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The Dynamics of S&P 500 Index and S&P 500 Futures Intraday Price Volatilities

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Abstract

This paper empirically examines the dynamics of both intraday price changes and volatilities in the S&P 500 Index and S&P 500 futures markets. Causality tests on the correlation in price changes and volatility across these two markets are also performed, and the tests are robust to changing volatility. Results show that while futures prices lead spot prices for the first 15 minutes of trading, the evidence is weak for spot prices to have a significant impact on futures prices. We also show that there exists some feedback in the S&P 500 futures and Index intraday volatilities relation.

I. Introduction

The stochastic behavior of stock index futures price and the ability of index futures to predict stock index levels always have been of practical and academic interest. Recently, there is considerable evidence that stock market movements show substantial time-varying volatility, and these movements have been attributed to stock index futures and the role of program trading. Studies have shown that stock market returns exhibit clustering of predictive variances, so that large changes tend to be followed by large changes, small by small, of either sign.[1] Engle, Ito, and Lin [1988] interpret such volatility process as either the arrival of information or the time required by market participants in processing new information. Market response is, therefore, said to exhibit autoregressive conditional heteroscedastic (ARCH) behavior. Since it has been alleged that futures trading destabilizes cash markets and, hence, induces the volatility of cash prices, one would infer that futures price volatility exhibits the same temporal dynamics as the cash price volatility. Thus, any change in the conditional variance of the futures market, which is caused by the arrival of new information or time taken for prices to reflect the differing information of traders in the markets, would be expected to have an impact on the volatility in the stock markets. If these markets are effectively linked by arbitrageurs, then the variance of the rate of return on the index futures contracts should be equal to the variance of the rate of return on the underlying cash index.[2]

While a great deal of attention has been focused on modeling the dynamics of conditional means,[3] very little work has been done on modeling the dynamics of conditional variances in the futures markets. In this paper, we attempt to empirically examine the dynamics of both the intradaily price changes and volatility in the S&P 500 Index and S&P 500 futures markets. Our primary goal is to determine the predictive information in the relation between stock index futures and the underlying stock index, in light of the heteroscedastic intraday price volatilities in these markets. Evidence of the nature and existence of this relationship should provide useful information to both investors and practitioners, enabling them to take advantage of any perceived arbitrage opportunities in the markets.

Most studies that focus on the relationship between price changes in the stock index and stock index futures contracts assume that price volatilities

[1] For example, French, Schwert, and Stambaugh [1987], Ng [1990], and Bollerslev [1987] have modeled the stock market volatility to follow a GARCH process.
[2] This assumes that the expected rate of return from a stock index futures contract is equal to the expected rate of return from the corresponding index plus a constant rate of carrying cost.
[3] See, for example, Zeckhauser and Niederhoffer [1983], Kawaller, Koch, and Koch [1987], Herbst, McCormack, and West [1987], Ng [1987], Stoll and Whaley [1990], and Laatsch and Schwarz [1989].

are homoscedastic. Given evidence that the volatility in the stock markets is time-varying and if volatility in the index futures market also changes with time, then earlier inferences based on time-invariant volatility would be misleading.[4] In this study, we perform causality tests on the correlation in price changes and volatility across the stock markets and stock index futures market, using minute-by-minute transaction data on nearby S&P 500 futures contracts. The "causality" tests used in this context are interpreted as Granger's [1969] causality tests of incremental predictive ability of one time-series variable for another, as opposed to the philosophical definition of cause and effect.[5] The tests for causal relationship between the conditional second moments in the futures market and the spot market presented in this study stem from Granger, Robins, and Engle's [1986] concept of causality in the variance. The concept of causation can be viewed as an extension of the well-know Granger's [1969] causality in the mean. This Granger causality framework allows us to examine both the contemporaneous and lagged correlations between a pair of intraday series in price changes and in volatility.

The remainder of the paper proceeds as follows. The next section describes the data employed. In Section III, we model the dynamics of intraday price changes in the S&P 500 Index and S&P 500 futures with the volatility process assumed to follow a generalized ARCH formulation. Unlike previous studies, the model simultaneously takes into account (1) the temporal volatility clustering in index futures and spot prices, (2) the nonsynchronous trading that causes the index to be more autocorrelated than the underlying index value, and (3) the overnight/weekend relative price changes. Section IV presents the univariate analysis of the cash index and index futures intraday price volatilities. The cross-sectional behavior of the intraday volatility in the futures and spot markets is also examined. Section V introduces a new statistical methodology that tests the forecast performance of index futures volatility for spot index volatility. The results are given in Section VI, and the conclusions are contained in Section VII.

II. Data

The data used in this study were obtained from the Chicago Mercantile Exchange (CME). The CME provided the S&P 500 Index and index futures data for the period April 1982 (the first trading date of the futures contract) to June 1987. The futures prices are actual transaction prices for all trades during a day. The data include the contract identification, time stamp, and price of every futures transaction, in which the price has changed from the previously recorded transaction. The exchange offers contracts maturing in March, June, September, and December. Futures trading opens at 8:30 a.m. CST (9:00 a.m. CST before October 1, 1985) and closes at 3:15 p.m. CST.

The S&P 500 Index quotes are time-stamped approximately one minute apart. Although the index is updated continuously using the most recent transaction prices of the component stocks recorded, a general move in prices of smaller, less active stocks may not be recorded in a given interval

[4] Using daily data on S&P 500 futures contracts, Ng [1987] applies Hansen's generalized method of moments to adjust for heteroscedasticity.
[5] See Zellner [1979] for a critique of philosophical definitions of causality.

of time. This infrequent trading tends to induce serial correlation in the stock index, and thus causes the index to lag the true value of the underlying 500 stocks.[6] This nonsynchronous trading problem becomes more severe when prices are analyzed over very short intervals.

In this study, we focus on nearby futures contracts for which trading volume is high. We employ quotes that are approximately 15 minutes apart, and look at the nearest quotes available after the quarter-hour mark. This results in 24 (26 after September 30, 1985) equal periods of 15 minutes each within a trading day. Each index futures contract is followed from the expiration date of the previous contract until its expiration. Unlike the index futures market, markets for all S&P 500 stocks close at 3:00 p.m. CST. Although the index futures market closes 15 minutes later, the quarter-hour price series is constructed until 3:00 p.m. Consistent with previous studies, we only focus on the futures contract beginning September 1983.[7] Thus, there are 16 futures contracts used in this study.

Table 1 reports summary statistics for the first differences in the logarithm of S&P 500 Index levels and in the logarithm of S&P 500 futures prices by contract using the 15-minute interval. We ignore the changes of the logarithm of prices during the turn-of-the-week and/or the turn-of-the-day intervals. The first-order autocorrelation estimates for the changes in the logarithm of futures price are close to zero, and the sign of these estimates

Table 1. Summary statistics for the first differences in the logarithm of S&P 500 futures and S&P 500 Index prices using 15-minute interval transaction data.

		S&P 500 Futures		S&P 500 Index	
Contract	Number of observations	Standard deviation[a]	First-order autocorrelation	Standard deviation[a]	First-order autocorrelation
Sep 1983	1512	0.163	0.022	0.128	0.408
Dec 1983	1512	0.125	−0.001	0.095	0.409
Mar 1984	1488	0.147	−0.005	0.119	0.313
Jun 1984	1440	0.150	−0.010	0.114	0.369
Sep 1984	1632	0.176	−0.011	0.149	0.289
Dec 1984	1536	0.155	−0.055	0.114	0.213
Mar 1985	1368	0.145	−0.078	0.112	0.156
Jun 1985	1632	0.115	−0.079	0.093	0.178
Sep 1985	1512	0.108	−0.020	0.083	0.249
Dec 1985	1654	0.128	−0.065	0.102	0.184
Mar 1986	1612	0.172	−0.029	0.137	0.410
Jun 1986	1638	0.171	−0.005	0.142	0.103
Sep 1986	1638	0.202	−0.018	0.173	0.045
Dec 1986	1664	0.182	−0.021	0.147	0.079
Mar 1989	1612	0.219	−0.136	0.168	0.038
Jun 1987	1612	0.219	0.048	0.214	0.086

[a]Standard deviation is multiplied by 100.

[6] See, for example, Scholes and Williams [1977] and Fisher [1966], who have shown how the nonsynchronous trading in individual stocks can induce serial correlation in the returns of stock portfolios and stock indexes.
[7] Previous studies such as Figlewski [1984] had reported that earlier contracts display erratic behavior.

tends to be negative.[8] On the other hand, the first-order autocorrelation coefficients for the index series are positive and the magnitude of these coefficients ranges from 0.038 to 0.409 across 16 contracts. This is evident of the nonsynchronous trading problem that is persistent in the observed stock index levels.

The unconditional standard deviations of the futures series are all higher than those of the index series. The variability of these two series should be equal if the two markets are well-linked by arbitrageurs, who trade in both markets. The difference in these series might be attributed to the difference in the rate of flow of information incorporated into the prices, or it might perhaps imply that the futures market is more volatile than the stock markets. This finding is further verified in the following section, in which the behavior of the intraday (conditional) variability in these two markets is examined.

III. Conditionally Heteroscedastic Time-Series Models

Recent studies such as Bollerslev [1987], Bollerslev, Engle, and Wooldridge [1988], Ng [1990], and French, Schwert, and Stambaugh [1987], have shown that relative changes in stock index levels display leptokurtosis and conditional heteroscedasticity. Other studies such as McCurdy and Morgan [1987] have modeled the time-varying volatility of foreign currency futures and spot price changes as conditional heteroscedasticity that is a function of lagged forecast errors. Like these studies, we model the conditional heteroscedasticity of relative price changes in the stock index and stock index futures explicitly as a function of lagged squared predictive errors, as in the generalized ARCH (GARCH) model.

