The Effect of Futures Trading on the Stability of Standard and Poor 500 Returns

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INTRODUCTION

The effect of the inception of stock index futures contracts on the underlying stock markets is a principal concern of the regulatory agencies, exchanges, and investors. The issue is important because corporations raise equity capital by issuing shares. Regulatory agencies might conclude that restrictions on futures trading are in the public interest if, in fact, futures trading increases the cost of capital. Such an increase can result if futures trading destabilizes the stock market and if this increased volatility increases the expected return required by investors to hold stocks.

Theoretical studies on the effects of futures trading on the cash market show that the effect is ambiguous.[1] Most of the empirical studies suggest that the introduction of a futures market has stabilized, or at least not destabilized, the underlying spot market. [Kamara (1982) reviews the literature. Also see Weaver and Banerjee (1990).] Yet studies by Figlewski (1981) on GNMA futures and Simpson and Ireland (1985) on Treasury-bill futures argue that financial futures trading destabilizes the underlying spot markets.

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[1]Financial futures trading reduces the cost of entry of small traders into the financial markets [Kamara (1988)]. Introducing new speculators into the markets improves risk sharing and increases liquidity, but can make cash prices more noisy and reduce net social welfare if these new speculators are less informed than traders already in the market [Stein (1987)]. Futures trading can increase cash price volatility if increased liquidity causes cash prices to reflect new information more quickly. In this case, the increase in cash price volatility should increase net social welfare.

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Edwards (1988a, b), and Harris (1989) studied the effect of futures trading on the underlying stock market.[2] Using variance ratio tests of daily returns from June 1973 to May 1987, Edwards concludes that the introduction of financial futures trading in interest rates and stock indexes has not destabilized the underlying cash markets. Harris (1989) compares daily return volatilities pre-futures (1975–1982) and post-futures (1982–1987) between the Standard and Poor's 500 stocks (henceforth S&P) and a non-S&P group of stocks. Controlling for differences in firm attributes (beta, price level, size, and trading frequency), Harris finds that individual stock returns in the S&P group are more volatile in the post-futures period than the non-S&P stock returns.

This article investigates the effects of the S&P 500 stock index futures market on the stability of the underlying cash index from 1976 through 1988. Two methods are used to examine these effects. First, the unconditional volatilities of returns on the cash index are compared before and after futures trading. Second, conditional volatilities, controlling for the effects of macroeconomic factors, are compared.

This study extends earlier studies in two ways. First, the changes in volatilities of daily and monthly returns are examined using parametric and nonparametric tests. The variance ratio F-tests used by Edwards (1988a, b) are sensitive to the underlying assumption of normally distributed stock returns. This study rejects the hypotheses that daily and monthly stock returns are normally distributed. Nonparametric tests are used and it is found that the dispersion of daily S&P returns is significantly higher in the post-futures period (April 21, 1982 to December 31, 1988) than in the pre-futures period (January 1, 1976 to April 20, 1982). This study does not reject the hypothesis that the dispersion of monthly returns in the two periods are equal. Upon further investigation, statistically significant evidence is found that the distribution of daily returns could be frequently (and non-event induced) changing. Consequently, one cannot conclude that the significant increase in the volatility of daily S&P 500 index returns after the inception of futures trading is necessarily futures induced.

Second, while Harris (1989) examines individual stocks adjusting for the effects of firm attributes, this study examines the volatility of the monthly returns of the S&P 500 index conditional on macroeconomic effects based on Chen, Roll, and Ross (1986), henceforth CRR.[3] Empirical studies of the effects of stock index futures trading on the stability of the cash market are "one-shot" event studies examining characteristics of returns before and after the inception of futures trading. To draw conclusions about the effects of futures trading, one must rule out all other possible explanations that could have had the same timing. While it is impossible to control for and refute all conceivable alternatives to the hypothesis that the inception of futures trading affects the volatility of stock returns, there is a need to account for the most likely alternative explanations. The two most likely alternative explanations for changes in the volatility of stock returns are microeconomic factors and macroeconomic. Harris (1989) investigates the former and this study investigates the latter.

[2]Stoll and Whaley (1987) examined the effect of options and futures expiration on stock market volatility. They found an increase in stock market volatility on the so-called "Triple-Witching" days when futures and options contracts on stock indices expire. Using an ARCH model, Baldauf and Santoni (1991) found no evidence that program trading caused a shift in the model's parameters.

