THE INTRODUCTION OF DERIVATIVES ON THE DOW JONES INDUSTRIAL AVERAGE AND THEIR IMPACT ON THE VOLATILITY OF COMPONENT STOCKS

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This article examines the impact of trading in the Dow Jones Industrial Average (DJIA) index futures and futures options on the conditional volatility of component stocks. It investigates the contention that the introduction of futures and futures options on the DJIA could increase volatility in the 30 stocks comprising the DJIA. The conditional volatility of intraday returns for each stock before and after the introduction of derivatives is estimated with the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Estimated parameters of conditional volatility in prefutures and postfutures periods are then compared to determine if the estimated parameters have changed significantly after the introduction of the various derivatives. The results

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suggest that the introduction of index futures and futures options on the DJIA has produced no structural changes in the conditional volatility of component stocks. Jrl Fut Mark 21: 633–653, 2001

INTRODUCTION

The issue of the impact of derivatives trading on stock market volatility has received considerable attention in recent years, particularly after the stock market crash of 1987 and the minicrash of 1989 (e.g., Campbell, 1991; Kawaller, Koch, & Koch 1990; Report of the Presidential Task Force on Market Mechanisms, 1988).[1] Although many factors contribute to stock market volatility, there is concern about the impact of derivative securities, particularly index futures and options, on the underlying spot market. One perception is that derivatives trading is responsible for higher stock market volatility (e.g., Conrad, 1989; Harris, Sofianos, & Shapiro, 1994). It is argued that derivatives encourage speculation, which destabilizes the spot market. The alleged destabilization takes the form of higher spot market volatility. This has led to the suggestion that there is a need for closer regulation and supervision of the derivatives industry.[2]

On October 6, 1997, the Chicago Board of Trade (CBOT) opened its newest pit for trading in futures and futures options on the Dow Jones Industrial Average (DJIA). This article examines the impact of trading in the DJIA index futures and futures options on the volatility of component stocks. Specifically, it investigates whether the introduction of futures and futures options on the DJIA increases volatility of the 30 stocks comprising the DJIA. The introduction of derivative products may increase volatility in component stocks. This is because the spot and futures markets are linked through risk transfer (hedging) and price discovery, two major contributions of the futures markets to economic

[1]The Report of the Presidential Task Force on Market Mechanisms (1988), popularly known as the Brady Commission Report, attributed the sharp fall in stock prices during the 1987 crash to program trading or, more specifically, the derivative-based trading strategies known as *index arbitrage* and *portfolio insurance*. It may be pointed out that derivatives trading was not blamed for the market crash during the 1997 Asian financial crisis. Unlike during the 1987 and 1989 crashes, market participants did not point the finger at derivatives trading as the potential source of market instability. See Cheng, Fung, and Chan (2000) for an analysis of the Asian financial crisis.

[2]The regulatory proposals for reform advanced by the Brady Commission Report include a single agency to coordinate regulatory issues across all financial markets, a unified clearing system for all financial markets, consistent margin requirements in the cash and futures markets, circuit breaker mechanisms such as price limits and planned trading halts, and integrated information systems across related financial markets. There is continuing action on all of these fronts, and much has already been implemented.

activity.[3] The index arbitrageurs could use these markets to take advantage of price discrepancies between the DJIA spot price and the DJIA futures price.

This study employs the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to estimate the conditional volatility of intraday returns before and after the introduction of derivatives. Estimated parameters of conditional volatility in prefutures and postfutures periods are then compared to determine if the estimated parameters have changed significantly after the introduction of derivatives. The results suggest that the introduction of index futures and futures options on the DJIA has produced no structural changes in the conditional volatility of component stocks.

Investigations of the type conducted in this article are of interest because they can provide useful information on the efficiency of the futures markets and can be useful to regulators in designing regulations. The extent to which the futures markets are to be regulated depends on the precise impact of futures trading on spot market volatility. Increased spot market volatility resulting from futures trading may suggest a need for more regulations.

Conversely, increased spot market volatility due to a liquid and efficient market resulting from futures trading could imply that more regulations might reduce the benefits of futures trading.

REVIEW OF THE LITERATURE

Despite the public outcry concerning increasingly volatile stock prices due to the introduction of derivatives, the empirical evidence regarding this issue is far from conclusive. Some studies find no evidence of increased volatility associated with the introduction of derivatives trading (Becketti & Roberts, 1990; Chatrath, Ramchander, & Song, 1995; Darrat & Rahman, 1995; Edwards, 1988a, 1988b; Fortune, 1989; Galloway & Miller, 1997; Kamara, Miller, & Siegel, 1992; Schwert, 1990). Other studies report the opposite conclusion (Chang, Cheng, & Pinegar, 1999; Gilbert, 1989; Harris, 1989; Maberly, Allen, & Brorsen, 1991).

[3]Witherspoon (1993) described how the price discovery function of futures markets impacts the spot market volatility. The author pointed out that the extent to which price discovery by futures markets impacts the spot market depends on the levels of dominance by price discovery over the spot market:

> If price discovery by futures exceeds certain critical threshold levels of dominance, then cash market autocorrelation and long-term volatility are increased. On the other hand, if price discovery by futures is not excessive, it leads to lower long-term volatility, more liquidity, and better efficiency. (p. 470)

Pizzi, Economopoulos, and O'Neill (1998) examined price discovery in the S&P 500 spot and futures indexes with intraday data.

From a theoretical viewpoint, the volatility in the spot market can either increase or decrease over time on the basis of the underlying assumptions that are made. Most empirical studies have examined the impact of index futures and index options by comparing the unconditional variance of returns before and after the introduction of futures and options. The introduction of stock index futures trading may lead to a change in the speed of information flow to the stock market. To examine the effects of futures trading on spot market volatility, several studies (Antoniou & Homes, 1995; Antoniou, Holmes, & Priestley, 1998; Baldauf & Santoni, 1991; Lee & Ohk, 1992; Pericli & Koutmos, 1997) used a model that recognized the temporal dependence of stock return volatility.

Baldauf and Santoni (1991) tested for the presence of Autoregressive Conditional Heteroscedasticity (ARCH) effects in daily stock returns, controlled for these effects by modeling them, and tested to check whether model parameters shifted after the institution of program trading. They found no evidence of a shift in the model parameters. Lee and Ohk (1992) examined the effects of introducing index futures trading on stock return volatility in Australia, Hong Kong, Japan, the United Kingdom, and the United States of America. They found that stock volatility increased significantly shortly after the listing of the stock index futures, with the exception of the stock markets in Australia and Hong Kong. Using U.K. data, Antoniou and Holmes (1995) modeled volatility as a GARCH process and found a significant increase in cash market volatility after the introduction of the Financial Times Stock Exchange (FTSE) 100 index in 1984. Pericli and Koutmos (1997), using an exponential GARCH model, found that the volatility of the Standard & Poor's (S&P) 500 index decreased after the introduction of futures trading. Antoniou et al. (1998) examined the impact of futures trading on the volatility of S&P 500 index with the asymmetric GARCH model proposed in Glosten, Jagannathan, and Runkle (1993). Their results suggest that the introduction of futures has not had a detrimental effect on the underlying spot market.