Let f_t and s_t be the change of the logarithm of price in the S&P 500 futures and Index, respectively, μ_f and μ_s denote their constant conditional means, ε_t and ξ_t denote their forecast errors, and h_{ft} and h_{st} represent their conditional variances. Following Engle [1982] and Bollerslev [1986], the dynamics of first differences in the logarithm of futures prices and index levels can be described as follows:

For the 15-minute-interval S&P 500 futures,

$$f_t = \mu_f + \varepsilon_t, \qquad \varepsilon_t|I_{t-1} \sim N(0,h_{ft}), \tag{1}$$
$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2, \text{ and}$$

the corresponding 15-minute-interval S&P 500 Index,

$$s_t = \mu_s + \xi_t,^9 \qquad \xi_t|I_{t-1} \sim N(0, h_{st}), \tag{2}$$
$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2,$$

[8] MacKinlay and Ramaswamy [1988] suggest that the negative sign is induced by the observed futures prices bouncing between the bid and asked prices.
[9] An alternative specification for the relative price change in the S&P 500 index is to allow the residual variance to enter the conditional mean equation. Given that the return on a risk-free asset is constant through time, such a specification would be consistent with Merton's [1980] formulation. Our preliminary empirical analysis of this, however, showed that the error variance does not significantly affect the conditional mean of the equation.

where I_{t-1} is the information set available to the market at time $t-1$, and (a_f, b_f, c_f) and (a_s, b_s, c_s) are the constant parameters in the conditional variance equations. In this specification, the innovations, ε_t (ξ_t), are defined in terms of the conditional density with time-varying variances, h_{ft}. This conditional variance is a linear function of past squared realizations and own lagged variance, and is analogous to the standard autoregressive moving average (ARMA) process in the conditional form. For finite variance and stationarity, it is necessary to impose that $a_f\,(a_s) > 0$, $b_f\,(b_s) \geq 0$, $c_f\,(c_s) \geq 0$, and $b_f + c_f\,(b_s + c_s) < 1$. A detailed proof of these conditions is given in Bollerslev [1986].

Empirically, it has been observed that the unconditional distribution of first differences of the logarithm of stock prices generally have fatter tails, that is, they exhibit leptokurtosis, and that error variances tend to cluster together (see Mandelbrot [1963] and Fama [1965]). The GARCH model formalizes this phenomenon observed in stock price changes reasonably well, and it also permits the simultaneous estimation of the mean and variance processes.

Since the study employs minute-by-minute transaction data, two issues need to be addressed: (1) the turn-of-the-day/turn-of-the-week effect on the change in the logarithm of S&P 500 futures/Index prices relative to the 15-minute-interval change in logarithm prices, and (2) the nonsynchronous trading problem in the stock index price series.

A. Turn-of-the-Day/Turn-of-the-Week Effect

In this study, we use the 15-minute differencing interval to examine the intraday behavior of volatility. However, both index futures and the underlying index do not trade continuously around the clock. These markets are closed during a holiday, overnight, and over the weekends. In constructing a 15-minute-interval futures/spot series, the rate of return calculated using the previous day's closing and next day's opening prices, or the Friday's closing and Monday's opening, would have to be discarded. In doing this, we would be throwing away information that is accumulated between this interval, especially information that is released from the time the spot markets are closed to the close of the futures market, i.e., 15 minutes later. Even though if spot index is constant between 3:00 and 3:15 p.m. CST, the futures price will respond to any new information released during the brief 15-minute interval that will affect the following day's spot price. Our empirical results would then be biased toward futures prices leading spot prices.

Series of the first differences in the logarithm of S&P 500 futures and Index prices constructed contain both a 15-minute interval as well as the turn-of-the-day/turn-of-the-week relative price changes. To mitigate the magnitude of bias induced by nonsynchronous price quotes and by overnight/weekend observations, dummy variables are used in this study to represent the types of relative price change. Thus, equations (1) and (2) can be rewritten as

$$f_t = \mu_f + \beta_f D_{ft} + \varepsilon_t, \tag{3}$$

$$s_t = \mu_s + \beta_s D_{st} + \xi_t, \tag{4}$$

where D_{ft} (D_{st}) takes the value of one if the observation represents the turn-of-the-day/turn-of-the-week relative price change and zero otherwise, with their respective error-variance equations as

$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2 + d_f D_{f,ht}$$
$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2 + d_s D_{s,ht}$$

where $D_{f,ht}$ ($D_{s,ht}$) takes the value of one if the observation represents the turn-of-the-day/turn-of-the-week relative price change and zero otherwise.

In our preliminary analysis of the data, we found that the estimated turn-of-the-day/turn-of-the-week volatility level was greater than those for the 15-minute interval.[10] Given that the current volatility depends on the previous volatility level, any unusually high previous volatility will be incorporated into the current volatility, causing the current volatility level to be high as well. To isolate this overnight/weekend volatility effect, we adjust the current level in the following manner.[11]

$$h_{ft} = a_f + b_f(h_{ft-1} - d_f) + c_f \varepsilon_{t-1}^2$$
$$h_{st} = a_s + b_s (h_{st-1} - \mathrm{d_s}) + c_s \xi_{t-1}^2$$

With the above formulations, any spillover of the overnight/weekend high volatility on the next day's volatility level would be adjusted by subtracting the component of the previous volatility that is due to overnight/weekend effect.

B. The Problem of Nonsychronous Trading

Using transaction data on S&P 500 futures contracts, MacKinlay and Ramaswamy [1988] have found that futures series using the 15-minute interval is not correlated, but the index series is positively correlated at the first lag, with first-order autocorrelations ranging from 0.04 to 0.41 across all 16 futures contracts. Their findings are consistent with evidence of earlier studies by Scholes and Williams [1977] and Fisher [1966]. Due to the problem of infrequent trading, the empirical results may be biased toward one price series leading or lagging the other. Following Bollerslev [1987], and French, Schwert, and Stambaugh [1987], we explicitly take into account the nonsynchronous trading problem by including a first-order moving average error process in the stock index's conditional mean return equation (4).

[10] The cross-sectional average standard deviations (in percent) of the S&P 500 futures and S&P 500 Index are 0.36 and 0.28, respectively.
[11] We are grateful to Paul Newbold for suggesting this to us.

Thus, this paper focuses on the following two relations:

for the S&P 500 futures,

$$f_t = \mu_f + \beta_f D_{ft} + \varepsilon_t, \qquad \varepsilon_t | I_{t-1} \sim N(0, h_{ft}), \tag{5}$$
$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2 + d_f D_{f,ht},$$
$$h_{ft} = a_f + b_f(h_{ft-1} - d_f) + c_f \varepsilon_{t-1}^2, \text{ and}$$

for the S&P 500 Index,

$$s_t = \mu_s + \beta_s D_{st} + \xi_t - \gamma\, \xi_{t-1}, \qquad \xi_t | I_{t-1} \sim N(0, h_{st}), \tag{6}$$
$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2 + d_s D_{s,ht}$$
$$h_{st} = a_s + b_s\,(h_{st-1} - d_s) + c_s \xi_{t-1}^2$$

A general log-likelihood function for equations (5) or (6) can be expressed as

$$\ln L(\phi) = \text{constant} - \tfrac{1}{2}\Sigma_t \ln h_{z,t} - \tfrac{1}{2}\Sigma_t(\varepsilon_{zt}^2 / h_{z,t}) \tag{7}$$

where ϕ contains the unknown parameters in the conditional mean and variance equations. The log-likelihood function can be maximized numerically to obtain consistent, asymptotically normal and efficient estimates of ϕ.[12]

IV. The Stochastic Behavior of Futures and Index Intraday Volatilities

In this section, we empirically examine the time-series behavior of S&P 500 Index and S&P 500 futures intraday price volatilities, by applying the univariate models developed in the preceding section. The analysis is based on minute-by-minute transaction data on nearby futures contracts, beginning September 1983 through June 1987.

A. Intraday Patterns in Stock Index and Index Futures Volatilities

Tables 2a-d report the maximum likelihood estimates of the univariate models given by (5) and (6),[13] described in the preceding subsection. Few interesting results emerge from these tables. The first-order moving average term in the conditional mean equation for the stock index series is significantly different from zero for all 16 contracts. The coefficients range from 0.08 (in September 1986 futures contract) to 0.44 (in September 1983 futures contract), which are fairly close to the unconditional first-order autocorrelation coefficients of the same contract calculated in Table 1. The coefficients of the dummy variable in the variance equations are strongly significant at the 5 percent level. This may be attributed to the arrival of new information, which is impounded into the prices between the time the stock markets are closed and the time the markets are open. The results also

[12] This study uses the Davidon-Powell-Fletcher numerical algorithm for the performance of all estimations of the models.
[13] A few functional forms were estimated. Based on the likelihood ratio test and Akaike's information criterion test, the specifications given by relations (5) and (6), by far, provide the best description of the data used.

