							
75	370	2.43%	2.45%	2.42%	2.38%	2.30%	2.26%
76	346	1.88	1.89	1.87	1.84	1.79	1.75
77	376	1.62	1.61	1.60	1.57	1.52	1.44
78	397	1.79	1.83	1.84	1.85	1.86	1.85
79	407	1.81	1.84	1.83	1.79	1.75	1.73
80	414	2.19	2.24	2.25	2.23	2.22	2.23
81	409	2.05	2.09	2.08	2.05	2.00	1.96
82	410	2.33	2.40	2.43	2.45	2.44	2.39
83	423	1.97	2.03	2.05	2.03	1.95	1.87
84	414	1.89	1.95	1.97	1.98	1.96	1.89
85	420	1.65	1.69	1.71	1.70	1.68	1.66
86	436	1.98	2.04	2.05	2.04	2.00	1.96
87	408	2.75	2.86	2.87	2.84	2.94	2.89
Pre-Crash 87	408	2.06	2.13	2.14	2.12	2.02	1.94
Post-Crash	408	4.36	4.14	3.69	3.44	2.86	2.45

Table III

Independent Variable Means

Beta is the stock beta, measured from overlapping five-day returns; *Price* is the stock price level; *LogMkVal* is the log market capitalization; *NoTradeFreq* is the percentage of trading days for which no trade occurred. The S&P 500 sample consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency. The pre-crash period is January 2, 1987 to October 16, 1987. The post-crash period starts with October 19, 1987 and extends through December 31, 1987.

Year	*N* (firms)	*Beta*	*Price*	*LogMkVal*	*NoTradeFreq*
Panel A: S&P 500 Stocks					
75	370	0.86	27.6	12.5	0.54%
76	346	0.79	33.2	13.0	0.30
77	376	1.05	30.3	13.1	0.31
78	397	0.84	29.9	13.2	0.30
79	407	0.92	30.6	13.3	0.18
80	414	0.91	33.4	13.5	0.19
81	409	0.94	33.9	13.6	0.19
82	410	1.11	30.0	13.8	0.19
83	423	0.94	38.4	13.9	0.10
84	414	1.11	34.0	14.1	0.11
85	420	1.05	38.0	14.2	0.02
86	436	1.26	43.5	14.4	0.02
87	408	1.04	42.0	14.4	0.03
Pre-Crash 87	408	1.30	45.8	14.4	0.03
Post-Crash	408	0.90	42.0	14.4	0.03
Panel B: Control Sample Stocks					
75	370	0.86	19.3	11.7	1.01%
76	346	0.77	23.4	12.1	0.61
77	376	1.05	23.6	12.2	0.71
78	397	0.84	25.3	12.4	0.72
79	407	0.91	25.7	12.6	0.50
80	414	0.91	27.4	12.6	0.34
81	409	0.94	27.3	12.9	0.33
82	410	1.11	23.8	12.9	0.49
83	423	0.94	31.1	13.0	0.20
84	414	1.09	27.2	13.0	0.32
85	420	1.03	29.4	13.1	0.08
86	436	1.13	30.2	13.2	0.09
87	408	1.04	31.7	13.4	0.04
Pre-Crash 87	408	1.25	33.1	13.3	0.02
Post-Crash	408	0.90	31.6	13.4	0.05

Table IV

Mean Difference Between S&P 500 and Non-S&P 500 Stock Return Standard Deviations, Adjusted for Cross-Sectional Differences in Determinants of Volatility

The adjusted mean stock return standard deviation difference is measured by OLS estimate of b_1 in the following cross-sectional analysis of covariance model:

$$STD_i = b_0 + b_1\, InS\&P_i + b_2\, (AbsBeta_i \times MkSTD) + b_3\, InvPrice_i$$
$$+ b_4\, LogMkVal_i + b_5\, NoTradeFreq_i + e_i,$$

where STD_i is the percent log price relative standard deviation of stock i, expressed as a daily rate, $InS\&P_i$ is a dummy classification variable that takes the value of one if the stock is in the S&P 500 sample and zero otherwise, *AbsBeta* is the absolute value of the stock beta, *MkSTD* is the constant percent standard deviation of the CRSP equally weighted index, *InvPrice* is the inverse of the stock price level, *LogMkVal* is the log market capitalization, and *NoTradeFreq* is the percentage of trading days for which no trade occurred. The return differencing interval is the number of days over which differences are taken when computing returns. Overlapping returns are used. The S&P 500 sample consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency. The pre-crash period is January 2, 1987 to October 16, 1987. The post-crash period starts with October 19, 1987 and extends through December 31, 1987.