[3]This study also tested, and did not reject, the hypothesis that the response of mean S&P 500 returns to these factors is equal in the pre-futures and post-futures subperiods.

The control group on non-S&P firms used by Harris contains equities of firms that are, in general, much smaller than the firms in the S&P 500 index. The market value of these non-S&P firms in Harris' sample is about one third the market value of the S&P 500 firms. Therefore, to the extent that returns on the equities of different-sized firms react differently to macroeconomic variables, it is possible that Harris' study does not fully control for the effects of these macroeconomic variables. For example, suppose that the sensitivity to interest rates differs between S&P 500 firms and non-S&P 500 firms.[4] Huizinga and Mishkin (1986) and Roley (1986) establish that there was an important change in the behavior of real and nominal interest rates after September 1982. Because futures trading on the S&P 500 began in April 1982, stock return reactions to this change in interest rate behavior may incorrectly appear to be a result of futures trading. This study thus complements Harris' (1989) study by controlling for macroeconomic effects.

The stability of the residual volatility is tested after adjusting for the effects of macroeconomic factors as identified in CRR. The results depend critically on the events of October 1987. When the post-futures period includes the October 1987 observation, the conditional volatility in the post-futures period is almost twice as large as that of the pre-futures period and the increase in conditional volatility is significant at conventional levels. Without the October 1987 observation in the sample, the conditional volatility in the post-futures period is *lower* than that of the pre-futures period though the hypothesis that the conditional variances are equal is not rejected.[5] While the causes of the crash are not fully known, extant literature [e.g., Miller et al. (1989)] suggest that it was not caused by futures trading. Consequently, together with Harris' (1989) findings that the increase in the volatility of the returns of the S&P 500 stocks relative to non-S&P 500 stocks is not economically significant, the evidence presented below suggests that futures trading does not destabilize the S&P 500 index.

UNIVARIATE STABILITY TESTS

Futures trading on the S&P 500 began April 21, 1982. The sample period of this study begins January 1, 1976 and ends December 31, 1988. Daily returns on the S&P 500 cash index are continuously compounded. The daily S&P 500 closing prices for 1976–1987 are from CRSP and those for 1988 are from the *NYSE Data Book*. The monthly S&P 500 returns are from *Ibbotson and Associates' SBBI Yearbook* for 1989.[6]

Table I reports summary statistics for daily and monthly S&P 500 returns from 1976 to 1988. The mean and standard deviation of both daily and monthly returns in the post-futures period are higher than those in the pre-futures period. Using an F-test, as in Edwards (1988a, b), Table II shows that one cannot reject the null hypothesis that the variance of monthly returns is the same for the pre- and post-futures periods, but this null hypothesis is rejected for daily returns. These variance ratio F-tests are, however, sensitive to the assumption of normally distributed stock returns. Table I also reports normality tests for daily and monthly returns. The null

[4]Pearce and Roley (1988), for example, found that firms' equity returns react differently to unanticipated inflation depending on the level of their inventories and long-term debt as well as on the values of their betas.

[5]This result need not be inconsistent with Harris' (1989) findings because S&P and non-S&P firms are not compared.

[6]The data do not include dividends. The tests are repeated using monthly returns with dividends. The results are identical.

Table I
MEANS, STANDARD DEVIATIONS, SKEWNESS, KURTOSIS, AND NORMALITY TESTS FOR DAILY AND MONTHLY RATES OF RETURN ON THE S&P 500, (1976–1988) AND OVER THE PRE-FUTURES AND POST-FUTURES SUBPERIODS

Statistic	Entire Sample	Pre Futures[a]	Post Futures[b]	Post Futures (No Crash)[c]
Daily data:				
Sample size	3286	1591	1695	1692
Mean	0.000393	0.000187	0.000586	0.000704
Standard deviation	0.00995	0.00796	0.01152	0.00996
Skewness[d]	−2.63	0.0028	−3.32	−0.098
Kurtosis[d]	62.89	4.161	67.49	7.022
Normality test[e]	489653	90	292788	1113
p-value[f]	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Monthly data:				
Sample size	156	75	81	80
Mean	0.00829	0.0037	0.0125	0.0154
Standard deviation	0.0457	0.0414	0.0492	0.0422
Skewness[d]	−0.5744	0.0729	−1.018	0.2581
Kurtosis[d]	6.4738	3.4240	8.298	3.5250
Normality test[e]	63.50	1.47	80.99	4.36
p-value[f]	(0.0000)	(0.4795)	(0.0000)	(0.1130)