Table 2a. Maximum-likelihood estimates of the GARCH (1,1) specification using 15-minute-interval transaction data on the changes of the logarithm of price in the S&P 500 futures and Index

S&P 500 Futures

$$f_t = \mu_f + \beta_f D_{ft} + \varepsilon_t, \qquad \varepsilon_t | I_{t-1} \sim N(0, h_{ft})$$

$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2 + d_f D_{f,ht}$$

$$h_{ft} = a_f + b_f (h_{ft-1} - d_f) + c_f \varepsilon_{t-1}^2$$

S&P 500 Index

$$s_t = \mu_s + \beta_s D_{st} + \xi_t - \gamma \xi_{t-1}, \qquad \xi_t | I_{t-1} \sim N(0, h_{st})$$

$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2 + d_s D_{s,ht}$$

$$h_{st} = a_s + b_s (h_{st-1} - d_s) + c_s \xi_{t-1}^2$$

	Sep 1983		Dec 1983		Mar 1984		Jun 1984	
	Futures	Index	Futures	Index	Futures	Index	Futures	Index
μ	−0.0020	−0.0032	0.0006	−0.0013	−0.0038	−0.0035	−0.0058	−0.0085
	(0.0040)	(0.0031)	(0.0031)	(0.0027)	(0.0032)	(0.0034)	(0.0039)	(0.0027)
β	0.1555	−0.3362	−0.0105	−0.2867	0.0704	−0.2712	0.0147	−0.2321
	(0.0418)	(0.0236)	(0.0258)	(0.0204)	(0.0282)	(0.0255)	(0.0389)	(0.0210)
γ		−0.4445		−0.3899		−0.3820		−0.3499
		(0.0195)		(0.0223)		(0.0230)		(0.0232)
$a \times 100$	0.6324	0.4132	0.4548	0.3468	0.0386	0.5027	2.1132	0.3737
	(0.0639)	(0.0178)	(0.0567)	(0.0120)	(0.0048)	(0.0244)	(0.0464)	(0.0129)
b	0.6028	0.0695	0.5941	0.0634	0.9220	0.1003	−0.0000	0.1066
	(0.0313)	(0.0173)	(0.0421)	(0.0157)	(0.0067)	(0.0248)	(0.3000)	(0.0147)
c	0.1434	0.4644	0.1103	0.3694	0.0551	0.3572	0.0978	0.4942
	(0.0140)	(0.0238)	(0.0132)	(0.0208)	(0.0057)	(0.0209)	(0.0132)	(0.0269)
d	0.1580	0.1237	0.0362	0.0931	0.0537	0.0863	0.0816	0.0912
	(0.0166)	(0.0144)	(0.0048)	(0.0113)	(0.0070)	(0.0117)	(0.0093)	(0.0107)
log-likelihood	2043.8	2909.7	2463.5	3155.5	2256.9	2826.2	2159.0	2710.3

Note:

1. All changes in the log of prices are multiplied by 100.
2. Standard errors in parentheses.
3. The dummy variables (D_{ft}, D_{st}, $D_{s,ht}$, and $D_{f,ht}$) in the mean and variance equations take the value of 1 if turn-of-the-day/turn-of-the-week relative price change, and 0, otherwise.

Table 2b. Maximum-likelihood estimates of the GARCH (1,1) specification using 15-minute-interval transaction data on the changes of the logarithm of price in the S&P 500 futures and Index

S&P 500 Futures

$$f_t = \mu_f + \beta_f D_{ft} + \varepsilon_t, \qquad \varepsilon_t | I_{t-1} \sim N(0, h_{ft})$$
$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2 + d_f D_{f,ht}$$
$$h_{ft} = a_f + b_f (h_{ft-1} - d_f) + c_f \varepsilon_{t-1}^2$$

S&P 500 Index

$$s_t = \mu_s + \beta_s D_{st} + \xi_t - \gamma \xi_{t-1}, \qquad \xi_t | I_{t-1} \sim N(0, h_{st})$$
$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2 + d_s D_{s,ht}$$
$$h_{st} = a_s + b_s (h_{st-1} - d_s) + c_s \xi_{t-1}^2$$

	Sep 1984		Dec 1984		Mar 1985		Jun 1985	
	Futures	Index	Futures	Index	Futures	Index	Futures	Index
μ	0.0029	−0.0019	−0.0049	−0.0040	0.0019	0.0043	−0.0058	0.0018
	(0.0039)	(0.0357)	(0.0039)	(0.0030)	(0.0037)	(0.0033)	(0.0039)	(0.0023)
β	0.0334	−0.3557	0.0692	−0.1738	−0.0256	−0.1846	0.0147	−0.2637
	(0.0346)	(0.0320)	(0.0322)	(0.0225)	(0.0336)	(0.0447)	(0.0389)	(0.0226)
γ		−0.3232		−0.2317		−0.1339		−0.2580
		(0.0262)		(0.0300)		(0.0327)		(0.0254)
$a \times 100$	0.4134	0.5325	0.5265	0.3097	0.0181	0.7548	2.1132	0.3258
	(0.0481)	(0.0309)	(0.0766)	(0.0290)	(0.0044)	(0.0053)	(0.0464)	(0.0169)
b	0.7058	0.2306	0.6885	0.3941	0.0000	0.1292	−0.0000	0.1379
	(0.0235)	(0.0226)	(0.0373)	(0.0387)	(0.4444)	(0.0488)	(0.3000)	(0.0274)
c	0.1482	0.4666	0.0878	0.3787	0.1287	0.2677	0.0978	0.3874
	(0.0120)	(0.0266)	(0.0106)	(0.0276)	(0.0163)	(0.0238)	(0.0132)	(0.0258)
d	0.1119	0.1280	0.0539	0.0269	0.0436	0.0272	0.0816	0.0684
	(0.0123)	(0.0171)	(0.0076)	(0.0053)	(0.0060)	(0.0094)	(0.0093)	(0.0090)
log-likelihood	2130.7	2710.3	2161.9	2988.9	2022.2	2426.5	2818.6	3371.7

Note:
1. All changes in the log of prices are multiplied by 100.
2. Standard errors in parentheses.
3. The dummy variables (D_{ft}, D_{st}, $D_{s,ht}$, and $D_{f,ht}$) in the mean and variance equations take the value of 1 if turn-of-the-day/turn-of-the-week relative price change, and 0, otherwise.

Table 2c. Maximum-likelihood estimates of the GARCH (1,1) specification using 15-minute-interval transaction data on the changes of the logarithm of price in the S&P 500 futures and Index

S&P 500 Futures

$$f_t = \mu_f + \beta_f D_{ft} + \varepsilon_t, \qquad \varepsilon_t | I_{t-1} \sim N(0, h_{ft})$$

$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2 + d_f D_{f,ht}$$

$$h_{ft} = a_f + b_f (h_{ft-1} - d_f) + c_f \varepsilon_{t-1}^2$$

S&P 500 Index

$$s_t = \mu_s + \beta_s D_{st} + \xi_t - \gamma \xi_{t-1}, \qquad \xi_t | I_{t-1} \sim N(0, h_{st})$$

$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2 + d_s D_{s,ht}$$

$$h_{st} = a_s + b_s (h_{st-1} - d_s) + c_s \xi_{t-1}^2$$

	Sep 1985		Dec 1985		Mar 1986		Jun 1986	
	Futures	Index	Futures	Index	Futures	Index	Futures	Index
μ	−0.0028	−0.0002	0.0054	0.0071	0.0072	0.0119	0.0026	0.0053
	(0.0027)	(0.0017)	(0.0029)	(0.0024)	(0.0036)	(0.0033)	(0.0040)	(0.0036)
β	0.0305	−0.1289	0.0256	−0.1169	0.0160	−0.2169	0.0486	−0.2549
	(0.0244)	(0.0144)	(0.0247)	(0.0200)	(0.0374)	(0.0231)	(0.0347)	(0.0278)
γ		−0.2397		−0.2566		−0.2300		−0.1996
		(0.0290)		(0.0293)		(0.0304)		(0.0263)
$a \times 100$	0.4007	0.1971	0.3215	0.1632	0.7418	0.3303	0.5550	1.1903
	(0.0531)	(0.0097)	(0.0401)	(0.0138)	(0.0727)	(0.0249)	(0.0850)	(0.0306)
b	0.5491	0.2572	0.6739	0.5388	0.5892	0.4545	0.7099	0.0000
	(0.0522)	(0.0204	(0.0326)	(0.0238)	(0.0297)	(0.0223)	(0.0353)	(0.3333)
c	0.0984	0.4751	0.1206	0.3286	0.1608	0.4377	0.0989	0.4275
	(0.0133)	(0.0290)	(0.0131)	(0.0214)	(0.0157)	(0.0252)	(0.0118)	(0.0288)
d	0.0225	0.0202	0.0296	0.0135	0.0554	0.0334	0.0583	0.0605
	(0.0031)	(0.0032)	(0.0042)	(0.0034)	(0.0083)	(0.0068)	(0.0080)	(0.0102)
log-likelihood	2705.1	3306.9	2690.0	3230.6	2116.0	2660.9	2135.1	2543.4

Note:
1. All changes in the log of prices are multiplied by 100.
2. Standard errors in parentheses.
3. The dummy variables (D_{ft}, D_{st}, $D_{s,ht}$, and $D_{f,ht}$) in the mean and variance equations take the value of 1 if turn-of-the-day/turn-of-the-week relative price change, and 0, otherwise.

Table 2d. **Maximum-likelihood estimates of the GARCH (1,1) specification using 15-minute-interval transaction data on the changes of the logarithm of price in the S&P 500 futures and Index**

S&P 500 Futures

$$f_t = \mu_f + \beta_f D_{ft} + \varepsilon_t, \qquad \varepsilon_t | I_{t-I} \sim N(0, h_{ft})$$

$$h_{ft} = a_f + b_f h_{ft-1} + c_f \varepsilon_{t-1}^2 + d_f D_{f,ht}$$

$$h_{ft} = a_f + b_f (h_{ft-1} - d_f) + c_f \varepsilon_{t-1}^2$$

S&P 500 Index

$$s_t = \mu_s + \beta_s D_{st} + \xi_t - \gamma \xi_{t-1}, \qquad \xi_t | I_{t-1} \sim N(0, h_{st})$$

$$h_{st} = a_s + b_s h_{st-1} + c_s \xi_{t-1}^2 + \gamma_s D_{s,ht}$$

$$h_{st} = a_s + b_s (h_{st-1} - d_s) + c_s \xi_{t-1}^2$$

	Sep 1986		Dec 1986		Mar 1987		Jun 1987	
	Futures	Index	Futures	Index	Futures	Index	Futures	Index
μ	0.0058	0.0043	0.0102	0.0094	0.0080	0.0107	0.0015	0.0027
	(0.0004)	(0.0035)	(0.0037)	(0.0027)	(0.0039)	(0.0034)	(0.0048)	(0.0048)
β	−0.0253	−0.2883	−0.1545	−0.3374	0.1089	−0.3432	0.0762	−0.6369
	(0.0172)	(0.0336)	(0.0392)	(0.0310)	(0.0519)	(0.0280)	(0.0672)	(0.0570)
γ		−0.0763		−0.0932		−0.1533		−0.1417
		(0.0300)		(0.0314)		(0.0285)		(0.0267)
$a \times 100$	0.7464	0.4832	0.6712	0.4435	0.5829	0.4225	1.0241	1.3782
	(0.0170)	(0.0293)	(0.0573)	(0.0254)	(0.0510)	(0.0240)	(0.0924)	(0.0902)
b	0.5520	0.4282	0.4804	0.2646	0.5883	0.3944	0.5473	0.2513
	(0.0092)	(0.0190)	(0.0273)	(0.0208)	(0.0212)	(0.0171)	(0.0257)	(0.0281)
c	0.2540	0.4619	0.3252	0.5670	0.2527	0.4339	0.2190	0.3712
	(0.0599)	(0.0291)	(0.0216)	(0.0214)	(0.0159)	(0.0252)	(0.0161)	(0.0236)
d	0.0645	0.0846	0.1370	0.1159	0.0732	0.1210	0.3603	0.3755
	(0.0072)	(0.0145)	(0.0156)	(0.0167)	(0.0100)	(0.0170)	(0.0380)	(0.0525)
log-likelihood	2027.9	2373.6	2135.2	2713.9	2052.8	2475.1	1732.2	1928.3