	N	Return Differencing Interval					
Year	(firms)	Daily	2-day	3-day	5-day	10-day	20-day
		Panel A: Mean Difference in Standard Deviations, b_1					
75	370	0.04%	0.06%	0.06%	0.05%	0.05%	0.03%
76	346	0.01	0.03	0.03	0.04	0.05	0.03
77	376	0.06	0.08	0.09	0.09	0.11	0.12
78	397	0.04	0.04	0.04	0.05	0.05	0.07
79	407	−0.01	−0.01	−0.01	0.01	0.03	0.03
80	414	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02
81	409	−0.05	−0.05	−0.05	−0.04	−0.02	−0.01
82	410	−0.05	−0.04	−0.04	−0.04	−0.06	−0.09
83	423	0.04	0.04	0.04	0.05	0.06	0.07
84	414	0.03	0.03	0.03	0.02	0.01	0.03
85	420	0.12	0.11	0.10	0.09	0.09	0.08
86	436	0.14	0.11	0.09	0.06	0.04	0.06
87	408	0.11	0.09	0.08	0.03	−0.01	−0.05
Pre-Crash 87	408	0.06	0.02	−0.01	−0.04	−0.06	−0.09
Post-Crash	408	0.39	0.26	0.26	0.16	0.21	0.19
		Panel B: Regression *t*-Statistics					
75	370	1.20	1.72	1.75	1.51	1.25	0.80
76	346	0.39	0.89	1.04	1.40	1.43	1.02
77	376	2.13	2.72	3.05	3.32	3.63	3.66
78	397	1.61	1.51	1.69	1.92	1.87	2.60
79	407	−0.45	−0.45	−0.33	0.28	1.10	1.20
80	414	−1.16	−1.34	−1.30	−1.05	−1.35	−0.78
81	409	−1.62	−1.63	−1.58	−1.29	−0.61	−0.41
82	410	−1.51	−1.18	−1.27	−1.35	−1.89	−2.69
83	423	1.26	1.20	1.45	1.89	2.03	1.97
84	414	1.02	0.91	0.96	0.62	0.40	0.90
85	420	4.61	3.88	3.51	3.17	3.11	2.66
86	436	4.48	3.45	2.92	2.05	1.36	1.60
87	408	3.10	2.62	2.28	1.05	−0.45	−1.37
Pre-Crash 87	408	2.04	0.60	−0.26	−1.44	−2.08	−2.39
Post-Crash	408	5.01	4.02	4.39	3.35	3.67	3.41

Table V

Mean OLS Parameter Estimates from the Annual Standard Deviation Regressions

The parameter estimates are obtained from the following cross-sectional analysis of covariance model:

$$STD_i = b_0 + b_1\ InS\&P_i + b_2\ (AbsBeta_i \times MkSTD) + b_3\ InvPrice_i$$
$$+ b_4\ LogMkVal_i + b_5\ NoTradeFreq_i + e_i,$$

where STD_i is the percent log price relative standard deviation of stock i, expressed as a daily rate, $InS\&P_i$ is a dummy classification variable that takes the value of one if the stock is in the S&P 500 sample and zero otherwise, *AbsBeta* is the absolute value of the stock beta, *MkSTD* is the constant percent standard deviation of the CRSP equally weighted index, *InvPrice* is the inverse of the stock price level, *LogMkVal* is the log market capitalization, and *NoTradeFreq* is the percentage of trading days for which no trade occurred. The mean estimates are computed from 13 estimations of the model for each year between 1975 and 1987. The annual parameter estimates for *InS&P* are presented in Table IV. The return differencing interval is the number of days over which differences are taken when computing returns. Overlapping returns are used. The S&P 500 sample consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency.