[a] Daily: January 2, 1976 through April 20, 1982. Monthly: January 1976 through April 1982.
[b] Daily: April 21, 1982 through December 30, 1988. Monthly: May 1982 through December 1988.
[c] Days omitted: 16th, 19th, and 20th of October 1987; for monthly data October 1987 was omitted.
[d] The standard measures of skewness and kurtosis are: $\beta_1 = \mu_3^2/\sigma^3$ and $\beta_2 = (\mu_4/\sigma^4) - 3$, where $\mu_3 = E(x-\mu)^3$ and $\mu_4 = E(x-\mu)^4$. The sample estimates of β_1 and β_2, b_1 and $b_2 - 3$, are reported. [Source: Mood, Graybill, and Boes (1974), p. 76.]
[e] H_0: $\beta_1 = 0$ and $\beta_2 = 0$. H_A: H_0 is not true *and* the distribution belongs to the Pearson family. The test statistic is:

$$n\left[\frac{b_1}{6} + \frac{(b_2-3)^2}{24}\right] \sim \chi_2^2,$$

where b_1 and b_2 are sample estimates of β_1 and β_2. [Source: Bowman and Shenton, *Biometrika* (1975).]
[f] Two-tailed p-values for the hypothesis that the returns are normally distributed.

hypotheses that daily and monthly returns are normally distributed are rejected at a 0.0001 level for all but two subgroups: the monthly returns in the pre-futures subgroup and the monthly returns in the post-futures subgroup without the crash of 1987. The relative size of the skewness and kurtosis measures suggest that the normality rejections stem primarily from leptokurtosis.

The stability issue is examined further by using two statistical tests that do not depend on the assumption of normally distributed stock returns. The first nonparametric test is the Kolmogorov-Smirnov two-sample test that tests whether two independent samples come from populations with the same distribution. The two-tailed version of this test is sensitive to any differences in the sample distributions such as location (central tendency), dispersion, skewness, or kurtosis.[7] The procedure

[7] Siegel (1956), p. 127.

Table II

TESTS OF EQUALITY OF DISTRIBUTIONS, MEANS AND VARIANCES OF RATES OF RETURN ON S&P 500 BEFORE AND AFTER THE INTRODUCTION OF S&P 500 FUTURES (TWO-TAILED p-VALUES IN PARENTHESES)

	Nonparametric		Parametric	
Data Periods	**Wilcoxon Rank Sum (Z-Statistic)**	**Kolmogorov-Smirnov (χ_2^2 Stat.)**	**Test for Equal Means[a]**	**Test for Equal Variances[b]**
Daily data:				
Pre- vs. post-futures[c]	1.211 (0.2258)	8.200 (0.0166)	1.1627 (0.2450)	2.0945[d] (0.0000)
Pre- vs. post-futures (without crash)[e]	1.2409 (0.2146)	8.207 (0.0165)	1.6181 (0.1056)	1.7037[d] (0.0000)
Monthly data:				
Pre- vs. post-futures[c]	1.4773 (0.1396)	2.698 (0.2595)	1.2084 (0.2269)	1.4133[d] (0.0658)
Pre- vs. post-futures (without crash)[e]	1.6256 (0.1040)	2.395 (0.3019)	1.7370 (0.0824)	1.0356 (0.4400)

[a] H_0: $\mu_1 - \mu_2 = 0$. Test statistic: $Z = (\bar{x}_1 - \bar{x}_2)/\sigma_{(\bar{x}_1 - \bar{x}_2)}$, where: $\sigma_{(\bar{x}_1 - \bar{x}_2)} = \left(\sigma_1^2/n_1 + \sigma_2^2/n_2\right)^{1/2}$. This test assumes: (1) both samples are approximately normally distributed; and (2) both samples are random and independent.

[b] H_0: $\sigma_1^2 = \sigma_2^2$. Test statistic: $F_{\nu_1,\nu_2} = s_1^2/s_2^2$, where $s_1^2 > s_2^2$ and ν_1 and ν_2 are numerator and denominator degrees of freedom. This test assumes: (1) both samples are normally distributed; and (2) both samples are random and independent.