Note:
1. All changes in the log of prices are multiplied by 100.
2. Standard errors in parentheses.
3. The dummy variables (D_{ft}, D_{st}, $D_{s,ht}$, and $D_{f,ht}$) in the mean and variance equations take the value of 1 if turn-of-the-day/turn-of-the-week relative price change, and 0, otherwise.

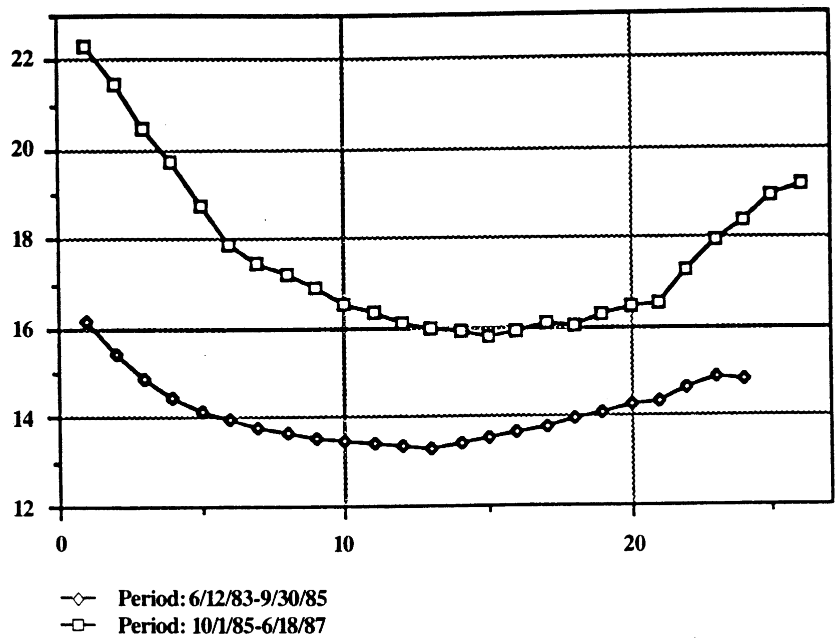
indicate the presence of the ARCH effects in the variance equations of both index futures and spot index series for all contracts, which clearly suggests that the error terms exhibit conditional heteroscedasticity.

We next examine the cross-sectional behavior of the resulting conditional error variances within a trading day. Table 3 reports the cross-sectional averages of the 15-minute-interval residual standard deviation for the S&P 500 Index and S&P 500 futures before October 1, 1985, and after September 30, 1985, reflecting the change in the trading time as mentioned in Section II. The relation between the average 15-minute-interval standard deviation of changes in the logarithm of futures price and the time of the day is plotted in Figure 1. It is observed that the standard deviation is relatively high early in the day and late in the day compared to the middle of the trading day. This pattern is consistent across the two subsample periods. One striking observation is that the variability hits its lowest point between 12:00 and 12:15 p.m. CST.

Table 3. Cross-sectional averages of percent conditional standard deviation for the S&P 500 Index and S&P 500 futures by intraday period (6/17/83-6/18/87)

	S&P 500 Futures		**S&P 500 Index**	
	6/17/83-9/30/85	**10/1/85-6/18/87**	**6/17/83-9/30/85**	**10/1/85-6/18/87**
15-minute interval	**average**	**average**	**average**	**average**
8:30-8:45		0.223		0.253
8:45-9:00		0.215		0.272
9:00-9:15	0.162	0.205	0.191	0.211
9:15-9:30	0.154	0.198	0.193	0.178
9:30-9:45	0.149	0.188	0.128	0.153
9:45-10:00	0.145	0.179	0.103	0.137
10:00-10:15	0.141	0.175	0.092	0.131
10:15-10:30	0.139	0.172	0.087	0.129
10:30-10:45	0.138	0.169	0.085	0.126
10:45-11:00	0.136	0.165	0.082	0.123
11:00-11:15	0.135	0.164	0.083	0.122
11:15-11:30	0.135	0.161	0.082	0.121
11:30-11:45	0.134	0.160	0.082	0.120
11:45-12:00	0.134	0.159	0.082	0.117
12:00-12:15	0.133	0.158	0.081	0.118
12:15-12:30	0.134	0.159	0.083	0.118
12:30-12:45	0.135	0.161	0.083	0.119
12:45-13:00	0.137	0.161	0.084	0.120
13:00-13:15	0.138	0.163	0.085	0.123
13:15-13:30	0.140	0.165	0.089	0.123
13:30-13:45	0.141	0.166	0.087	0.124
13:45-14:00	0.143	0.173	0.091	0.129
14:00-14:15	0.144	0.179	0.093	0.134
14:15-14:30	0.147	0.184	0.098	0.142
14:30-14:45	0.148	0.189	0.099	0.151
14:45-15:00	0.149	0.192	0.100	0.159

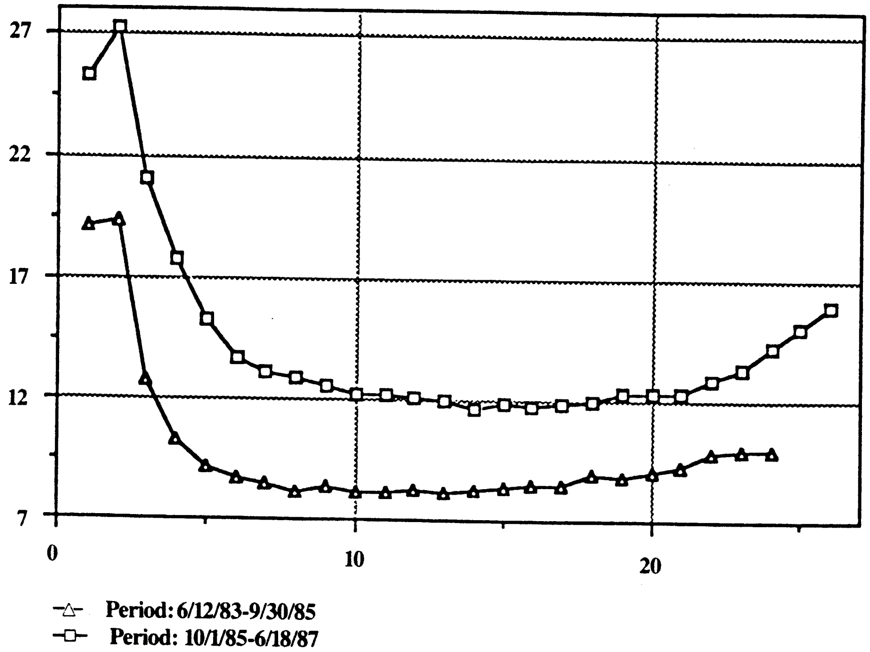
Figure 1. Cross-sectional relation between the average 15-minute-interval standard deviation of changes in the logarithm of S&P 500 futures price and the time of the day. (Sample period: June 12, 1983 - June 18, 1987)



This pattern has also been noted in other studies. For example, Harris [1986], and Wood, McInish, and Ord [1985] observe the same pattern in intraday stock return variances. Edwards [1988] examines the hourly volatility of various index futures and spot prices, and also detects a similar pattern. Jordan, Seale, Dinehart, and Kenyon [1988] study the intraday variability of soybean futures prices and report that the intraday variability of soybean futures prices exhibits a U-shaped pattern. These studies suggest that the relatively high variance early in the day is attributed to information (public and private) released since the previous day's close of trading that is incorporated into the prices. Jordan, Seale, Dinehart, and Kenyon, however, suggest that the increase in variance late in the day is less attributable to the flow of information. They argue that the increased trading toward the end of the trading day is induced by trading activities by traders who do not wish to hold open positions overnight. Such trading need not be based on information, but only traders' intentions to close out their positions.

Figure 2 plots the relation between the average 15-minute-interval cash index standard deviation and the time of the day. Unlike those of futures series, the magnitude of the standard deviation drops dramatically during the first 45 minutes of trading, and thereafter remains fairly stable. Like in the futures market, the magnitude of the standard deviation is smallest between 12:00 and 12:15 p.m., except in the subsample period after September 30, 1985, when standard deviation is smallest between 11:45 and 12:00 p.m. The magnitude of the 15-minute-interval mean standard deviation is consistently higher in the index futures series than that of the stock market series across the two periods, except for the first 30 to 45 minutes of trading, where the index volatility is greater than the futures price volatility.

Figure 2. Cross-sectional relation between the average 15-minute-interval standard deviation of changes in the logarithm of S&P 500 Index price and the time of the day. (Sample period: June 12, 1983 - June 18, 1987)



Note: All standard deviations are multiplied by 10,000.