Independent Variable	Return Differencing Interval					
	Daily	2-day	3-day	5-day	10-day	20-day
Panel A: Mean of the Annual OLS Parameter Estimates (Sample Standard Errors in Parentheses)						
Intercept	1.67%	1.78%	1.83%	1.88%	1.96%	1.92%
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)
InS&P	0.03	0.03	0.03	0.03	0.03	0.03
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
AbsBeta × *MkSTD*	0.82	0.92	0.95	0.99	1.00	1.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
InvPrice	7.30	5.63	4.82	3.96	3.21	2.88
	(0.34)	(0.40)	(0.42)	(0.45)	(0.44)	(0.47)
LogMkVal	−0.06	−0.07	−0.07	−0.08	−0.08	−0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
NoTradeFreq	−0.02	−0.01	−0.01	0.00	0.01	0.02
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Panel B: Mean of the Annual Regression t-Statistics						
Intercept	7.94	8.34	8.67	9.09	9.33	8.34
InS&P	1.07	0.99	0.98	0.94	0.87	0.82
AbsBeta × *MkSTD*	22.40	24.81	26.16	28.00	28.36	25.90
InvPrice	17.51	13.47	11.74	10.03	8.12	6.69
LogMkVal	−4.17	−4.51	−4.79	−5.23	−5.69	−5.23
NoTradeFreq	−1.48	−1.21	−0.91	−0.38	0.28	0.68
Mean R^2	0.64	0.62	0.62	0.63	0.61	0.56

500 Index returns is 0.769 percent while the expiration day standard deviation is 0.827 percent, a difference of 0.058 percent. The 1982–1985 average b_1 estimate of 0.035 percent (daily data), if allocated only to four expiration days per year, implies that the typical S&P 500 stock expiration day standard deviation would be 3.8 percent, 1.8 percentage points greater than the typical non-expiration standard deviation of 2.0. Although the index standard deviation is much smaller than mean stock standard deviation because of the effects of diversification, differences in these respective measures may be compared since any liquidity-induced price effect associated with futures trading should be in the same direction for all included stocks. Since 1.8 is much greater than 0.058, these results suggest that only a small fraction of the volatility associated with inclusion is attributable to the four expiration days. The increase in volatility must affect many other days as well.

The data for 1987 are separately analyzed over the pre-crash period, January 2 to October 16, and over the post-crash period, October 19 to December 31. The pre-crash period results are similar to those obtained in the preceding years. The later results, however, differ. The S&P 500 stocks were much more volatile than the control sample firms during and after the crash, even after adjustment for firm size.

III. Serial Autocorrelations

The slight increase in S&P 500 stock price volatilities, measured relative to the matching control sample, is largest for price changes measured over short intervals. Since a multiperiod return (log price relative) is identically equal to the sum of its constituent single-period returns, this observation implies that serial correlation in daily S&P 500 returns is more negative (or less positive) than that found in the control sample.

The decrease in serial correlation is documented using variance ratios. A variance ratio is the ratio of a long interval return variance to a short interval return variance. Cochrane (1986) shows that variance ratios estimate positively weighted linear sums of sample autocorrelation coefficients. High variance ratios, therefore, imply high serial correlation.[15]

Table VI presents mean percentage differences in standard deviations measured at different intervals, classified by inclusion in the S&P 500. The multiperiod standard deviations (expressed in daily rates) are generally larger than the single-period standard deviations. This implies positive serial correlation in daily data. The 10- and 20-day standard deviations, however, tend to be smaller than the 5-day standard deviations, implying negative serial correlation in weekly data. The latter results differ from those obtained by Lo and MacKinlay (1988a), who found positive serial correlation in weekly index data.[16] The difference suggests

[15] Cochrane (1988), Fama and French (1988), Lo and MacKinley (1988a), and Poterba and Summers (1988) discuss the use of variance ratios in autocorrelation analyses. Variance ratio methods are particularly well suited for identifying serial dependence when autocorrelation coefficients are nonstationary.

[16] These results can be replicated by computing ratios of the index standard deviations presented in Table I. Some positive autocorrelation in the equally weighted index is due to the nonsynchronous trading problem. The value-weighted index is less sensitive to this problem. It also displays positive correlation in weekly returns (not reported), but to a lesser extent.