[c] Pre-futures daily: January 2, 1976 through April 20, 1982. Monthly: January 1976 through April 1982. Post-futures daily: April 21, 1982 through December 30, 1988. Monthly: May 1982 through December 1988.

[d] The F-test statistic is invalid because normality is rejected using the Bowman-Shenton (1975) test for one or more of the underlying distributions used to calculate this statistic.

[e] Sample excludes the crash of October 1987. Days omitted: 16th, 19th, and 20th of October 1987. Month omitted: October 1987.

measures the largest absolute difference between the two cumulative distribution functions. If this difference is larger than a critical value, then the null hypothesis that the two distributions are identical is rejected.

The second nonparametric test is the Wilcoxon Rank Sum test. This test is especially likely to reject the null hypothesis when the populations have unequal locations (central tendencies). The Wilcoxon Rank Sum test pools the observations from the two samples and then ranks these observations from the smallest to the largest. The test statistic depends on the totals of the ranks for both samples. If the probability distributions are identical, then these rank rums will be of similar size.

Table II reports the results of the two nonparametric tests. For daily data, the Wilcoxon Rank Sum test does not reject the null hypothesis that the pre-futures and the post-futures subgroups have the same distribution while the Kolmogorov-Smirnov test does reject. The results of the two nonparametric tests are consistent with the hypothesis that the daily location (mean) has not changed but the daily dispersion (variance) has changed between the periods. For monthly data, neither the

Wilcoxon Rank Sum nor the Kolmogorov-Smirnov test rejects the null hypothesis that the pre-futures and post-futures returns have the same distribution. These results are consistent with the hypothesis that neither the monthly location (mean) nor the monthly dispersion (variance) has changed between the subgroups. The nonparametric tests thus suggest that the daily volatility of the S&P 500 returns is higher after futures trading commenced, but the volatility of monthly returns is unchanged.

One possible alternative explanation of why a change in daily volatility is found, but not in monthly volatility, is simply that the monthly test has less statistical power than the daily test because monthly returns capture only a subset of the information reflected in daily returns. Another possible alternative explanation for a change in daily volatility, but not in monthly volatility, is that the distribution of daily returns is frequently and randomly changing, whereas the distribution of monthly returns is not so.[8] Although they do not test the significance of these annual changes, both Edwards (1988a) and Harris (1989) report substantial changes in the variance of daily S&P 500 returns from year to year. To investigate this possibility, the parametric and nonparametric test based on two alternative (non-event induced) splittings of the data set: (i) 1976–1979 versus 1980–1988 and (ii) 1976–1984 versus 1985–1988 are retested. The results are similar to those reported in Table II. For example, using the Kolmogorov-Smirnov test, the hypothesis that the two samples come from populations with the same distribution is always rejected (at conventional levels, with and without the crash) for daily returns, but never for monthly returns.

Consequently, it can be concluded from Tables I and II that futures trading has no significant effect on the volatility of monthly returns. But, it cannot be concluded from Tables I and II that the significant increase in the volatility of daily returns in the post-futures subgroup is necessarily related to the inception of futures trading.

The crash of October, 1987 led regulatory agencies to implement various measures designed to reduce volatility in the stock market. Because the popular press seems to equate volatility with "big" absolute price movements in the stock market,[9] the hypothesis that there are more outliers in the daily returns of the S&P 500 index since the inception of futures trading is tested. Assuming outliers were as likely before futures trading as after, a "big" return is defined as an outlier that is identified by using the interquartile range calculated from the entire sample.[10] This procedure classifies only three monthly returns as outliers out of the 156 months in the sample: March 1980 (−10%), January 1987 (+13%), and October 1987 (−22%). For daily data, 114 of the 3286 observations are classified as outliers.[11]

Table III presents the results of the outlier test of daily returns. Using the binomial distribution, this test calculates the probability of observing a number of outliers that is at least as extreme as were observed in the post-futures group if outliers were randomly distributed among all observations. This test confirms that there are significantly more daily return outliers (low, high, and total) in the post-futures

[8]This suggestion comes from an anonymous referee.

[9]For example, "Stock Prices Fall by Record Amount in Busiest Session," *The New York Times*, September 12, 1986. The substantial increase in kurtosis (i.e., outliers) in daily returns in the post-futures subgroup also motivates testing this "popular press" hypothesis.