This article contributes to the ongoing debate regarding the impact of index futures and options on the volatility of the stock market. It extends the studies of Baldauf and Santoni (1991), Lee and Ohk (1992), Antoniou and Holmes (1995), Pericli and Koutmos (1997), and Antoniou et al. (1998). This study models the well-known tendency of stock returns to exhibit volatility clustering (i.e., conditional heteroskedasticity) by using the GARCH model of Bollerslev (1986) and tests for changes in conditional volatility after the introduction of derivatives. French, Schwert, and Stambaugh (1987) and Akgiray (1989) applied

GARCH models to stock indexes. Schwert and Seguin (1990) applied the GARCH model to portfolios. Lamoureux and Lastrapes (1990) and Kim and Kon (1994) applied the GARCH model to individual stocks.

Foster (1995) employed the GARCH model for investigating the volume–volatility relationship in the oil futures markets. Kyriacou and Sarno (1999) employed the GARCH model to construct a spot market volatility proxy in empirically examining the dynamic relationship between derivatives trading and spot market volatility with daily data for the FTSE index in the United Kingdom. Hogan, Kroner, and Sultan (1997) used the bivariate error correction GARCH model to examine the relationship between program trading and volatility in the S&P 500 cash and futures markets. Tse (1999) used the GARCH model to examine minute-by-minute price discovery and volatility spillovers between the DJIA cash and futures markets. Baillie and Bollerslev (1990) examined intraday volatility in foreign exchange markets with a seasonal GARCH model. Locke and Sayers (1993) employed the GARCH model to examine the intraday variance structure of index futures return series. Andersen and Bollerslev (1997) examined the characteristics of intraday return volatility in the foreign exchange market and index futures markets with a GARCH specification.

This article is different in several important ways from the majority of studies that employ the standard model or the GARCH model to examine volatility shift. First, these studies use daily observations to estimate volatility, whereas intraday data are used here. Given that financial markets display high speeds of adjustment, studies based on longer intervals such as daily observations may fail to capture information contained in intraday market movements. Moreover, because of modern communications systems and improved technology, volatility measures based on daily observations ignore critical information concerning intraday price patterns. Andersen (1996) pointed out that the focus of the market microstructure literature is on intraday patterns rather than interday dynamics.

Second, many of the studies use a single sample containing a time series of observations around the introduction of derivatives. These studies introduce a dummy variable in the model specification to capture the impact of the introduction of derivatives. This methodology fails to allow derivatives to mature. Newly introduced derivatives may take time to mature and have an impact on the spot market. Aggarwal (1988) argued that index arbitrage and other trading strategies based on derivatives do not become an important activity immediately after their introduction. In this article, two separate and independent samples are selected, and observations around the introduction of derivatives on the DJIA are excluded. The prefutures sample is several months before the introduction of derivatives, and the postfutures sample is several months after the introduction of derivatives. Conditional volatility for each period is computed and then compared to determine whether the estimated parameters of the model shift subsequent to the introduction of derivatives.

DATA AND METHODOLOGY

Data

The data for this study consist of transaction prices for the 30 stocks comprising the DJIA. Intraday transaction data (quotes) come from the New York Stock Exchange (NYSE) trade and quote database. Transaction prices for April through June 1997 (prefutures period) and April through June 1998 (postfutures period) are used. A 3-month sample for prefutures and postfutures periods are matched to avoid any seasonality or month-of-the-year effects associated with calendar months. Each trading day is partitioned into 5-min intervals, beginning with the opening of the NYSE at 9:30 a.m. Eastern Standard Time. From the data, 5-min interval returns are computed. Because returns are computed within each day with only intraday prices, overnight returns are not included in any of these series.

Following Stoll and Whaley (1990a), I also excluded from the analysis the first two 5-min returns. Stoll and Whaley (1990b) reported that the average time to open for stocks in the S&P 500 index (average time elapsed between the exchange opening and the opening transaction) is between 5 and 7 min. Prices during these intervals may reflect the stale closing price of the previous day. Disregarding the first two 5-min return observations each day, therefore, mitigates the effects of stale price information.

Methodology

The natural log of the price relative is computed for 5-min intervals to generate a time series of 5-min returns [$r_t = \ln(P_t/P_{t-1})$], where P_t and P_{t-1} represent price at time t and $t - 1$, respectively. The GARCH (1,1) specification is employed because it has been shown to be a parsimonious representation of conditional variance that adequately fits many high-frequency time series (see Bollerslev, 1987, and Engle, 1993, for details). Akgiray (1989) estimated volatility with various ARCH and

GARCH specifications and found that the GARCH (1,1) model performed best. The test results reported in the next section confirm this. The GARCH (1,1) model for conditional volatility of the 5-min return series can be specified as follows:

$$h_t = \alpha_o + \alpha_1 r_{t-1}^2 + \alpha_2 h_{t-1} \tag{1}$$

where h_t is the conditional variance (volatility) of r_t at time t; α_o is a constant; α_1 is a coefficient that relates the lagged value of the squared return, r_{t-1}^2, to current volatility; and α_2 is a coefficient that relates current volatility to the volatility of the previous period. After the volatility equation (Equation 1) is estimated for both sample periods (i.e., prefutures and postfutures), conditional volatilities for the two periods are compared to determine if they differ significantly.

EMPIRICAL RESULTS

As a step toward determining whether the introduction of derivatives has changed the spot market volatility, actual variances and mean values of the 5-min returns for the 30 stocks during prefutures and postfutures sample periods are compared. Table I presents sample means and variances of the 5-min returns for the 30 stocks for both periods. Visual inspections of the set of return variances for the two periods do not indicate significant changes in volatility between the prefutures and postfutures periods for the overall sample. For a closer examination of prefutures and postfutures conditional volatility, the GARCH model is fitted to the data.

To justify fitting the GARCH model to the data, the distributional properties of the intraday return series for both sample periods are examined first. The results for the April through June 1998 period are reported here. The various descriptive statistics are reported in Tables II and III in addition to the sample means and variances reported in Table I. These wide ranges of statistics provide a conclusive rejection of the hypothesis that the 5-min return series of the DJIA stocks are strict white-noise processes. The sample mean of each series is indistinguishable from 0 at the .01% significance level.[4] All series exhibit statistically significant skewness and excess kurtosis (>3) at the .01% level. The chi-square goodness-of-fit test for normality is computed by the entire 5-min return series for each stock being divided into 60 groups. The null

[4]Sample sizes vary from 4924 to 5156. Lindley (1957) suggested using lower significance levels for large sample sizes. All tests in this article use the significance level .01% to avoid Lindley's paradox.