Table VI

Mean Percent Differences Between Stock Return Standard Deviations Measured over Various Differencing Intervals

The percent difference between return standard deviations measured over various differencing intervals is computed for each stock in the sample and then averaged across stocks. Log price relatives are used for returns. The multi-day standard deviations are computed from overlapping data and are expressed in daily percentage rates. The S&P 500 sample consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency. The pre-crash period is January 2, 1987 to October 16, 1987. The post-crash period starts with October 19, 1987 and extends through December 31, 1987.

	N	Numerator/Denominator Return Measurement Interval						
Year	(firms)	2/1	3/1	5/1	10/1	20/1	10/5	20/5
Panel A: S&P 500 Stocks								
75	370	2.83%	2.47%	1.32%	−2.00%	−2.76%	−3.47%	−4.41%
76	346	2.43	2.69	2.35	−0.29	−2.73	−2.77	−5.18
77	376	1.68	2.06	1.23	−1.91	−7.18	−3.29	−8.50
78	397	1.84	3.13	4.14	3.76	3.59	−0.49	−0.68
79	407	1.88	1.97	1.44	0.49	0.44	−1.14	−1.26
80	414	2.76	3.96	3.40	2.58	2.74	−0.94	−0.76
81	409	3.03	3.59	2.86	1.52	−0.54	−1.43	−3.48
82	410	3.53	4.74	5.91	4.11	0.01	−1.85	−5.74
83	423	2.97	4.16	3.38	−1.08	−5.56	−4.45	−8.86
84	414	3.21	4.19	3.64	1.43	−1.12	−2.31	−4.84
85	420	2.33	2.43	1.13	−0.82	−1.80	−2.10	−3.10
86	436	2.87	2.95	1.87	−0.71	−2.41	−2.71	−4.40
87	408	2.99	2.18	−1.06	0.46	−2.54	1.11	−2.15
Pre-Crash 87	408	2.20	1.97	−0.38	−5.89	−10.48	−5.66	−10.28
Post-Crash	408	−9.07	−18.37	−26.51	−38.09	−46.57	−14.78	−26.63
Panel B: Control Sample Stocks								
75	370	1.09%	0.41%	−0.95%	−4.17%	−5.53%	−3.52%	−5.07%
76	346	0.25	−0.27	−1.72	−4.52	−6.69	−3.07	−5.39
77	376	−0.43	−0.98	−2.45	−5.63	−10.53	−3.50	−8.62
78	397	2.08	3.02	3.76	4.13	3.78	0.24	−0.09
79	407	1.49	1.20	−0.33	−2.24	−2.67	−2.12	−2.58
80	414	2.58	3.54	3.12	2.79	3.12	−0.45	−0.05
81	409	1.86	1.92	0.69	−1.21	−3.36	−2.15	−4.40
82	410	3.18	4.52	5.92	5.33	3.20	−0.70	−2.73
83	423	3.01	3.99	3.29	−0.49	−4.54	−3.92	−7.91
84	414	3.31	4.47	5.17	4.31	0.61	−1.06	−4.60
85	420	2.96	3.91	3.94	3.07	1.77	−1.05	−2.37
86	436	3.49	4.31	4.21	2.93	0.64	−1.47	−3.68
87	408	4.27	4.49	3.54	7.24	5.25	3.11	0.91
Pre-Crash 87	408	3.50	4.18	3.36	−1.18	−5.20	−4.58	−8.50
Post-Crash	408	−5.28	−15.50	−21.13	−33.60	−43.22	−15.24	−27.33

that systematic and nonsystematic return components have different time-series properties.[17]

The average percentage difference in standard deviations measured over long versus short intervals for the S&P 500 stocks tends to be smaller than the same average observed for the matching sample. This may be due to differences related to inclusion or, alternatively, due to differences in firm characteristics between the two samples.

To control for the latter possibility, an analysis of covariance similar to that used for comparing volatilities is conducted using the following model:

$$StdRatio_i = c_0 + c_1\ InS\&P_i + c_2\ (AbsBeta_i \times MkSTD) + c_3\ InvPrice_i + c_4\ LogMkVal_i + c_5\ NoTradeFreq_i + e_i, \tag{2}$$

where $StdRatio_i$ is the ratio of a multiperiod standard deviation to a single-period standard deviation for stock i. The absolute beta is expected to have a positive coefficient since market indices tend to be positively autocorrelated. The lower the price level, the stronger should be the negative autocorrelation due to transitory components such as those caused by the bid/ask spread and discreteness. The inverse price is therefore expected to have a negative coefficient. Since bid/ask spreads are likely to be small for firms with large market values and large for those not frequently traded, the coefficients for these two variables should be negative and positive, respectively.