B. Diagnostic Tests

To avoid making erroneous inferences because of inconsistent and inefficient estimates of the parameters, we perform some diagnostic checks for serial correlation on the conditional first and second moments of the resulting residuals. Two diagnostic tests, namely (1) the Ljung-Box [1978] portmanteau test on the first 12 lags of the standardized residuals, $\varepsilon_t/\sqrt{h_{ft}}$ $(\xi_t/\sqrt{h_{st}})$, which is denoted by $Q(12)$,[14] and (2) the Ljung-Box test on the first 12 lags of the squared standardized residuals, ε_t^2/h_{ft} (ξ_t^2/h_{st}), which is denoted by $Q^2(12)$, (see McLeod and Li [1983]), are conducted. These test statistics are distributed asymptotically as an $\chi^2(12)$ distribution, under the null hypothesis.

Table 4 reports the Ljung-Box test statistics for the standardized residuals and squared standardized residuals, from the estimated GARCH models given by (5) and (6). Notice that all test statistics are not significant at the 5 percent level, and thus indicate the absence of first and second order dependence in the standardized residuals. This, henceforth, suggests that the GARCH models seem to fit the data fairly well.

[14] Since we incorporate an MA(1) error term in the conditional mean equation of the cash price series, the Ljung-Box portmanteau test on the first 12 lags of the standardized residuals is distributed asymptotically as a chi-square distribution with 11 degrees of freedom under the null hypothesis.

V. A Causality Test in the Variance

The well-known Granger's [1969] definition of causality is that a time series Y_t "causes" another time series X_t if current X can be better predicted using past observations of Y than by not doing so, with other pertinent information (including past observations of X) being used in either case. The concept of causation used here is the "Granger causation" in the mean. To state this more formally, Y_t is said to "cause" X_t with respect to an information set J_t if

$$E\,[X_{t+1}|I_t] \neq E\,[X_{t+1}\,|\,J_t] \tag{8}$$

where I_t and J_t are two information sets, defined as follows:

$$I_t = \{\,X_{t-n};\, n \geq 0\,\}, \text{ and}$$
$$J_t = \{\,X_{t-n},\, Y_{t-n}\,;\, n \geq 0\,\}.$$

Several procedures for the empirical investigation of causal relationships between two variables have been proposed, and a survey of some of these are given in Pierce and Haugh [1977]. These are, however, focused entirely on the dynamics of the mean with the conditional variance of the innovation assumed to be constant, and tests are based on causality in the mean. Unfortunately, there seems no reason to assume that the conditional variance is time-invariant. If conditional variances are time-varying, then the standard statistical approach used in estimating the conditional means will

Table 4. Diagnostic Tests

	S&P 500 Futures		S&P 500 Index	
Contract	**$Q(12)$**	**$Q^2(12)$**	**$Q(11)^a$**	**$Q^2(12)$**
Sep 1983	11.239	15.972	16.264	17.574
Dec 1983	2.936	5.405	5.585	3.346
Mar 1984	4.680	4.350	3.538	0.311
Jun 1984	5.543	0.443	6.792	0.525
Sep 1984	8.348	10.913	18.204	5.661
Dec 1984	9.961	13.585	10.599	10.349
Mar 1985	15.276	10.175	5.528	2.765
Jun 1985	16.317	5.458	8.949	6.087
Sep 1985	5.621	16.635	2.272	0.389
Dec 1985	10.131	0.586	1.954	0.013
Mar 1986	6.584	6.097	4.578	4.623
Jun 1986	5.385	4.434	8.324	4.023
Sep 1986	8.352	2.459	12.589	2.644
Dec 1986	5.182	1.884	15.363	6.166
Mar 1987	6.454	17.971	7.262	5.149
Jun 1987	8.402	4.570	5.851	5.838

Note: $Q(12)$ and $Q^2(12)$ denote the Ljung-Box [1978] portmanteau tests for up to the 12th-order serial correlation in the levels and the squares of standardized residuals, respectively. Each test statistic is chi-square with 12 degrees of freedom under the null hypothesis, for which the critical value is 21.026 at the 5 percent significance level.

[a] The number of degree of freedom is adjusted to reflect the MA(1) in the error term, and, thus, the test statistic is distributed with 11 degrees of freedom under the null hypothesis, for which the critical value is 19.675 at the 5 percent significance level.

be subject to heteroscedasticity, and ignoring this can lead to misleading conclusions about the form of the conditional means, in particular conclusions about the causal relationship between the two variables. To form better confidence intervals and yield more information about the relationship between two time series of variables, a joint time-series modeling of first and second moments seems necessary.

Granger, Robins, and Engle [1986] recently extend this concept of predictability to include the causality in the second moment. By this definition, Y_t is said to cause X_{t+1} in the variance if

$$E[(X_{t+1} - \mu_{t+1})^2 \mid I_t] \neq E[(X_{t+1} - \mu_{t+1})^2 \mid J_t], \tag{9}$$

where μ_{t+1} denotes the conditional mean of X_{t+1}. Feedback in the variance occurs if Y causes X and, in addition, X causes Y. Then, Y causes X instantaneously in variance if

$$E[(X_{t+1} - \mu_{t+1})^2 \mid I_t] \neq E[(X_{t+1} - \mu_{t+1})^2 \mid I_t + Y_{t+1}]. \tag{10}$$

To test for causal relationships in a pair of price series, Granger, Robins, and Engle propose estimation of a model that takes the following form:

$$B_1(L)x_t = B_2(L)y_t + e_t \tag{11}$$

$$e_t = a_t\sqrt{h_t},\ a_t \sim IN(0,1),$$

$$h_t = \alpha_o + \alpha_1\Sigma_j d_j e_{t-j}^2 + \alpha_2\Sigma_j d_j(x_{t-j} - e_{t-j}) + \alpha_3\Sigma_j d_j y_{t-j}^2$$

where e_t represents the forecast error, and $B_1(L)$ and $B_2(L)$ are finite-order polynomials in the lag operator L. Y does not cause X in the mean if $B_2(L) = 0$, and in the variance if $\alpha_3 = 0$. The specification of the number of lags in the mean and variance equations, however, seems ad hoc in that the filter is specified a priori rather than from an empirical investigation of the data.[15]

This study adopts an alternative statistical test for causality in the variance, as proposed by Cheung and Ng [1989], in examining the lead-lag relationship between S&P 500 futures and S&P 500 Index prices. The test involves fitting a univariate model that incorporates time-varying conditional variances to each time series, and computing the cross-correlations of the resulting series of the squared standardized residuals, which represent the unexplained portions of X_t and Y_t, respectively. Thus, by cross-correlating the pair of volatility processes, the informational leads and lags in X_t and Y_t can be detected. When one volatility series has incremental predictive ability for the other, there is a causal relationship between the two processes.

Suppose X_t and Y_t satisfy the following GARCH specifications:

$$\mu_{x,t} = \Sigma_i a_i X_{t-i}, \tag{12}$$

[15] See Pierce and Haugh [1977].

$$\mu_{y,t} = \Sigma_j b_j Y_{t-j}, \tag{13}$$

$$h_{x,t} = E(\varepsilon_t^2 \mid I_{t-1}) = \theta_o + \Sigma_p \theta_p \varepsilon_{t-p}^2 + \Sigma_q \gamma_q h_{x,t-q},$$

$$h_{y,t} = E(\eta_t^2 \mid I_{t-1}) = \kappa_o + \Sigma_p \kappa_p \eta_{t-p}^2 + \Sigma_q \delta_q h_{y,t-q},$$

where $\varepsilon_t = X_t - \mu_{x,t}$, $\eta_t = Y_t - \mu_{y,t}$, and (p, q, i, and j) define the (finite) order of the lag functions. The parameters a_i, b_j, θ_p, γ_q, κ_p, and δ_q are assumed to satisfy the stationarity conditions.[16] Thus, the squares of the standardized residuals, U_t and W_t, have the following distributions,

$$U_t = \varepsilon_t^2/h_{x,t} \sim iid\,(1, \sigma_u^2),$$
$$W_t = \eta_t^2/h_{y,t} \sim iid\,(1, \sigma_w^2).$$

The cross-covariance of U_t and W_t at lag k is therefore given by

$$c_{uw}\,(\mathrm{k}) = T^{-1}\,\Sigma_t\,(U_t - 1)(W_{t-k} - 1),$$

and the estimator of the cross-correlation at lag k is

$$\rho_{uw}(k) = c_{uw}(k)\,(c_u c_w)^{-1/2},$$

where c_u and c_w are the sample variances of U_t and W_t, respectively.

Let $\Theta = \{a_i, b_j, \theta_p, \gamma_q, \kappa_p, \text{and } \delta_q\}$ represents the vector of true parameters and $\underline{\Theta}$ denotes the consistent estimator of Θ with convergence rate $\sqrt{T}$. $\underline{U}_t$ and $\underline{W}_t$ are estimators of U_t and W_t based on $\underline{\Theta}$. $\underline{c}_{uw}\,(k)$ and $\underline{r}_{uw}(k)$ are the sample cross-covariance and cross-correlation at lag k. Along the same argument of Haugh [1976], and McLeod and Li [1983], Cheung and Ng [1989] show that under the null hypothesis Y and X are not causally related, both $\sqrt{T}(r_{uw}(k_1),..., r_{uw}(k_m))$ *and* $\sqrt{T}(\underline{r}_{uw}(k_1),..., \underline{r}_{uw}(k_m))$ converge to $N(0,I_m)$ as $T \dashrightarrow \infty$, where $k_1, \ldots, k_m$ are m different integers.