TABLE I
Sample Means and Variances for Pre- and Postfutures Periods

		1997		*1998*	
Identification (I.D.) No.	*Security*	*M*	*Variance*	*M*	*Variance*
1	AT&T	-2.67×10^{-7}	1.13×10^{-5}	-2.84×10^{-5}	7.58×10^{-6}
2	Allied Signal	3.35×10^{-5}	4.6×10^{-6}	1.30×10^{-5}	8.73×10^{-6}
3	Alcoa	2.20×10^{-5}	3.85×10^{-6}	-9.12×10^{-6}	3.39×10^{-6}
4	American Express	4.42×10^{-5}	6.51×10^{-6}	4.18×10^{-5}	5.47×10^{-6}
5	Boeing	1.20×10^{-5}	5.91×10^{-6}	-3.01×10^{-5}	6.59×10^{-6}
6	Caterpillar	5.86×10^{-5}	3.77×10^{-6}	-8.15×10^{-6}	5.21×10^{-6}
7	Chevron	1.29×10^{-5}	4.83×10^{-6}	5.79×10^{-6}	3.02×10^{-6}
8	Coca-Cola	3.50×10^{-5}	9.47×10^{-6}	1.24×10^{-5}	6.7×10^{-6}
9	Du Pont	2.02×10^{-5}	5.95×10^{-6}	-1.91×10^{-6}	5.58×10^{-6}
10	Kodak	1.93×10^{-6}	4.21×10^{-6}	2.26×10^{-5}	3.96×10^{-6}
11	Exxon	2.72×10^{-5}	7.78×10^{-6}	9.28×10^{-6}	3.59×10^{-6}
12	GE	5.30×10^{-5}	6.56×10^{-6}	1.15×10^{-5}	4.27×10^{-6}
13	GM	2.21×10^{-6}	5.44×10^{-6}	0.00	3.92×10^{-6}
14	Goodyear Tire	3.77×10^{-5}	4.19×10^{-6}	-3.19×10^{-5}	3.21×10^{-6}
15	H-P	7.16×10^{-6}	1.46×10^{-5}	1.69×10^{-5}	8.14×10^{-6}
16	IBM	0.00	8.10×10^{-6}	1.98×10^{-5}	4.11×10^{-6}
17	Int'l Paper	4.40×10^{-5}	7.29×10^{-6}	-1.82×10^{-5}	6.17×10^{-6}
18	J.P. Morgan	1.40×10^{-5}	3.40×10^{-6}	-2.77×10^{-5}	4.05×10^{-6}
19	Johnson & Johnson	3.84×10^{-5}	5.36×10^{-6}	1.86×10^{-6}	4.08×10^{-6}
20	McDonald's	5.65×10^{-6}	4.61×10^{-6}	2.76×10^{-5}	3.39×10^{-6}
21	Merck	3.27×10^{-5}	4.86×10^{-6}	8.92×10^{-6}	4.59×10^{-6}
22	3M	3.86×10^{-5}	4.25×10^{-6}	-2.41×10^{-5}	5.12×10^{-6}
23	Philip Morris	9.00×10^{-6}	2.10×10^{-5}	-1.08×10^{-5}	9.62×10^{-6}
24	Proctor & Gamble	4.22×10^{-5}	4.10×10^{-6}	1.84×10^{-5}	4.12×10^{-6}
25	Sears	1.42×10^{-5}	5.49×10^{-6}	1.38×10^{-5}	4.47×10^{-6}
26	Travelers	5.48×10^{-5}	9.42×10^{-6}	4.95×10^{-7}	9.53×10^{-6}
27	Union Carbide	1.46×10^{-5}	4.84×10^{-6}	1.24×10^{-5}	7.56×10^{-6}
28	United Technology	1.96×10^{-5}	4.97×10^{-6}	9.59×10^{-7}	3.02×10^{-6}
29	Wal-Mart	3.96×10^{-5}	8.23×10^{-6}	3.46×10^{-5}	5.27×10^{-6}
30	Disney	2.34×10^{-5}	3.95×10^{-6}	-3.61×10^{-6}	5.21×10^{-6}

hypothesis of normality is rejected at the .01% significance level for all 30 stocks with the test statistic of chi square with 57 degrees of freedom.

To test the hypothesis of independence, a test of white-noise process given by the Ljung–Box–Pierce (Box & Pierce, 1970; Ljung & Box, 1978) portmanteau test statistics is used. The test statistics for lags 6, 12, and 24, [denoted LB(6), LB(12), and LB(24), respectively] are reported in Table III. LB(m) is asymptotically distributed as chi square with m degrees of freedom. The critical values for LB(6), LB(12), and LB(24) at the .01% significance level are 27.86, 39.13, and 58.61, respectively. The null hypothesis of strict white noise is rejected in most cases. This implies that the 5-min return series are not made up of independent variates.

TABLE II

Sample Statistics for Intraday Returns (April 1, 1998 to June 30, 1998)

I.D. No.	*N*	*Skewness*	*Excess Kurtosis*	*Maximum*	*Minimum*	*Interquartile Range (IQR)*
1	5093	−2.5366	164.25	5.54×10^{-2}	-6.66×10^{-2}	2.04×10^{-3}
2	4938	.8318	32	3.88×10^{-2}	-3.91×10^{-2}	2.86×10^{-3}
3	4976	3.688	72.4842	3.38×10^{-2}	-2.27×10^{-2}	1.70×10^{-3}
4	4973	2.4355	42.4222	3.96×10^{-2}	-1.90×10^{-2}	1.29×10^{-3}
5	5061	.3476	59.1833	3.99×10^{-2}	-3.99×10^{-2}	2.49×10^{-3}
6	4975	2.3521	52.2514	4.89×10^{-2}	-1.93×10^{-2}	2.24×10^{-3}
7	4968	.4645	21.018	2.15×10^{-2}	-2.38×10^{-2}	1.53×10^{-3}
8	4924	2.8143	51.8403	5.13×10^{-2}	-1.73×10^{-2}	3.16×10^{-3}
9	5024	.5018	18.4991	2.97×10^{-2}	-2.32×10^{-2}	1.71×10^{-3}
10	5003	1.2956	24.2182	2.62×10^{-2}	-1.81×10^{-2}	1.77×10^{-3}
11	5023	.4063	6.8106	1.7×10^{-2}	-1.13×10^{-2}	1.78×10^{-3}
12	5115	.4206	36.6611	2.94×10^{-2}	-3.17×10^{-2}	1.49×10^{-3}
13	5031	3.705	75.7613	4.54×10^{-2}	-1.95×10^{-2}	1.78×10^{-3}
14	4969	−.3637	18.8361	1.37×10^{-2}	-2.74×10^{-2}	1.79×10^{-3}
15	5062	.7705	40.0847	4.77×10^{-2}	-3.58×10^{-2}	2.05×10^{-3}
16	5117	1.1779	28.7371	3.37×10^{-2}	-2.05×10^{-2}	1.20×10^{-3}
17	4961	.8161	18.888	3.08×10^{-2}	-2.63×10^{-2}	2.47×10^{-3}
18	4953	4.4414	110.7689	5.14×10^{-2}	-1.99×10^{-2}	1.78×10^{-3}
19	5026	−.1624	18.34	2.05×10^{-2}	-2.38×10^{-2}	1.76×10^{-3}
20	5035	.7487	55.4059	3.28×10^{-2}	-3.17×10^{-2}	1.93×10^{-3}
21	5037	−.1048	75.2806	3.94×10^{-2}	-3.89×10^{-2}	1.93×10^{-3}
22	4971	−5.5271	269.0492	4.27×10^{-2}	-6.78×10^{-2}	1.35×10^{-3}
23	5156	.9676	55.99	5.11×10^{-2}	-4.63×10^{-2}	3.16×10^{-3}
24	5011	−.2462	9.2984	1.29×10^{-2}	-1.94×10^{-2}	1.51×10^{-3}
25	4989	.1144	11.1305	1.9×10^{-2}	-2.64×10^{-2}	2.10×10^{-3}
26	5049	3.9582	417.1513	8.91×10^{-2}	-9.1×10^{-2}	2.02×10^{-3}
27	4949	5.6157	181.9652	8.09×10^{-2}	-4.29×10^{-2}	2.45×10^{-3}
28	4943	−.0551	8.868	1.4×10^{-2}	-1.52×10^{-2}	1.33×10^{-3}
29	5028	.5303	17.7917	2.47×10^{-2}	-2.19×10^{-2}	2.3×10^{-3}
30	5066	.5158	66.52	4.0×10^{-2}	-3.66×10^{-2}	1.17×10^{-3}