The estimates of c_1 in equation (2) (Table VII) show that, in the first half of the sample, S&P 500 stock returns tend to be more positively correlated than those of non-S&P 500 stocks. After 1983, however, the S&P stock serial correlations trend downward relative to those observed in the control sample. The trend is expected given the volatility results.

The complete regression results summarized in Table VIII confirm the ancillary predictions of this analysis of covariance model. The absolute beta coefficient estimate is significantly positive; the inverse price estimate is significantly negative; and the log market value estimate is generally negative, while the trade frequency estimate is generally positive.

IV. Summary, Interpretation and Limitations

Cross-sectional analysis of covariance methods are used to measure whether S&P 500 stocks have higher return standard deviations than do a matching sample of non-S&P 500 stocks, after adjustment for several factors known to affect price volatilities. There was little difference before 1983. After that time, S&P 500 volatilities increased relative to the control sample volatilities. The increase is largest and most significant in daily data but is also observed for returns measured over intervals as long as 10 and 20 days.

These results are consistent with the hypothesis that trade in index futures and/or index options markets increases cash market volatility. Support for this

[17] Lo and MacKinley (1988b) also present and interpret evidence of different time-series properties in systematic and nonsystematic return components.

Table VII

Mean Difference Between S&P 500 and Non-S&P 500 Stock Standard Deviation Ratios, Adjusted for Cross-Sectional Differences in Determinants of Serial Correlation

The adjusted mean difference in standard deviation ratios is measured by the OLS estimate of c_1 in the following cross-sectional analysis of covariance model:

$$StdRatio_i = c_0 + c_1\ InS\&P_i + c_2\ (AbsBeta_i \times MkSTD) + c_3\ InvPrice_i + c_4\ LogMkVal_i + c_5\ NoTradeFreq_i + e_i,$$

where $StdRatio_i$ is the percent difference between return standard deviations measured over the indicated return differencing intervals and expressed as daily rates, $InS\&P_i$ is a dummy classification variable that takes the value of one if the stock is in the S&P 500 sample and zero otherwise, *AbsBeta* is the absolute value of the stock beta, *MkSTD* is the constant percent standard deviation of the CRSP equally weighted index, *InvPrice* is the inverse of the stock price level, *LogMkVal* is the log market capitalization, and *NoTradeFreq* is the percentage of trading days for which no trade occurred. The return differencing interval is the number of days over which differences are taken when computing returns. Overlapping returns are used. The S&P 500 sample consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency. The pre-crash period is January 2, 1987 to October 16, 1987. The post-crash period starts with October 19, 1987 and extends through December 31, 1987.