[10]The procedure defines observations as outliers if they are less than $Q_L - 1.5D_Q$ or if they exceed $Q_U + 1.5D_Q$ where Q_U and Q_L denote the upper and lower quartiles of the data set and $D_Q = Q_U - Q_L$. See Hoaglin, Mosteller, and Tukey (1983).

[11]When the outliers are calculated from each subgroup's interquartile range, the test results are similar.

Table III
TEST OF DAILY OUTLIERS USING THE BINOMIAL PROBABILITY DISTRIBUTION

Description	Entire Sample	Without October 1987
Pre-futures observations	1591	1591
Post-futures observations	1695	1673
Low outliers, post-futures	34	26
All low outliers	51	43
PROB (post-futures outliers)	(0.0423)	(0.2918)
High outliers, post-futures	50	45
All high outliers	63	58
PROB (post-futures outliers)	(0.0000)	(0.00007)
All outliers, post-futures	84	71
All outliers	114	101
PROB (post-futures outliers)	(0.0000)	(0.0002)

The *two-tailed p-value,* PROB (post-futures outliers), is the probability of observing at least this extreme total number of outliers in the post-futures period if outliers are randomly distributed among all observations. An observation is classified as an outlier if it is less than $Q_L - 1.5D_Q$ or if it exceeds $Q_U + 1.5D_Q$ where Q_U and Q_L denote the upper and lower quartiles and $D_Q = Q_U - Q_L$. See Hoaglin, Mosteller, and Tukey (1983).

trading period than in the pre-futures trading period. Excluding October 1987, however, low daily outliers are statistically no more frequent in the post-futures period than in the pre-futures period. With or without October 1987, daily high outliers are significantly more prevalent in the post-futures period. These last two facts counter popular press perceptions that futures trading is associated with only "big" daily *declines* in the stock market.

The outlier test and the data in Table I illustrate the effects of October 1987 on the distribution of daily stock returns. Thirteen of the 22 trading days in October 1987 are classified as outliers, with 8 of them classified as low outliers. In fact, October 1987 accounts for 13 of the 114 daily outliers and 8 of the 51 low outliers in the sample. Including October 1987, one can reject, at the 5% level, the null hypothesis that there are no more low daily outliers in the post-futures era than in the pre-futures era. However, excluding October 1987, this null hypothesis cannot be rejected at conventional levels. Similarly, Table I shows that by including the 16th, 19th, and 20th of October 1987 in the sample, the skewness of daily returns in the post-futures era changes from about zero to -3.32, and the measure of kurtosis increases from 7 to 67.[12]

MULTIVARIATE STABILITY TESTS

The above section compares the unconditional volatility of returns before and after futures inception. Yet, other factors influence stock returns. In this section the conditional volatilities of monthly returns in the pre- and post-futures periods are examined after adjusting for macroeconomic effects. This is done by testing the stability of the residual volatility after the effects of the macroeconomic factors, based on CRR, are removed.

[12]Because 13 of the 22 daily observations in October 1987 are classified as outliers, the parametric and nonparametric tests of the distribution of daily returns are repeated on a sample period that excludes the entire month of October 1987. The results are similar to those reported in Table II.

A. Description of the Factors

CRR suggest that the following factors affect stock returns:

1. Innovations in the rate of productive activity.
2. Unanticipated changes in the default risk premium.
3. Unanticipated changes in the discount rate.
4. Unanticipated price level changes.
5. Changes in expected inflation.

The CRR calculations of the proxies for the factors are replicated as follows. The monthly growth in industrial production, MP_t, proxies innovations in the rate of productive activity. This factor is calculated as $MP_t = \log[IP_{t+1}/IP_t]$, where IP is the Industrial Production Index (not seasonally adjusted) taken from the *Survey of Current Business.* Following CRR, IP is led by one month to make industrial production and stock returns contemporaneous.

The default risk factor, $URP_t = BAA_t - LGB_t$, is the end-of-period monthly return on BAA bonds minus the end-of-period monthly return on long-term government bonds. The LGB_t return series is from *Ibbotson and Associates.* The BAA return series are calculated from BAA yields obtained from *Moody's Bond Record* using the procedure described in Schwert (1989).