To test for the presence of the autocorrelation characteristics in the 5-min return series, the first-order autocorrelations ($\hat{\rho}_1$) are computed. Out of 30 securities, 26 securities have statistically significant $\hat{\rho}_1$ at the .01% level. The sample autocorrelations for lag up to 25 for r_t, $|r_t|$, and r_t^2 are computed, and those for a subset of 30 stocks are reported in Figures 1 to 8. From these figures, it is apparent that all return series exhibit statistically significant serial correlations at the first lag, although autocorrelation decays more rapidly as the lag increases. The corresponding modified Box–Pierce statistics for the 30 stocks are presented in Table III. The p values for these Box–Pierce statistics are indistinguishable from 0, indicating that these statistics are significant at the .01% level.

TABLE III
Sample Statistics for Intraday Returns (April 1, 1998 to June 30, 1998)

I.D. No.	*Log Likelihood*	*LB(6)*	*LB(12)*	*LB(24)*	*Goodness of Fit*	$\hat{\rho}_1$	*Box–Pierce for Lag One (P Value in Parentheses)*
1	22798	403	414.8	426.8	18482	−.257	336.74 (0.0)
2	21753	147.9	155	172	17254.7	−.16844	140.18 (0.0)
3	24278	59.26	63.06	67.45	18033	−.09767	47.50 (0.0)
4	23071	15.19	34.03	48.58	10106	−.05464	14.85 (0.0)
5	23006.5	222.46	233.63	242.79	17397.48	−.20463	212.05 (0.0)
6	23199	65.24	77.42	95.01	16204	−.106	56.02 (0.0)
7	24520.6	31.05	39.56	56.5	18111.5	−.0727	26.27 (0.0)
8	22343.7	74.27	78.72	90.86	27386.23	−.11715	67.61 (0.0)
9	23255.5	23.13	35.94	45.49	11490.9	−.04209	8.91 (0.003)
10	24016.5	39.73	47.97	57.71	18993.98	−.07622	29.08 (0.0)
11	24361.2	173.17	181.11	190.24	17090.63	−.16925	143.98 (0.0)
12	24362.5	192.17	202.54	212.45	14365.91	−.18578	176.65 (0.0)
13	24178.9	20.82	30.7	35.93	21844.26	−.03321	5.55 (0.018)
14	24379.6	24.05	32.57	45.84	19734.65	−.05699	16.15 (0.0)
15	22477.7	60.2	68.6	86.68	10496.82	−.08686	38.21 (0.0)
16	24471.8	37.68	48.4	56.32	9586.84	−.05434	15.12 (0.0)
17	22717.8	61.72	66.86	84.79	14708.19	−.10501	54.74 (0.0)
18	23724.8	25.22	31.31	41.34	7411.82	−.06179	18.92 (0.0)
19	24053.4	66.42	80.33	91.55	18770.97	−.09337	43.84 (0.0)
20	24565.9	112.75	116.74	130.36	20944.69	−.14655	108.20 (0.0)
21	23809.9	135.27	136.72	176.89	8074.988	−.13174	87.47 (0.0)
22	23225.3	343.02	363.24	395.99	12538.86	−.18621	172.47 (0.0)
23	22464.8	326.84	332.65	356.79	28241.26	−.24957	321.32 (0.0)
24	23954.7	55.57	62.43	76.19	12669.11	−.09349	43.82 (0.0)
25	23650.5	10.36	18.93	32.82	13722.71	−.03613	6.52 (0.011)
26	22022.5	134.44	145.37	153.46	17823.27	−.16032	129.85 (0.0)
27	22159.7	16.91	25.41	30.97	21920.19	−.05322	14.03 (0.0)
28	24400.1	7.8	14.52	18.93	13084.16	.02194	2.38 (0.123)
29	23419.4	182.5	191.84	196.75	15025.43	−.1871	176.11 (0.0)
30	23624	70.76	94.49	116.85	9985	−.10574	56.68 (0.0)

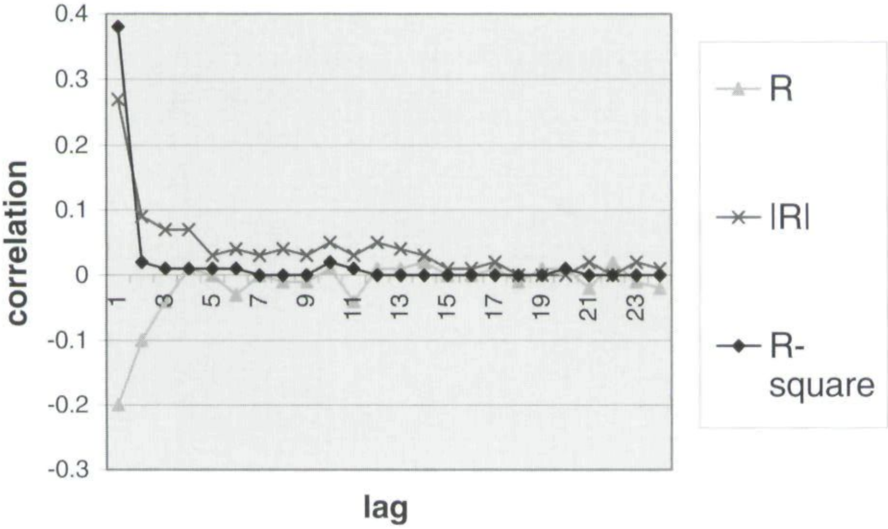

FIGURE 1
Autocorrelation for Identification (I.D.) Number 5.