		Numerator/Denominator Return Differencing Interval						
Year	*N* (firms)	2/1	3/1	5/1	10/1	20/1	10/5	20/5
		Panel A: Mean Difference in Standard Deviation Ratios, c_1						
75	370	0.98%	1.09%	0.96%	0.68%	0.11%	−0.20%	−0.81%
76	346	1.38	1.85	2.67	2.98	2.40	0.38	−0.05
77	376	1.67	2.40	2.90	3.36	3.92	0.56	1.32
78	397	−0.11	0.13	0.32	0.20	−0.17	1.41	0.91
79	407	0.10	0.47	1.53	2.71	1.11	2.96	1.27
80	414	−0.05	0.10	0.36	0.07	−0.37	0.52	−0.01
81	409	0.53	0.75	1.21	1.86	0.78	1.89	0.89
82	410	0.70	0.72	0.70	−0.02	−0.68	−1.68	−2.23
83	423	−0.07	0.24	0.74	0.97	0.32	1.10	0.47
84	414	−0.20	−0.26	−0.78	−1.00	−0.23	0.10	0.72
85	420	−1.08	−1.85	−2.63	−2.83	−0.20	−2.92	−0.26
86	436	−1.78	−2.85	−4.25	−5.39	−1.19	−4.28	−0.27
87	408	−0.77	−1.16	−2.70	−4.41	−5.37	−1.67	−2.71
Pre-Crash 87	408	−2.11	−3.28	−4.87	−5.73	−6.51	−1.07	−2.04
Post-Crash	408	−1.60	−0.72	−2.46	−0.65	−0.25	1.79	1.62
		Panel B: Regression *t*-Statistics						
75	370	2.78	2.08	1.36	0.75	0.09	−0.47	−1.02
76	346	3.56	3.33	3.67	3.10	1.99	0.82	−0.06
77	376	4.68	4.76	4.32	3.72	3.39	1.23	1.55
78	397	−0.31	0.26	0.48	0.23	−0.41	1.25	1.11
79	407	0.31	0.99	2.40	3.01	2.37	2.46	1.42
80	414	−0.14	0.20	0.53	0.08	−0.91	0.46	−0.01
81	409	1.66	1.56	1.79	2.08	1.83	1.65	1.10
82	410	2.27	1.52	1.07	−0.02	−1.68	−1.44	−2.58
83	423	−0.22	0.51	1.11	1.08	0.73	0.93	0.56
84	414	−0.60	−0.51	−1.13	−1.07	−0.52	0.08	0.85
85	420	−3.06	−3.62	−3.74	−2.96	−0.44	−2.40	−0.31
86	436	−5.33	−5.79	−6.10	−5.50	−2.57	−3.45	−0.31
87	408	−2.06	−2.10	−3.38	−4.21	−4.02	−4.07	−3.23
Pre-Crash 87	408	−6.12	−6.52	−7.09	−6.02	−5.25	−2.16	−2.19
Post-Crash	408	−2.26	−0.70	−2.10	−0.49	−0.20	1.94	1.57

Table VIII

Mean OLS Parameter Estimates from the Annual Standard Deviation Ratio Regressions

The parameter estimates are obtained from the following cross-sectional analysis of covariance model:

$$StdRatio_i = c_0 + c_1\ InS\&P_i + c_2\ (AbsBeta_i \times MkSTD) + c_3\ InvPrice_i$$
$$+\ c_4\ LogMkVal_i + c_5\ NoTradeFreq_i + e_i,$$

where $StdRatio_i$ is the percent difference between return standard deviations measured over the indicated return differencing intervals and expressed as daily rates, $InS\&P_i$ is a dummy classification variable that takes the value of one if the stock is in the S&P 500 sample and zero otherwise, *AbsBeta* is the absolute value of the stock beta, *MkSTD* is the constant percent standard deviation of the CRSP equally weighted index, *InvPrice* is the inverse of the stock price level, *LogMkVal* is the log market capitalization, and *NoTradeFreq* is the percentage of trading days for which no trade occurred. The mean estimates are computed from 13 estimations of the model for each year between 1975 and 1987. The annual parameter estimates for *InS&P* are presented in Table VII. The return differencing interval is the number of days over which differences are taken when computing returns. Overlapping returns are used. The S&P 500 sample consists of all NYSE stocks that were on the S&P 500 List for the entire year. For each sample year, the control set is chosen to ensure that, for every common stock in the S&P 500 set, there would be a NYSE stock in the control set with similar values of market capitalization, beta, price level, and trade frequency.

Independent Variable	Numerator/Denominator Return Differencing Interval						
	2/1	3/1	5/1	10/1	20/1	10/5	20/5
Panel A: Mean of the Annual OLS Parameter Estimates (Sample Standard Errors in Parentheses)							
Intercept	2.73	4.27	6.32	10.75	9.17	3.50	1.54
	(1.99)	(2.81)	(4.31)	(5.73)	(7.08)	(1.60)	(3.50)
InS&P	0.06	0.08	0.04	−0.04	0.04	−0.07	−0.01
	(0.25)	(0.37)	(0.55)	(0.70)	(0.72)	(0.21)	(0.32)
AbsBeta × *MkSTD*	4.30	6.08	7.99	9.28	10.57	1.59	3.13
	(0.54)	(0.70)	(0.80)	(0.98)	(1.25)	(0.41)	(0.77)
InvPrice	−71.83	−104.46	−136.98	−161.26	−169.31	−27.31	−38.37
	(7.32)	(10.53)	(13.65)	(15.07)	(16.04)	(2.51)	(4.82)
LogMkVal	−0.07	−0.17	−0.40	−0.90	−1.02	−0.44	−0.55
	(0.13)	(0.19)	(0.30)	(0.40)	(0.50)	(0.11)	(0.25)
NoTradeFreq	0.36	0.66	1.15	1.74	2.23	0.51	0.97
	(0.17)	(0.27)	(0.43)	(0.61)	(0.85)	(0.16)	(0.39)
Panel B: Mean of the Annual Regression *t*-Statistics							
Intercept	1.07	1.15	1.20	1.56	0.96	1.09	0.17
InS&P	0.16	0.16	0.13	0.05	0.10	−0.20	−0.01
AbsBeta × *MkSTD*	9.91	9.78	9.63	8.55	7.60	3.49	3.41
InvPrice	−13.56	−13.55	−13.00	−11.49	−9.37	−4.23	−3.05
LogMkVal	−0.39	−0.67	−1.13	−1.93	−1.67	−2.05	−1.27
NoTradeFreq	1.99	2.64	3.43	3.87	3.76	2.50	2.32
Mean R^2	0.30	0.30	0.29	0.25	0.20	0.07	0.06