The term structure factor, $UTS_t = LGB_t - TB_{t-1}$, is the end-of-period monthly return on long-term government bonds minus the end-of-period return on one-month T bills. This variable measures the unanticipated return on long-term bonds. Both series are from *Ibbotson and Associates.*

The unanticipated inflation factor, $UI_t = I_t - E(I_t|t - 1)$, is actual inflation minus expected inflation. The fifth factor, DEI_t, is the change in expected inflation. Expected inflation is estimated by using Fama and Gibbons' (1984) methodology as did CRR. Defining $I_t = \log[CPI_t/CPI_{t-1}]$, let the change in the ex-post real rate of interest be: $U_t = (TB_{t-1} - I_t) - (TB_{t-2} - I_{t-1})$, where TB_{t-1} is the return on one-month T bills from $t - 1$ to t. Estimating $\hat{\theta}$ from the moving average process $U_t - \theta U_{t-1}$, the estimated expected real rate of interest from $t - 1$ to t at time $t - 1$ is: $E(R_t) = (TB_{t-2} - I_{t-1}) - \hat{\theta}\hat{U}_{t-1}$. From the Fisher equation, expected inflation is $E(I_t|t - 1) = TB_{t-1} - E(R_t|t - 1)$, and unanticipated inflation is $UI_t = I_t - E(I_t|t - 1)$.

B. Multivariate Test Results

The following regression is estimated for the entire sample, the pre-futures and the post-futures subsamples where SP_t is the monthly return (without dividends) on the S&P 500 Index.

$$SP_t = \beta_0 + \beta_1(MP_t) + \beta_2(URP_t) + \beta_3(UTS_t) + \beta_4(UI_t) + \beta_5(DEI_t) + \epsilon_t \tag{1}$$

Table IV presents two sets of regression results that differ only in the data set used to calculate $\hat{\theta}$, the moving average parameter used in the calculation of expected inflation. To allow for changes in the expected real rate of interest between the two subperiods, $\hat{\theta}$ is estimated in two ways. In the first set of regressions, the

Table IV

REGRESSIONS OF MONTHLY S&P 500 RETURNS ON MACROECONOMIC FACTORS, 1976–1988 (TWO-TAILED p-VALUES IN PARENTHESES)

Macroeconomic Factor	Entire Sample (January 1976 to December 1988)	Moving Average Parameter for Expected Inflation (θ) is Estimated Using all Data		Moving Average Parameter for Expected Inflation (θ) is Estimated Separately for Each Subperiod	
		Pre-S&P 500 Futures (January 1976 to April 1982)	Post-S&P 500 Futures (May 1982 to December 1988)	Pre-S&P 500 Futures (January 1976 to April 1982)	Post-S&P 500 Futures (May 1982 to December 1988)
Intercept	0.00702	0.00220	0.00822	0.00218	0.01801
	(0.0685)	(0.6224)	(0.2532)	(0.6263)	(0.0175)
Industrial production	0.48525	0.70064	0.37819	0.70096	−1.422
	(0.2741)	(0.1669)	(0.6397)	(0.1670)	(0.0954)
Default risk premium	−0.2151	−0.5873	−0.0858	−0.5840	−0.1473
	(0.2282)	(0.0126)	(0.7701)	(0.0130)	(0.6187)
Term structure	0.38824	0.07825	0.51243	0.08244	0.41568
	(0.0017)	(0.6322)	(0.0108)	(0.6125)	(0.0361)
Unanticipated inflation	1.5461	−2.911	3.4305	−2.932	4.0178
	(0.2042)	(0.1234)	(0.0418)	(0.1261)	(0.0253)
Change in expected inflation	−0.6274	−1.852	−0.5106	−1.829	0.34511
	(0.5925)	(0.2987)	(0.7474)	(0.3026)	(0.8358)
N	152	71	81	71	77
Adj. R^2	0.1290	0.1752	0.1203	0.1747	0.1537
F-statistic	5.471	3.973	3.188	3.964	3.761
p-value	(0.0001)	(0.0034)	(0.0116)	(0.0035)	(0.0046)
Durbin-Watson	1.923	2.038	1.910	2.036	1.816

$\hat{\theta}$ calculation uses the entire sample. In the second set, $\hat{\theta}$ is calculated for each subperiod separately. Both sets yield similar results.[13]