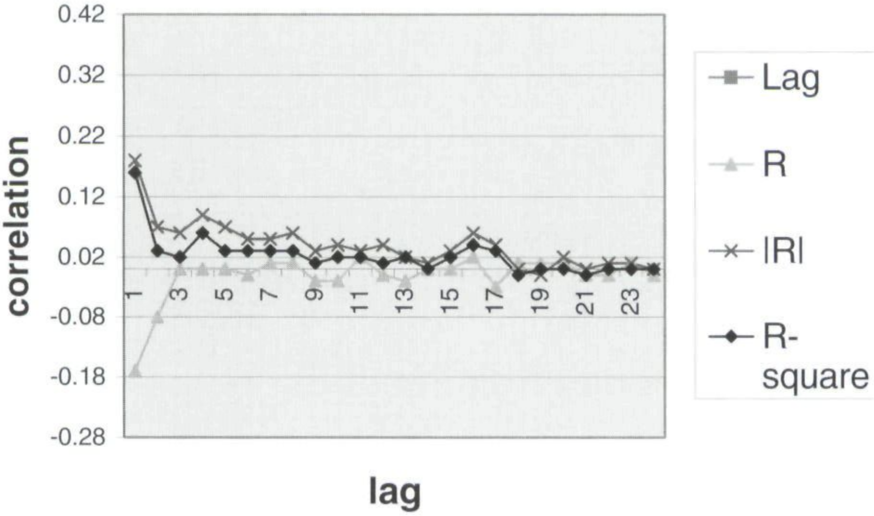

FIGURE 2
Autocorrelation for I.D. Number 11.

These results are evidence that the 5-min returns tend not to be independent but instead exhibit volatility clustering, where periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes. This implies that large returns tend to be followed by large returns (of either sign), whereas small returns tend to be followed by small returns. This suggests that the usual measures

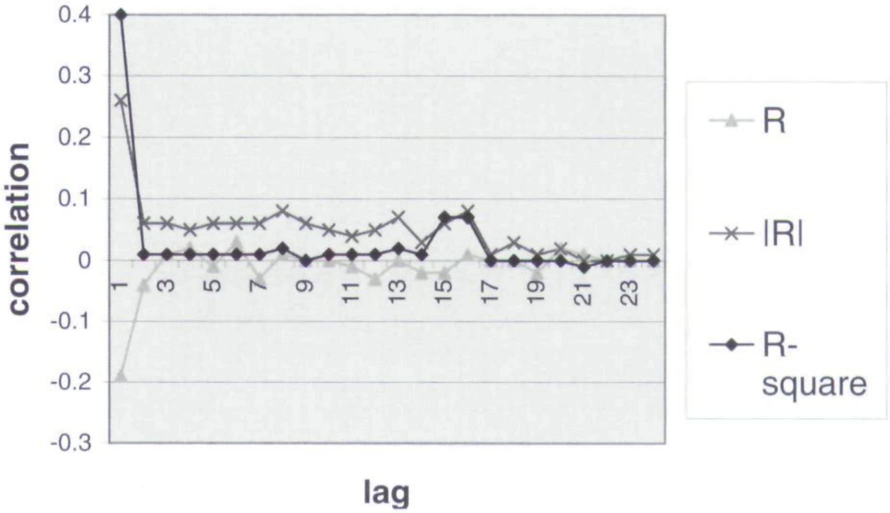

FIGURE 3
Autocorrelation for I.D. Number 12.

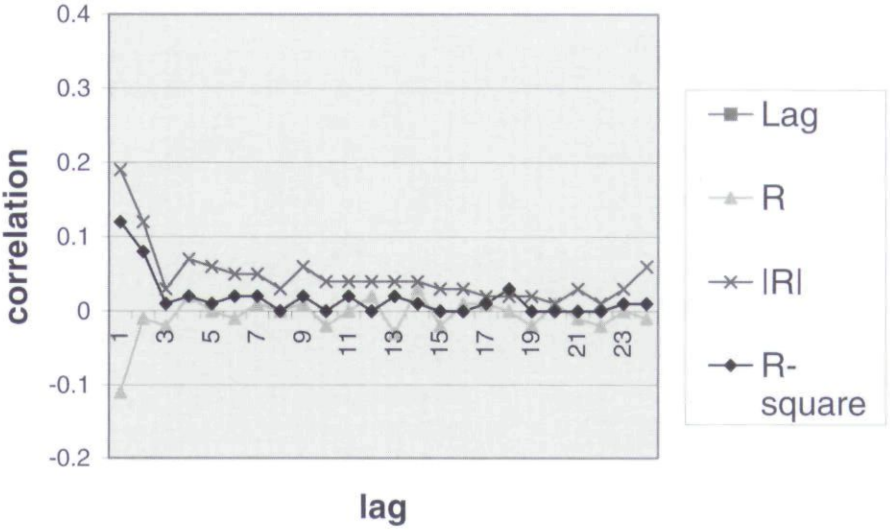

FIGURE 4
Autocorrelation for I.D. Number 17.

of return volatility are temporally dependent (heteroskedastic). In summary, the data display all the characteristics of the unconditional distribution of returns that are used to justify fitting the GARCH model to the return series. Moreover, because the autocorrelation for each of the series cuts off after one lag, the GARCH (1,1) appears to be an appropriate model.

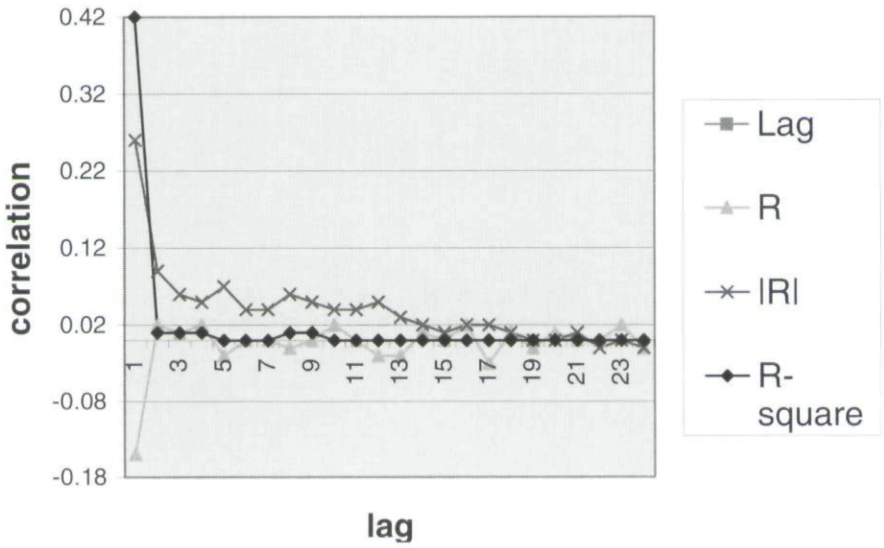

FIGURE 5
Autocorrelation for I.D. Number 20.

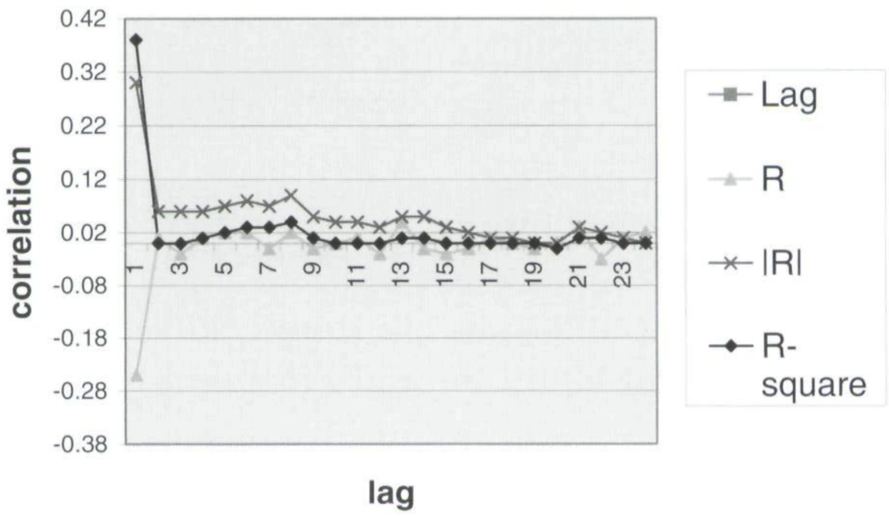

FIGURE 6
Autocorrelation for I.D. Number 23.