Given the asymptotic behavior of $\underline{r}_{uw}\,(k)$, a normal test statistic or a chi-square test statistic can be developed to test the null hypothesis that there is no causality in variance. To test for the causal relationship at a specific lag k, we can compare $\sqrt{T}\underline{r}_{uw}(k)$ with the standard normal distribution. Alternatively, the causal relationship can be tested using a chi-square test statistic, which is defined as [17]

$$S = T\,\Sigma_i \underline{r}_{uw}(i)^2,\; i = -j,...,k, \tag{14}$$

which has a chi-square distribution with the degree of freedom equal to the number of terms included under the summation sign. The choice of j and k

[16] See Box and Jenkins [1970], Engle [1982], Bollerslev [1986], and Mihoj [1985].
[17] When T is small relative to the lag length k, the chi-square statistic S can be modified to

$$S_m = T\Sigma_i[T/(T - \mid i \mid)]\,\underline{r}_{uw}(i)^2,\; i = -j,...,k,$$

in order to obtain a more accurate small sample approximation to the chi-square distribution.

depends on the specification of alternative hypotheses. With no a priori information on the causal direction, we may set $-j=k=m$, and m should be large enough to include the largest nonzero lag that may appear significant.

Thus, the chi-square test statistic, $S_1 = T\Sigma_i r_{uw}(i)^2$, $i = 1,...,k$, with k degrees of freedom may be used to test the null hypothesis that Y does not cause X in the variance. On the other hand, $S_2 = T\Sigma_i r_{uw}(i)^2$, $i = -n,..., -1$, with n degrees of freedom may be used to test the null hypothesis that X does not cause Y in the variance. The null hypotheses that Y and X are independent may then be tested by using the statistic $S_3 = T\Sigma_i r_{uw}(i)^2, i = -n,...,k$, with $(n+k+1)$ degrees of freedom.

VI. Empirical Results

To facilitate comparison of our findings with those of other causality studies on index futures contracts, we present two causality test results in this section. Like most empirical studies, we investigate the causality in the mean by testing whether changes in the S&P 500 futures (Index) price provide predictive information about subsequent changes in the S&P 500 Index (futures) price. We also include tests for the lead-lag relationship between the intraday futures price volatility and cash price volatility in order to examine whether the volatility of prices helps illuminate the informational role of futures markets.

A. *Results from Tests on the Causality in the Conditional Mean*

Following the Pierce and Haugh [1977] test for Granger causality in the mean, we fit univariate GARCH models to time series of changes in the logarithm of S&P 500 Index and S&P 500 futures prices, as conducted in Section III. In order to investigate the causal relationships, the cross-correlation test statistic of the resulting series of standardized residuals at each specific lag k is computed as follows:

$$S^* = Tr_{\varepsilon\xi}(k)^2 = T[\Sigma_t \varepsilon_t \cdot \xi_{t-k} / \sqrt{(\Sigma_t \varepsilon_t^2 \cdot \Sigma_t \xi_t^2)}]^2, \tag{15}$$

Under the null hypothesis that the futures and cash prices are not causally related, the cross-correlation test statistic in (15) possesses the same asymptotic distribution as in equation (14). A detailed derivation of this is presented in Haugh[1976]. Results on these hypothesis testings are reported in Tables 5a-d. Due to the possibility of arbitrage activity between the two markets, any informational lags for these markets would not be expected to persist much longer than a day. We therefore report the test statistics up to the 24th lag (26th lag after September 30, 1985), which is the number of lags necessary to capture the one-day lead/lag causal relationship between futures price and spot price.

Evidence indicates that while futures price consistently leads the index price for at least 15 minutes, and extends to 30 minutes in 7 out of the 16 contracts examined, the incremental predictive ability of spot price for current changes in futures price seems weak. Although one or two of the cross-correlation test statistics are significant at higher-order lags for each contract, they are not stable across the contracts, and we also do not observe any systematic pattern that allows us to make any reasonable inferences

Table 5a. Results of the cross-correlation test statistic of standardized residuals at each specific lag k for September 1983-June 1984 contracts

$$S_1^* = Tr_{\xi\varepsilon}(k)^2 = T\,[\,\Sigma_t\,\varepsilon_{t-k}\cdot\xi_t/\surd(\,\Sigma_t\varepsilon_t^2\cdot\Sigma_t\xi_t^2\,)]^2$$

$$S_2^* = Tr_{\varepsilon\xi}(k)^2 = T\,[\,\Sigma_t\varepsilon_t\cdot\xi_{t-k}/\surd(\,\Sigma_t\varepsilon_t^2\cdot\Sigma_t\xi_t^2\,)]^2$$

	Sep 1983		Dec 1983		Mar 1984		Jun 1984	
Lag	S_1^*	S_2^*	S_1^*	S_2^*	S_1^*	S_2^*	S_1^*	S_2^*
0[a]	0.587	0.587	0.635	0.635	0.583	0.583	0.663	0.663
1	252.505	1.604	193.386	0.021	122.577	0.273	133.216	0.211
2	8.333	1.915	13.732	0.039	16.963	0.052	12.744	1.548
3	0.206	1.237	5.237	3.658	0.418	0.319	0.000	0.586
4	0.070	0.046	0.001	0.636	4.265	2.380	0.232	0.093
5	0.419	2.747	0.196	0.042	0.137	0.743	0.072	0.278
6	0.002	0.350	0.025	0.273	0.000	0.111	0.386	0.019
7	1.200	1.753	0.058	0.086	0.093	0.000	0.490	0.283
8	0.450	0.535	2.620	0.027	0.829	0.328	1.598	2.250
9	0.023	0.012	0.168	0.397	0.405	0.320	0.747	1.790
10	0.011	2.206	0.339	0.312	2.076	0.211	0.040	0.003
11	0.059	0.880	0.199	0.286	0.238	0.009	0.342	0.553
12	0.212	1.608	0.571	0.233	0.216	0.068	0.082	0.898
13	0.429	1.718	0.840	0.009	3.048	1.775	0.278	0.176
14	1.463	6.286	0.335	0.001	0.520	0.064	2.644	2.697
15	0.028	0.593	0.377	4.257	0.084	0.002	0.003	1.881
16	0.093	0.012	3.151	2.704	1.938	0.250	0.137	0.235
17	5.535	0.003	1.304	1.573	0.280	1.129	0.200	0.231
18	0.001	2.549	0.630	0.016	0.149	0.003	0.610	0.104
19	3.469	0.960	0.121	0.018	0.279	0.027	0.045	1.202
20	0.004	2.510	0.076	0.770	0.719	5.286	0.697	0.020
21	1.433	1.998	0.091	0.534	0.534	1.563	1.916	1.232
22	2.128	1.959	0.227	1.816	0.183	0.030	0.982	1.271
23	0.776	0.104	0.624	0.044	0.635	0.250	1.914	0.409
24	0.001	0.368	0.258	0.044	0.185	0.140	0.010	5.596

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.
[a]The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{\varepsilon\xi}(0) = [\,\Sigma_t u_\xi\cdot w_\varepsilon/\surd(\,\Sigma_t u_\varepsilon^2\cdot\Sigma_t w_\xi^2\,)]$, is $1/\surd T$.

about them. The empirical findings, however, indicate a strong instantaneous causality between futures price and spot price, with the correlation coefficients ranging from 0.58 to 0.71.

The results are consistent with recent causality studies such as Kawaller, Koch, and Koch [1987], and Stoll and Whaley [1990]. Both studies use intraday data to examine the causality in the mean; their tests, unfortunately, are not robust to time-varying volatility. Furthermore, Kawaller, Koch, and Koch do not account for nonsynchronous trading in the investigation of the lead/lag relation between index spot and futures prices. Nonetheless, our results suggest that new information is impounded into prices with greater speed in the futures market than the stock markets, or that investors who have prior information for the purpose of trading or price speculation are more likely to transact in the futures market than the spot market since the costs of transacting in the former are lower.

Table 5b. Results of the cross-correlation test statistic of standardized residuals at each specific lag k for September 1984-June 1985 contracts

$$S_1^* = Tr_{\xi\varepsilon}(k)^2 = T[\Sigma_t \varepsilon_{t-k}\cdot\xi_t/\sqrt{(\Sigma_t\varepsilon_t^2 \cdot \Sigma_t\xi_t^2)}]^2$$

$$S_2^* = Tr_{\varepsilon\xi}(k)^2 = T[\Sigma_t\varepsilon_t\cdot\xi_{t-k}/\sqrt{(\Sigma_t\varepsilon_t^2 \cdot \Sigma_t\xi_t^2)}]^2$$

	Sep 1984		Dec 1984		Mar 1985		Jun 1985	
Lag	S_1^*	S_2^*	S_1^*	S_2^*	S_1^*	S_2^*	S_1^*	S_2^*
0[a]	0.605	0.605	0.630	0.630	0.659	0.659	0.584	0.584
1	181.956	0.001	152.865	1.684	83.198	1.705	115.657	0.452
2	0.771	1.859	0.402	0.247	0.117	0.286	0.338	0.492
3	7.566	0.118	1.622	2.368	5.181	2.330	9.307	5.520
4	0.176	6.168	0.797	0.100	4.303	0.864	1.603	1.990
5	0.047	0.711	2.901	0.170	0.924	1.314	6.527	0.474
6	0.137	0.464	0.427	0.011	0.225	0.054	0.097	0.640
7	2.582	1.275	0.374	0.363	0.174	0.001	0.291	0.681
8	0.002	1.361	0.326	0.261	0.214	0.031	0.062	0.534
9	0.165	0.093	0.536	0.433	0.018	1.696	0.406	0.089
10	5.562	2.016	0.181	0.026	1.743	6.164	0.657	0.009
11	2.110	1.291	0.161	0.162	0.000	1.456	0.094	1.232
12	0.465	3.061	1.386	0.474	0.042	0.888	3.540	2.581
13	3.743	1.158	0.230	0.136	1.203	0.002	0.988	0.131
14	0.136	4.328	0.264	0.208	1.997	2.188	0.065	0.922
15	0.173	0.262	0.375	4.081	0.166	0.059	1.212	0.220
16	0.020	1.738	0.074	0.084	4.021	0.102	2.600	0.578
17	2.131	1.887	0.622	0.138	0.133	1.966	0.614	0.019
18	0.072	0.383	0.909	5.427	0.176	0.003	1.837	0.004
19	0.549	0.085	1.694	0.874	0.890	5.678	0.564	0.039
20	5.971	0.338	0.630	0.021	0.686	1.830	0.262	0.957
21	0.246	0.003	1.381	0.002	0.043	4.106	0.498	1.562
22	0.103	0.140	0.760	0.038	0.331	0.222	0.568	3.270
23	0.006	0.008	3.107	0.848	0.062	1.262	0.005	3.262
24	0.487	0.004	0.536	1.907	1.363	1.715	0.002	0.003

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a] The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{\varepsilon\xi}(0) = [\Sigma_t u_\xi \cdot w_\varepsilon/\sqrt{(\Sigma_t u_\varepsilon^2 \cdot \Sigma_t w_\xi^2)}]$, is $1/\sqrt{T}$.