conclusion, however, is circumstantial. It depends on the fact that index futures and options trading started in 1982 and 1983 and grew significantly over the next few years.

Other S&P 500-related phenomena, however, also experienced growth over the same period. These may also account for the results. The two most important phenomena are probably the growth in foreign ownership of American equities and the growth in index funds.

Foreign ownership may be concentrated in S&P 500 stocks because information about these securities is more widely available. If these investors tend to overreact to news, or if they make trading decisions on margins expressed in their home currencies so that exchange rate uncertainty becomes a factor, S&P 500 stock volatilities could be greater than those of comparable stocks.

Index funds are usually organized to replicate S&P 500 returns. Although it seems unlikely that volatility should increase when stock is placed under passive management, there are scenarios under which this conclusion can be obtained under extreme conditions. In particular, if passively managed funds crowd out shareholders who have greater propensity to supply liquidity, and if there is not a proportionate decrease in the demand for liquidity with the increase in passively managed funds, it is possible that the market can become more volatile. Although the crowding-out assumption may be plausible, it is not obvious why there should be a disproportionate change in the demand for liquidity.

If the growth in index futures and options trade is indeed responsible for the relatively higher S&P 500 stock volatilities, at least two interpretations of the results are possible. As suggested in the introduction, the increased volatility in daily returns and the associated negative serial correlation may be evidence of liquidity-induced noise caused by cash transactions related to plays in the index futures and options markets. The slightly higher volatility in returns measured over longer intervals may be due to more fundamental destabilization of the value formation process due to additional noise.

An alternative explanation, however, can be obtained by considering the average positive serial correlation observed in the daily stock price changes. Positive serial correlation is surprising since bid/ask bounce and (to a lesser extent) discreteness add negatively serially correlated variance components to daily price changes. Something else that causes positive correlation must offset the effects of these two processes. Hasbrouck and Ho (1987) suggest that the observed positive correlation in (transaction) price changes may be caused by slow adjustment of prices to new information. If so, rather than destabilizing the cash markets, trade in index futures and index options markets may serve to make the cash markets more efficient, causing them to adjust more quickly to new information. This conclusion is consistent with the fact that transactions costs are lower in futures and options markets.

Without further information, it is difficult to distinguish between these two alternatives. This will undoubtedly be the subject of future research.

Regardless of which alternative is true, it is likely that, if derivative trade increases volatility, the increase is underestimated. The reason lies in the fact that well diversified portfolios can be very good substitutes for each other. Most index strategies that can be undertaken with the S&P 500 stock index portfolio can also be implemented with only slightly less precision using a portfolio of non-S&P 500 stocks designed to replicate S&P 500 index returns. Even if such strategies are not being undertaken using a non-S&P 500 portfolio, stock-to-stock arbitrage and pricing off indices can distribute much of the effects of derivative trade from the S&P 500 stocks to the other stocks. The result will be underestimation of these effects (assuming that they exist) in any study that contrasts S&P 500 stock volatilities with non-S&P 500 stock volatilities. The underestimation problem affects all studies of the destabilization hypothesis that use a correlated asset to control for factors other than derivative trade that might affect volatility since correlated assets can be arbitraged.

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