Table IV presents the results of fitting the GARCH (1,1) process to the 5-min return series of each of the 30 DJIA stocks for both the prefutures and postfutures period. Most of the parameter estimates of the GARCH (1,1) model in the table are statistically significant at the .01% level. The estimates of α_0 are all positive and considerably smaller than the sample variances shown in Table I. This is due to changing

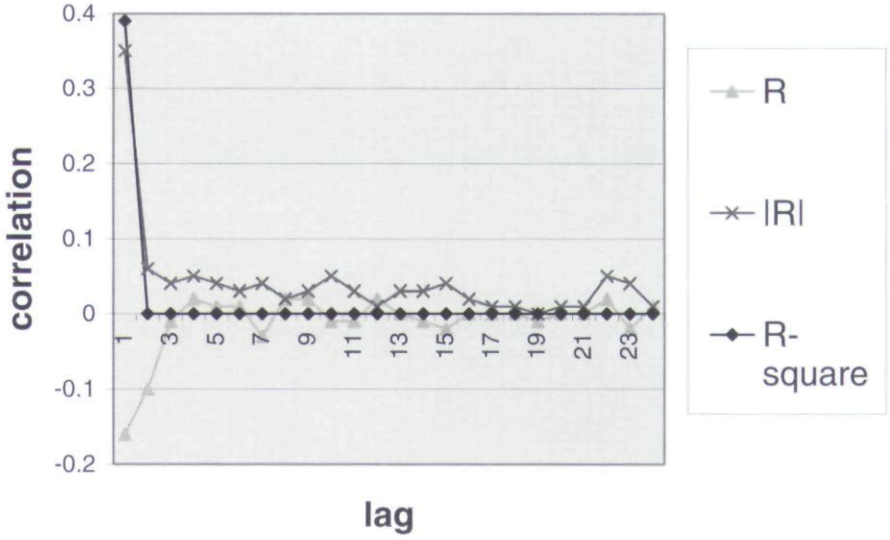

FIGURE 7
Autocorrelation for I.D. Number 26.

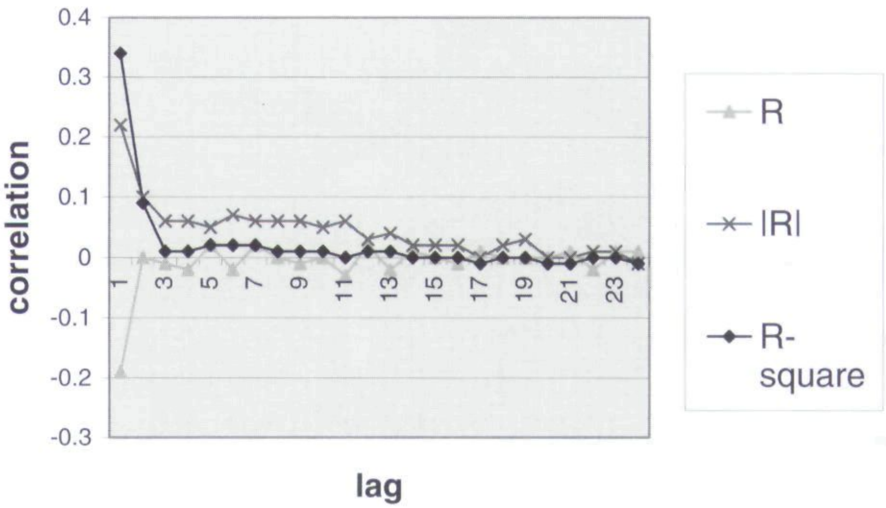

FIGURE 8
Autocorrelation for I.D. Number 29.

conditional variances over time and their eventual contribution to unconditional variances. The persistence in volatility, as measured by the sum of α_1 and α_2 in GARCH (1,1), is closer to unity for several of the securities. The fact that the sums of α_1 and α_2 are fairly close to 1 indicates the persistence of past volatility in explaining current volatility (see Engle & Bollerslev, 1986).

TABLE IV

GARCH Model Estimates of Equation 1

	1997		*1998*	
Security	α_1	α_2	α_1	α_2
1	$-.37574 \times 10^{-3}$	0.000	.42116*	0.00
	(−.4734)	(0.000)	(11.39)	(0.00)
2	$.94623 \times 10^{-1}$*	.73222*	.16976*	0.00
	(7.614)	(22.72)	(7.738)	(0.00)
3	$.72152 \times 10^{-1}$	$-.27785 \times 10^{-2}$	.18215*	0.00
	(1.173)	(−1.162)	(7.760)	(0.00)
4	.13806*	.81371*	.16179*	.80951*
	(13.27)	(75.73)	(13.52)	(79.75)
5	$.17240 \times 10^{-3}$	$.982 \times 10^{-2}$	.52302	$-.23662 \times 10^{-3}$
	(3.33)	($.5779 \times 10^{-2}$)	(1.84)	(−.6322)
6	.11084*	.66648*	.18386*	.72961*
	(9.435)	(34.07)	(12.06)	(41.00)
7	.14706*	$.53187 \times 10^{-5}$	.15544*	0.00
	(38.27)	(3.429)	(7.748)	(0.00)
8	$-.17242 \times 10^{-3}$	.99608*	$.9562 \times 10^{-1}$*	.37747*
	($.2451 \times 10^{-1}$)	(2407)	(5.658)	(4.848)
9	.047072*	$.78194 \times 10^{-1}$*	$.29986 \times 10^{-1}$	0.00
	(39.15)	(17.63)	(2.409)	(0.00)
10	.10694*	.67562*	.27231*	0.00
	(7.622)	(20.68)	(10.29)	(0.00)
11	$-.21094 \times 10^{-3}$	$.1013 \times 10^{-1}$	.10856*	.74386*
	(.4689)	($.7197 \times 10^{-2}$)	(8.571)	(26.84)
12	.061375*	.11995*	.28299*	.12236
	(40.34)	(17.33)	(10.57)	(3.419)
13	$.77921 \times 10^{-1}$*	.53222*	.11207*	.70979*
	(5.353)	(8.307)	(6.11)	(24.92)
14	.57935*	$.50306 \times 10^{-3}$	.21237*	.71976*
	(45.05)	(1.339)	(12.22)	(44.02)
15	.13838*	0.00	1.2379*	.28757*
	(5.237)	(0.00)	(18.71)	(14.62)
16	.029512*	.45815*	.18268	$-.57918 \times 10^{-3}$
	(41.23)	(5.245)	(1.034)	(−.6447)
17	.14103*	.65857*	.10689*	.75881*
	(8.807)	(19.47)	(8.709)	(32.23)
18	.57074*	$.35283 \times 10^{-3}$	.29208*	$-.21323 \times 10^{-2}$
	(46.84)	(1.321)	(10.13)	(−.7555)
19	$.63731 \times 10^{-1}$*	0.00	.13343*	.69618*
	(4.391)	(0.00)	(9.298)	(27.53)
20	.49979	0.000	.27239*	0.00
	(1.408)	(0.000)	(10.42)	(0.00)
21	.49979	0.000	$-.38246 \times 10^{-3}$*	0.00
	(2.336)	(0.000)	(−21.22)	(0.00)
22	.18301*	.69598*	.51959*	$.94248 \times 10^{-2}$
	(11.42)	(33.07)	(12.24)	(1.057)
23	$-.14238 \times 10^{-3}$	0.000	.16542	$-.11839 \times 10^{-2}$
	(−1.583)	(0.000)	(1.109)	(−1.106)
24	.16666*	0.00	1.0201*	$.4407 \times 10^{-3}$*
	(8.307)	(0.00)	(49.80)	(3.995)