For the pre-futures period the model as a whole is significant, as the F-value shows, though the only significant regressor is the default risk factor. Recall that the default risk factor, $BAA_t - LGB_t$, is the difference in end-of-period monthly returns. An unexpected increase in the default risk over the monthly holding period reduces end-of-period *BAA* bond prices relative to end-of-period *LGB* bond prices; and, thus, reduces the difference in the end-of-period monthly returns. Consequently, the negative value of the coefficient of the default risk factor implies that the S&P 500 returns increase with default risk. In the post-futures period, the model as a whole is also significant and two regressors are significantly positive: term structure and unanticipated inflation. The negative correlation of -0.6 between the term structure and default premium suggests that the finding that the default premium is significant in the pre-futures period while the term structure factor is significant in the post-futures period may be a result of multicollinearity and not an economic result.

Before testing whether the conditional variance between two periods is different, it is necessary to test the stability of the regression coefficients in eq. (1) between the periods. Table VA presents the results of Weerahandi's (1987) test of regression coefficient stability. This test allows for unequal variances across the subgroups. The Weerahandi test does not reject the hypothesis that the regression coefficients are stable between the pre- and post-futures periods.[14]

To test the hypothesis that the conditional variances for the pre- and post-futures eras are equal, the Goldfeld-Quandt test is used.[15] This test examines the residuals from the same regression model fitted separately to the two subgroups. The null hypothesis is that the variance of the errors for one part of the sample is the same as the variance of the errors in another part of the sample. Dropping some observations out of the middle of the sample and then running the regression model on the remaining two parts of the sample increases the power of this test. Table VB presents the results this test. The results of the Goldfeld-Quandt test depend on whether the post-futures sample includes the crash of October 1987. Including the crash, the Goldfeld-Quandt test rejects the null hypothesis of equal conditional variances. The conditional volatility in the post-futures period is almost twice as large as that of the pre-futures period and the increase in conditional volatility is significant at conventional levels. Excluding the crash, the Goldfeld-Quandt test does not reject the null hypothesis of equal conditional variances and the conditional volatility in the post-futures period is lower (but not significantly lower) than that of the pre-futures period.[16]

While the causes of the crash of October 1987 are not yet fully known, extant literature suggest that is was not caused by futures trading. Miller et al. (1989), for

[13]The results in Table IV include the crash of October 1987. Similar results are found if the regressions exclude October 1987.

[14]The traditional Chow (1960) test [see Maddala (1977), p. 198] assumes equal residual variance between the two periods. The results of the Weerahandi and Chow tests are, however, similar in this study.

[15]See Kmenta (1986, p. 292).

[16]This result is robust in that many iterations of the Quandt test with the first subgroup ending in any month from August 1981 through December 1982 *always* presents the same results: When the crash is included in the "post-futures" sample, the null hypothesis of equal conditional variances is rejected; whereas, when the crash is excluded from the "post-futures" sample, this null hypothesis is not rejected.

Table VA
WEERAHANDI TEST FOR REGRESSION COEFFICIENT STABILITY

Unrestricted Sum of Squared Errors				
Pre-Futures (January 1976 to March 1982)	**N**	**Post-Futures (April 1982 to December 1988)**	**N**	**F-Statistic[a] (p-Value)**
0.0861	71	0.1599	81	1.6477 (0.1384)
Excluding October 1987				
0.0861	71	0.0946	80	2.1186 (0.0549)

[a] Here, the F-statistic is:

$$F_{k,r} = \frac{r}{k}(\hat{\beta}_1 - \hat{\beta}_2)'\left(\frac{V_1}{R}(X_1'X_1)^{-1} + \frac{V_2}{1-R}(X_2'X_2)^{-1}\right)^{-1}(\hat{\beta}_1 - \hat{\beta}_2)$$

where k is the number of independent variables, $r = n_1 + n_2 - 2k$, $V_i = (Y_i - \hat{Y}_i)'(Y_i - \hat{Y}_i)$, $R = V_1/\sigma_1^2/(V_1/\sigma_1^2 + V_2/\sigma_2^2)$, Y_i is the $n \times 1$ vector of S&P 500 returns, $\hat{\beta}_i$ is the $k \times 1$ vector of OLS slop coefficients, and X_i is the $n \times k$ matrix of macroeconomic variables. See Weerahandi (1987).