B. Results from Tests on the Causality in the Conditional Variance

In this subsection, we apply the test methodology, described in Section IV, in order to investigate the causal relationships between futures price volatility and spot price volatility. To ensure that the existence of causality in the conditional mean will not have any spillover effect on the causality in volatility across the markets, we cross-correlate the squares of the resulting standardized residuals from the filtered price series. The filtered series takes the form of [18]

$$f_t = \mu_f + \beta_f D_{ft} + s_t + \Sigma_j q_{fj} s_{t-j} + \varepsilon_t, \quad j=1,5 \tag{16}$$

$$s_t = \mu_s + \beta_s D_{st} + f_t + \Sigma_j g_{sj} f_{t-j} + \xi_t - \gamma\xi_{t-1}, \quad j=1,5, \tag{17}$$

[18] This number of lags is selected because the lead/lag relationship between the S&P 500 Index and S&P 500 futures price is usually not significant beyond five lags.

Table 5c. Results of the cross-correlation test statistic of standardized residuals at each specific lag k for September 1985-June 1986 contracts

$$S_1^* = Tr_{\xi\varepsilon}(k)^2 = T\,[\,\Sigma_t\,\varepsilon_{t-k}\cdot\xi_t/\sqrt{(\,\Sigma_t\varepsilon_t^2\cdot\Sigma_t\xi_t^2\,)}]^2$$

$$S_2^* = Tr_{\varepsilon\xi}(k)^2 = T\,[\,\Sigma_t\varepsilon_t\cdot\xi_{t-k}/\sqrt{(\,\Sigma_t\varepsilon_t^2\cdot\Sigma_t\xi_t^2\,)}]^2$$

	Sep 1985		Dec 1985[b]		Mar 1986		Jun 1986	
Lag	S_1^*	S_2^*	S_1^*	S_2^*	S_1^*	S_2^*	S_1^*	S_2^*
0[a]	0.616	0.616	0.615	0.615	0.630	0.630	0.641	0.641
1	117.520	1.127	70.339	2.038	106.262	0.087	132.312	0.427
2	11.742	0.653	4.581	0.953	0.800	0.808	2.757	0.086
3	2.178	0.025	6.219	0.081	5.374	0.383	0.142	0.094
4	2.266	0.863	0.208	0.547	0.400	0.031	1.719	1.959
5	1.930	1.174	0.062	0.144	5.384	0.189	7.200	1.617
6	9.389	1.721	1.227	0.148	0.001	0.028	2.876	1.873
7	0.310	0.112	0.175	0.741	3.040	0.001	2.919	0.500
8	2.888	0.159	1.406	0.028	5.272	0.001	0.000	0.008
9	0.115	0.751	0.016	0.031	0.828	0.882	0.372	0.029
10	0.121	0.016	0.352	0.116	0.313	0.286	0.644	0.061
11	0.620	0.031	0.568	0.743	0.288	0.008	0.040	0.401
12	0.308	4.024	0.029	0.196	0.239	0.466	2.296	0.007
13	6.461	0.037	0.811	0.916	0.160	0.207	1.867	0.253
14	0.259	0.415	0.060	0.682	0.679	0.047	0.048	0.011
15	0.181	0.193	3.058	5.416	0.959	0.150	0.547	0.003
16	0.384	0.772	1.945	0.036	0.388	0.437	0.140	0.989
17	1.865	0.139	0.019	0.051	1.144	1.760	1.661	4.945
18	0.422	1.992	0.681	0.390	0.348	0.017	0.002	1.051
19	0.067	2.853	0.780	0.240	0.081	0.057	0.618	1.229
20	1.041	0.297	0.189	5.054	2.999	0.264	2.247	0.241
21	1.942	0.029	0.036	0.046	0.265	1.388	1.421	1.988
22	0.067	0.000	0.004	5.313	3.292	4.455	0.586	2.339
23	0.494	4.105	2.490	0.066	1.949	0.186	0.163	0.293
24	0.062	0.678	0.843	0.114	0.421	0.127	0.569	1.086
25			0.228	0.131	0.949	0.162	0.250	0.359
26					2.596	1.483	1.412	1.150

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a] The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{\varepsilon\xi}(0) = [\,\Sigma_t u_\xi\cdot w_\varepsilon/\sqrt{(\,\Sigma_t u_\varepsilon^2\cdot\Sigma_t w_\xi^2\,)}]$, is $1/\sqrt{T}$.

[b] Since the change in trading hours occurred on October 1, 1985, we report the average number of lags in a day for this particular contract.

with their respective variance equations as specified in Section IV. Equations (16) and (17) differ from (5) and (6) in that the contemporaneous and lagged coefficients of the changes in the logarithm of cash (index futures) price now enter the conditional mean equation for the futures price (cash index). The contemporaneous coefficient accounts for the strong instantaneous causality between the two series. Diagnostic checks on the cross-correlations of standardized residuals from (16) and (17) are reported in Table 6. Notice that the magnitude of the contemporaneous cross-correlation coefficients (i.e., 0.002-0.096) has reduced dramatically, when compared to those given in Tables 5a-d. The results also provide no evidence against the null hypothesis that futures and spot prices are independent. We then proceed to

Table 5d. Results of the cross-correlation test statistic of standardized residuals at each specific lag k for September 1986-June 1987 contracts.

$$S_1{*} = Tr_{\xi\varepsilon}(k)^2 = T\,[\,\Sigma_t\, \varepsilon_{t-k}\cdot\xi_t/\surd(\,\Sigma_t\varepsilon_t^2\cdot\Sigma_t\xi_t^2\,)]^2$$

$$S_2{*} = Tr_{\varepsilon\xi}(k)^2 = T\,[\,\Sigma_t\varepsilon_t\cdot\xi_{t-k}/\surd(\,\Sigma_t\varepsilon_t^2\cdot\Sigma_t\xi_t^2\,)]^2$$

	Sep 1986		Dec 1986		Mar 1987		Jun 1987	
Lag	S_1*	S_2*	S_1*	S_2*	S_1*	S_2*	S_1*	S_2*
0[a]	0.655	0.655	0.638	0.638	0.658	0.658	0.709	0.709
1	114.627	0.505	158.983	0.099	106.357	0.001	117.515	0.189
2	0.814	0.984	11.066	3.694	0.006	0.081	1.344	4.547
3	9.662	0.015	3.034	1.220	7.926	3.077	0.707	0.048
4	1.552	0.179	1.453	0.347	0.412	0.000	2.840	2.975
5	1.901	5.211	0.022	0.395	0.726	1.745	0.736	1.113
6	2.701	0.175	0.319	0.006	0.141	0.022	0.323	0.538
7	4.246	0.113	0.093	0.857	1.250	0.002	0.001	0.075
8	0.181	0.033	0.162	0.644	0.731	0.102	0.016	0.006
9	7.726	4.569	0.026	0.096	0.166	0.135	2.547	0.425
10	1.253	0.053	2.326	0.801	0.629	0.282	1.752	0.116
11	0.113	0.124	2.442	1.192	3.047	3.543	0.529	1.119
12	1.160	1.075	3.235	0.184	0.032	0.422	0.080	4.158
13	0.887	1.054	2.607	0.476	1.258	0.002	0.494	0.286
14	0.008	0.462	0.331	4.058	0.189	0.720	0.010	0.796
15	2.395	0.685	0.019	3.893	0.720	0.450	0.038	1.084
16	4.160	0.645	2.362	4.232	0.902	2.658	0.268	0.663
17	0.070	1.280	0.438	0.271	0.003	0.164	0.691	0.818
18	0.642	0.134	0.294	0.550	1.705	0.000	2.549	0.303
19	1.168	0.818	0.166	0.958	0.010	0.030	0.408	2.019
20	2.097	2.127	1.090	0.393	3.413	1.670	0.023	9.364
21	3.609	0.246	0.706	3.307	3.132	0.808	6.072	3.197
22	0.027	0.380	0.425	0.001	0.064	1.006	0.088	1.989
23	2.344	0.998	1.510	0.078	0.431	4.895	0.075	0.110
24	0.372	1.046	0.191	0.133	0.357	0.157	2.456	1.642
25	0.010	0.010	1.904	2.660	0.083	0.109	0.490	0.029
26	1.115	1.595	0.046	2.978	1.048	0.128	0.017	0.077

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a]The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{\varepsilon\xi}(0) = [\,\Sigma_t u_\xi\cdot w_\varepsilon/\surd(\,\Sigma_t u_\varepsilon^2\cdot\Sigma_t w_\xi^2\,)]$, is $1/\surd T$.

examine whether there exists a lead/lag relationship between each pair of the series in the squared standardized innovations.