(Continued)

TABLE IV
(Continued)

	1997		*1998*	
Security	α_1	α_2	α_1	α_2
25	−.17402	−.19402	.93364 × 10^{-1}*	0.00
	(−.7015 × 10^{-8})	(0.000)	(5.732)	(0.00)
26	1.6337*	.59129 × 10^{-4}	2.7806*	.61095 × 10^{-1}*
	(21.07)	(.1475)	(24.36)	(6.822)
27	.12252*	0.00	.7589 × 10^{-1}*	−.18538 × 10^{-2}
	(6.77)	(0.00)	(4.448)	(−.1113)
28	.90074 × 10^{-1}*	.47852*	.86425 × 10^{-1}*	.81164*
	(6.644)	(18.13)	(9.135)	(42.00)
29	.18422*	.43311*	.11717*	0.00
	(10.46)	(8.511)	(6.584)	(0.00)
30	.77921 × 10^{-1}*	.53222*	.28020*	0.00
	(5.353)	(8.307)	(9.245)	(0.00)

*Significant at the .01% level.

The contention that the introduction of futures and futures options on the DJIA could increase volatility in the 30 stocks comprising the DJIA is essentially a hypothesis that derivatives trading alters the parameters of conditional volatility of intraday returns. In Table IV, a casual comparison of the distribution of estimated parameters of conditional volatility for the prefutures and postfutures periods suggests that these parameters did not change significantly in aggregate subsequent to the introduction of derivatives. To determine this more precisely, a paired comparison test for the significance of the differences in the estimated parameters for the two periods is employed. The test is conducted for all 30 stocks together with the following test statistic described in Harnett and Soni (1991):

$$t_c = \frac{(\bar{x}_{\text{pre}} - \bar{x}_{\text{post}}) - (\mu_{\text{pre}} - \mu_{\text{post}})}{\sqrt{\left(\frac{(n_{\text{pre}} - 1)s^2_{\text{pre}}}{n_{\text{pre}} + n_{\text{post}} - 2} + \frac{(n_{\text{post}} - 1)s^2_{\text{post}}}{n_{\text{pre}} + n_{\text{post}} - 2}\right)\left(\frac{1}{n_{\text{pre}}} + \frac{1}{n_{\text{post}}}\right)}} \tag{2}$$

where $\bar{x}_{\text{pre}}$ and $\bar{x}_{\text{post}}$ are the sample means of a given parameter (e.g., either α_1 or α_2) for all 30 stocks for the prefutures and postfutures period, respectively; s^2_{pre} and s^2_{post} are the respective sample variances; μ_{pre} and μ_{post} are the respective population means; and n_{pre} and n_{post} are the sample sizes for prefutures and postfutures periods. In particular, the purpose of this test is to draw a conclusion about the average behavior of volatility of the group of 30 stocks before and after the introduction of derivatives. The test statistic is distributed as a t distribution with $(n_{pre} + n_{post} - 2)$ degrees of freedom.

The test statistics for α_1, α_2, and $\alpha_1 + \alpha_2$ are computed for all 30 stocks together by the consideration of estimated parameters for both periods. The term $\alpha_1 + \alpha_2$ measures persistence in volatility. The calculated test statistics for α_1, α_2, and $\alpha_1 + \alpha_2$ are -1.80, 0.33, and -1.28, respectively. These values are not large enough to reject the null hypothesis of no shift in the estimated parameters from prefutures to postfutures periods at the .01% significance level. These results suggest that the introduction of index futures and futures options on the DJIA has produced no structural changes on the conditional volatility in the spot market. This implies that the data examined here do not validate the contention that the introduction of derivatives trading has increased volatility in the spot market.

It is interesting to note that two other financial-derivative products based on the DJIA were introduced in the market about the same time the CBOT started trading the DJIA index futures and futures options. The Chicago Board Option Exchange introduced an index option on the DJIA on October 6, 1997. On January 20, 1998, the American Stock Exchange introduced the DIAMONDS, securities that allow investors to trade shares in an entire portfolio of the DJIA as easily as they do shares of a single stock. These products may affect trading activities (and thereby volatility) in the DJIA stocks. Nonoverlapping prefutures and postfutures samples in this study coincide with the periods before and after the introduction of these two products. The results of this study do not indicate any change in spot market volatility between these sample periods. This suggests that the DJIA index futures and futures options along with the DJIA index options and the DIAMONDS do not cause increased spot market volatility.

CONCLUSION

This article examines the impact of trading in the DJIA index futures on the volatility of the underlying spot market of component stocks. It investigates the contention that the introduction of futures and futures options on the DJIA increases volatility in the 30 stocks comprising the DJIA. Intraday return data on these stocks for April through June 1997 (prefutures period) and April through June 1998 (postfutures period) are used. The distributional properties of the intraday return series are first examined to determine whether the GARCH model can characterize the return series. The GARCH (1,1) model appears to be an appropriate model for intraday return series. The GARCH (1,1) model is employed to estimate the conditional volatility of intraday returns. Parameters of conditional volatility of prefutures and postfutures periods are estimated with the GARCH (1,1) model and compared to determine if the estimated parameters have, in aggregate, changed significantly after the introduction of derivatives. On the basis of empirical results, the null hypothesis of no change in conditional volatility from prefutures to postfutures periods cannot be rejected.

These findings are important because supporters of restrictions on index futures trading maintain that these derivatives increase volatility, thereby increasing the cost of capital. The empirical evidence that the conditional volatility of component stocks has not changed with the introduction of derivatives suggests that these arguments lack merit. Thus, the argument that the introduction of derivatives destabilizes the spot market appears to be unfounded. Consequently, calls for closer regulation of index futures on the basis that they increase spot market volatility are unjustified. These regulations are not likely to contribute to a more stable environment in the spot market. On the contrary, these regulations may be counterproductive because they may divert attention away from more relevant and urgently needed policy options, research efforts, or both.

BIBLIOGRAPHY

Aggarwal, R. (1988). Stock index futures and cash market volatility. Review of Futures Market, 7, 290–299.