Table VB
GOLDFELD-QUANDT TEST OF CONDITIONAL VARIANCE STABILITY

Middle Observations Deleted[a]	**Pre-Futures**		**Post-Futures**		**F-Statistic[c] (p-Value)**
	SSE[b]	**Observations**	**SSE[b]**	**Observations**	
26%	0.0698	56	0.1287	58	1.7734 (0.0219)
26%, But excluding Oct. 1987	0.0698	56	0.0654	57	1.0879 (0.3826)

[a] Similar test results occur when one-sixth of the middle observations were deleted.
[b] SSE is sum of squared errors.
[c] Here, $F_{n_1-k,n_2-k} = (SSE_1/n_1 - k)/(SSE_2/n_2 - k)$ where k is the number of estimated regression parameters (six in this test). See Kmenta (1986, pp. 292–294).

example, conclude that "the crash of October 19, 1987 did not originate in Chicago and flow from there by means of index arbitrage, carried out by program trading, to an otherwise calm and unsuspecting market in New York." Consistent with these findings, the tests used in this study fail to reveal any evidence that stock index futures trading has destabilized the stock market based on monthly returns.

CONCLUSIONS

This article investigates the effects of futures trading on the S&P 500 on the stability of the underlying index. While the testing methods differ from Edwards (1988a, b), Harris (1989), and Baldauf and Santoni (1991), the results are mostly consistent with theirs. Parameteric and nonparametric tests suggest that the volatility of daily returns in the post-futures period (April 21, 1982 to December 31, 1989) was higher than in the pre-futures period (January 1, 1976 to April 20, 1982), but the volatility of monthly returns remained unchanged. Further investigation, however, reveals statistically significant evidence that the distribution of daily returns could be frequently (and non-event induced) changing. Consequently, one cannot conclude that the significant increase in the volatility of daily returns after the inception of futures trading is necessarily futures induced.

Moreover, even if one is concerned that the increase in daily volatility in the post-futures era is indeed futures induced, the findings that daily volatility increased after the inception of futures trading but that monthly volatility is unaffecteed suggest that any effects of futures trading on the volatility of the stock market may be small and/or transitory and could stem from inadequate liquidity of the stock market.[17] Therefore, regulators concerned with the increased daily volatility may wish to look for ways to improve the liquidity of the stock market instead of ways to increase the costs of futures trading.

Controlling for the effects of macroeconomic variables, this study finds no evidence, apart from the month of October 1987, that monthly S&P 500 index volatility has increased after inception of the S&P 500 futures market. In fact, excluding October 1987, the conditional volatility of index returns is slightly lower in the post-futures era. While the causes of the crash are not fully known, extant literature [e.g., Miller et al. (1989)] suggests that it was not caused by futures trading. Consistent with these findings, no evidence is found here that stock index futures trading has an adverse effect on market stability.

Examining the implications of the results for the welfare of market participants, one needs to distinguish between two groups of traders: "speculators" (traders who trade very frequently, i.e., buy and sell stocks over very short periods) and "investors" (traders who buy stock and hold them over longer periods).[18] Regulators seem concerned about "investors." The results of this study regarding monthly volatilities suggest that futures trading has not destabilized the return flows (and wealth) of "investors."

Finally, as Working (1963) noted, in judging the net social benefits of a futures market, it is not necessary to find that the futures market stabilizes the underlying cash market, but only that futures trading does not destabilize it. The hedging benefits of the futures market are then sufficient to conclude that the existence of the futures market increases net social welfare. No evidence is found here that the stock index futures market destabilizes the underlying cash market based on monthly returns. The findings and the wide use of stock index futures by hedgers suggest that the introduction of stock index futures trading may have increased net social welfare.

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[17]This is consistent with the findings of Stoll and Whaley (1987) on price impacts on expiration days of futures and options contracts, and those of Kraus and Stoll (1972) on price impacts of "block" trading.

[18]A third group of traders are the market makers. However, as Miller (1990, p. 6) argues: "Their worry is not the *volatility* of prices, but the *velocity* of prices—the very rapid, minute-to-minute (sometimes even second-to-second) price moves that the sudden triggering of index arbitrage programs often brings in its wake." Professor Miller notes that this can be mitigated by updating the rules of market making on the New York Stock Exchange to speed up the adjustment of market makers' quotes.

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