Akgiray, V. (1989). Conditional heteroscedasticity in time series of stock returns: Evidence and forecasts. Journal of Business, 62, 55–80.

Andersen, T. (1996). Return volatility and trading volume, an information flow interpretation of stochastic volatility. Journal of Finance, 51, 169–204.

Andersen, T., & Bollerslev, T. (1997). Intra-day periodicity and volatility persistence in financial markets. Journal of Empirical Finance, 4, 115–158.

Antoniou, A., & Holmes, P. (1995). Futures trading, information and spot price volatility: Evidence for the FTSE-100 stock index futures contract using GARCH. Journal of Banking and Finance, 19, 117–129.

Antoniou, A., Holmes, P., & Priestley, R. (1998). The effects of stock index futures trading on stock index volatility: An analysis of the asymmetric response of volatility to news. Journal of Futures Markets, 18, 151–166.

Baillie, R., & Bollerslev, T. (1990). Intra-day and inter-market volatility in foreign exchange rates. Review of Economic Studies, 58, 565–585.

Baldauf, B., & Santoni, G. (1991). Stock price volatility: Some evidence from an ARCH model. Journal of Futures Markets, 11, 191–200.

Becketti, S., & Roberts, D. (1990). Will increased regulation of stock futures reduce stock market volatility? Federal Reserve Bank of Kansas City, Economic Review, 75, 33–46.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31, 307–327.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. Review of Economics and Statistics, 69, 542–547.

Box, G., & Pierce, D. (1970). Distribution of residual autocorrelation in autoregressive–integrated moving average time series models. Journal of the American Statistical Association, 5, 1509–1526.

Brorsen, W. (1991). Futures trading, transaction costs and stock market volatility. Journal of Futures Markets, 11, 153–163.

Campbell, J. (1991). A variance decomposition for stock prices. Economic Journal, 101, 157–179.

Chang, E., Cheng, J., & Pinegar, M. (1999). Does futures trading increase stock market volatility? The case of the Nikkei stock index futures markets. Journal of Banking and Finance, 23, 727–753.

Chatrath, A., Ramchander, S., & Song, F. (1995). Does options trading lead to greater cash market volatility? Journal of Futures Markets, 15, 785–803.

Cheng, L., Fung, J., & Chan, K. (2000). Pricing dynamics of index options and index futures in Hong Kong before and during the Asian financial crisis. Journal of Futures Markets, 20, 145–166.

Conrad, J. (1989). The price effect of option introduction. Journal of Finance, 44, 487–498.

Darrat, A., & Rahman, S. (1995). Has futures trading activity caused stock price volatility? Journal of Futures Markets, 15, 537–557.

Edwards, F. (1988a). Does the futures trade increase stock market volatility? Financial Analysts Journal, 44, 63–69.

Edwards, F. (1988b). Futures trading and cash market volatility: Stock index and interest rate futures. Journal of Futures Markets, 8, 421–439.

Engle, R. (1993). Statistical models for financial volatility. Financial Analysts Journal, 49, 72–78.

Engle, R., & Bollerslev, T. (1986). Modeling the persistence of conditional variances. Econometric Reviews, 5, 1–50.

Fortune, P. (1989). An assessment of financial market volatility: Bills, bonds, and stocks. Federal Reserve Bank of Boston, New England Economic Review, 13–28.

Foster, A. (1995). Volume–volatility relationships for crude oil futures markets. Journal of Futures Markets, 15, 929–951.

French, K., Schwert, G., & Stambaugh, R. (1987). Expected stock returns and volatility. Journal of Financial Economics, 19, 3–29.

Galloway, T., & Miller, M. (1997). Index futures trading and stock return volatility: Evidence from the introduction of MidCap 400 index futures. Financial Review, 32, 845–866.

Glosten, L., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the normal excess return on stocks. Journal of Finance, 45, 221–229.

Harnett, D., & Soni, A. (1991). Statistical methods for business and economics (4th ed.). Reading, MA: Addison-Wesley.

Harris, L. (1989). S&P 500 cash stock price volatilities. Journal of Finance, 44, 1155–1175.

Harris, L., Sofianos, G., & Shapiro, J. (1994). Program trading and intraday volatility. Review of Financial Studies, 7, 653–685.

Hogan, K., Kroner, K., & Sultan, J. (1997). Program trading, nonprogram trading, and market volatility. Journal of Futures Markets, 17, 733–756.

Kamara, A., Miller, T., & Siegel, A. (1992). The effects of futures trading on the stability of Standard and Poor 500 returns. Journal of Futures Markets, 12, 645–658.

Kawaller, I., Koch, P., & Koch, T. (1990). Intraday relationships between volatility in S&P 500 futures prices and volatility in the S&P 500 index. Journal of Banking and Finance, 14, 373–397.

Kim, D., & Kon, S. (1994). Alternative models for the conditional heteroskedasticity of stock returns. Journal of Business, 67, 563–598.

Kyriacou, K., & Sarno, L. (1999). The temporal relationship between derivatives trading and spot market volatility in the U.K.: Empirical analysis and Monte Carlo evidence. Journal of Futures Markets, 19, 245–270.

Lamoureux, C., & Lastrapes, W. (1990). Heteroskedasticity in stock return data: Volume versus GARCH effects. Journal of Finance, 45, 221–229.

Lee, S., & Ohk, K. (1992). Stock index futures listing and structural change in time-varying volatility. Journal of Futures Markets, 12, 493–509.

Lindley, D. V. (1957). A statistical paradox. Biometrika, 44, 187–192.

Ljung, G., & Box, G. (1978). On a measure of lack of fit in time series models. Biometrika, 66, 67–72.

Locke, P., & Sayers, C. (1993). Intra-day futures price volatility: Information effects and variance persistence. Journal of Applied Econometrics, 8, 15–30.

Maberly, E., Allen, D., & Gilbert, R. (1989). Stock index futures and cash market volatility. Financial Analysts Journal, 45, 75–77.

Pericli, A., & Koutmos, G. (1997). Index futures and options and stock market volatility. Journal of Futures Markets, 17, 957–974.

Pizzi, M., Economopoulos, A., & O'Neill, H. (1998). An examination of the relationship between stock index cash and futures markets: A cointegration approach. Journal of Futures Markets, 18, 297–305.

Report of the Presidential Task Force on Market Mechanisms. (1988). Washington, DC: U.S. Government Printing Office.

Schwert, G. (1990). Stock market volatility. Financial Analysts Journal, 46, 23–34.

Schwert, G., & Seguin, P. (1990). Heteroskedasticity in stock returns. Journal of Finance, 45, 1129–1155.

Stoll, H., & Whaley, R. (1990a). The dynamics of stock index and stock index futures returns. Journal of Financial and Quantitative Analysis, 25, 441–468.

Stoll, H., & Whaley, R. (1990b). Stock market structure and volatility. Review of Financial Studies, 3, 37–71.

Tse, Y. (1999). Price discovery and volatility spillovers in the DJIA index and futures markets. Journal of Futures Markets, 19, 911–930.

Witherspoon, J. (1993). How price discovery by futures impacts the cash market. Journal of Futures Markets, 13, 469–496.