Tables 7a-d report the cross-correlation test statistics of the squares of standardized residuals up to the tenth lag since the coefficients of higher-order lags are not sigificant at the 5 percent level. Each cross-correlation test statistic at a specific lag is therefore computed as follows:

$$S = T\,r_{uw}(k)^2 = T\,[\,\Sigma_t u_t\cdot w_{t-k}/\surd(\Sigma_t u_t^2\cdot\Sigma w_t^2)]^2,$$

where $u_t = \varepsilon_t^2/h_{ft}$ and $w_t = \xi_t^2/h_{st}$. As shown in the tables, the null hypothesis of no feedback at the first 15-minute interval between futures price volatility and spot price volatility is rejected because futures price

Table 6. Diagnostic checks for the lead-lag relationship in the conditional means between the first differences in the logarithm of the S&P 500 futures and Index prices

Contract	Contemporaneous cross-correlation coefficient[a]	H_1: Spot prices do not cause futures prices[b]	H_2: Futures prices do not cause spot prices[b]
Sep 1983	0.026 (1.004)	23.692	18.729
Dec 1983	0.069 (2.662)*	10.358	9.420
Mar 1984	0.007 (0.277)	11.355	3.897
Jun 1984	0.096 (3.745)*	19.784	27.857
Sep 1984	0.034 (1.385)	15.860	29.44
Dec 1984	0.053 (2.051)*	25.087	27.761
Mar 1985	0.011 (0.405)	12.172	33.214
Jun 1985	0.077 (3.127)*	18.721	33.796
Sep 1985	0.027 (1.050)	16.948	22.861
Dec 1985	0.002 (0.085)	25.390	31.79
Mar 1986	0.030 (1.201)	23.852	13.097
Jun 1986	0.029 (1.194)	16.815	20.208
Sep 1986	0.057 (2.315)*	13.884	30.522
Dec 1986	0.070 (2.847)*	15.907	33.669
Mar 1987	0.029 (1.170)	32.395	27.443
Jun 1987	0.018 (0.727)	29.494	21.869

Note:
[a] *T*-statistics are in parentheses.
[b] All tests are performed at the 5 percent significance level. Each test statistic is chi-square with 23 degrees of freedom under the null hypothesis, for which the critical value is 35.172.
* Significant at the 5 percent level.

volatility does cause spot price volatility,[19] and vice versa. This is observed in 6 out of the 16 futures contracts examined; in 8 of the futures contracts, the results reveal that futures price volatility leads spot price volatility during the first 15 minutes of trading. However, there is no persistent lead-lag patterns detected in the June 1984 contract. Thus, the causal analysis indicates that futures price volatility and cash price volatility seem to move in unison, which is consistent with the market's informational efficiency. Given evidence in Section III that futures price volatility is greater than spot price volatility, this implies that it is more difficult to distinguish whether the volatility in the futures market is due to the volatility of information or the volatility induced by noise. Henceforth, it suggests that even though the index futures price tends to lead the cash price during the first 15 minutes of trading, market participants are unlikely to establish profitable trading rules by exploiting this information.

VII. Conclusions

This paper empirically examines the dynamics of the intraday price changes in the logarithm of S&P 500 Index and S&P 500 futures prices, with the conditional variance assumed to follow a generalized ARCH process. The results indicate that the intraday price volatility in the S&P 500 futures and spot markets are time-varying, and that the futures market is more volatile than the stock markets. The magnitude of the variability is relatively high

[19] As noted by Pierce and Haugh [1979], the contemporaneous cross-correlation coefficients cannot be used as a condition for instantaneous causality if there is feedback between the pair of time-series variables.

early in the day and late in the day compared to the middle of the trading day. These results have implications for the mispricing in these futures and the choice of a model to price these futures.

We also test the informational role of futures market by investigating the cross-correlation in price changes and volatility across the futures market and stock markets. Unlike previous causality studies, our analysis takes into account the bias caused by nonsynchronous prices in the observed cash index, and also, our tests are robust to changing volatility. The results show that although futures prices consistently lead spot prices for at least 15 minutes, and extend to 30 minutes in some contracts, the evidence is weak for spot prices to have some predictive ability to anticipate movements in the futures price. While there is evidence of the direction of causality running from futures price volatility to cash price volatility during the first 15 minutes of trading, there also exists feedback between the two series in some contracts. Given these results and the evidence that the index futures market is more volatile than the spot market, it is not clear that traders could earn arbitrage profits by exploiting the information on the cross-correlations in the levels and squares of standardized residuals.

Table 7a. Results of the cross-correlation test statistic of the squares of standardized residuals at each specific lag *k* for September 1983-June 1984 contracts

$$S_1 = Tr_{wu}(k)^2 = T\,[\,\Sigma_t w_t \cdot u_{t-k} / \surd(\,\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

$$S_2 = Tr_{uw}(k)^2 = T\,[\,\Sigma_t u_t \cdot w_{t-k} / \surd(\,\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

	Sep 1983		Dec 1983		Mar 1984		Jun 1984	
Lag	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
0[a]	0.141	0.141	0.069	0.069	0.052	0.052	0.484	0.484
1	14.490	0.036	17.533	0.701	7.392	0.241	0.088	1.503
2	4.990	0.500	0.012	0.050	0.267	1.397	0.190	0.477
3	3.858	0.429	0.478	0.478	1.418	0.470	0.213	0.181
4	1.211	2.783	4.536	0.011	0.001	0.124	0.145	0.145
5	1.226	2.317	0.388	0.145	0.340	0.011	0.552	0.001
6	2.950	1.552	0.409	3.684	0.000	0.055	0.053	0.027
7	2.169	0.181	0.901	0.781	1.366	0.826	0.172	0.050
8	1.456	0.145	0.000	0.681	0.143	0.194	0.807	0.061
9	1.512	0.160	7.655	0.034	0.269	0.182	0.044	0.008
10	0.903	0.022	0.173	0.742	2.347	0.889	0.215	0.121

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a]The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{uw}(0) = [\,\Sigma_t u_t \cdot w_t / \surd(\,\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]$, is $1/\surd T$.

Table 7b. Results of the cross-correlation test statistic of the squares of standardized residuals at each specific lag *k* for September 1984-June 1985 contracts

$$S_1 = Tr_{wu}(k)^2 = T\,[\,\Sigma_t w_t \cdot u_{t-k} / \surd(\,\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

$$S_2 = Tr_{uw}(k)^2 = T[\,\Sigma_t u_t \cdot w_{t-k} / \surd(\,\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

	Sep 1984		Dec 1984		Mar 1985		Jun 1985	
Lag	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
0[a]	0.280	0.280	0.184	0.184	0.218	0.218	0.311	0.311
1	11.300	2.759	23.000	4.616	23.190	6.986	7.816	0.228
2	0.037	0.096	3.520	0.051	1.129	0.020	0.257	0.229
3	0.463	1.372	2.485	1.554	0.059	11.970	0.046	3.169
4	1.964	0.267	7.200	2.152	2.309	3.083	1.239	1.362
5	9.335	0.021	0.011	0.886	5.307	0.088	0.951	1.160
6	2.939	0.176	0.005	0.005	1.330	0.148	1.060	1.423
7	0.005	0.227	0.627	0.109	0.469	0.035	0.023	1.217
8	0.001	0.004	0.201	1.184	1.609	0.110	0.136	0.419
9	0.638	0.050	0.923	0.024	0.001	0.342	0.057	0.086
10	0.015	0.077	0.008	2.810	3.910	0.156	0.533	0.058

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a]The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{uw}(0) = [\,\Sigma_t u_t \cdot w_t / \surd(\,\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]$, is $1/\surd T$.

Table 7c. Results of the cross-correlation test statistic of the squares of standardized residuals at each specific lag k for September 1985-June 1986 contracts

$$S_1 = Tr_{wu}(k)^2 = T[\Sigma_t w_t \cdot u_{t-k} / \surd(\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

$$S_2 = Tr_{uw}(k)^2 = T[\Sigma_t u_t \cdot w_{t-k} / \surd(\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

	Sep 1985		Dec 1985		Mar 1986		Jun 1986	
Lag	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
0[a]	0.110	0.110	0.154	0.154	0.178	0.178	0.084	0.084
1	34.812	11.221	22.445	0.078	11.732	0.155	5.483	39.318
2	1.509	0.200	0.218	0.218	0.037	2.381	0.097	1.852
3	5.086	0.132	2.089	0.208	1.199	2.169	0.245	0.639
4	0.364	0.213	17.596	4.168	0.022	1.867	0.671	0.355
5	2.758	0.269	0.295	3.960	0.064	4.380	0.583	9.335
6	0.409	0.290	1.350	0.448	0.496	0.210	0.610	2.223
7	0.039	0.518	6.412	0.230	0.623	0.170	0.120	0.001
8	1.380	5.520	0.000	0.018	0.055	1.969	0.041	0.163
9	0.015	0.009	0.595	0.026	0.017	0.465	1.312	0.027
10	0.794	1.556	1.249	1.249	1.016	0.571	1.306	6.451

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a] The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{uw}(0) = [\Sigma_t u_t \cdot w_t / \surd(\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]$, is $1/\surd T$.

Table 7d. Results of the cross-correlation test statistic of the squares of standardized residuals at each specific lag k for September 1986-June 1987 contracts

$$S_1 = Tr_{wu}(k)^2 = T[\Sigma_t w_t \cdot u_{t-k} / \surd(\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

$$S_2 = Tr_{uw}(k)^2 = T[\Sigma_t u_t \cdot w_{t-k} / \surd(\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]^2$$

	Sep 1986		Dec 1986		Mar 1987		Jun 1987	
Lag	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
0[a]	0.099	0.099	0.241	0.241	0.142	0.142	0.155	0.155
1	43.925	2.396	17.978	13.542	4.354	0.056	60.766	33.494
2	0.006	0.038	8.640	0.960	0.214	1.720	13.148	6.287
3	0.013	12.532	0.072	0.094	1.848	153.415	2.282	2.761
4	0.355	0.937	0.317	0.001	0.012	1.485	9.624	0.307
5	0.224	0.529	0.774	0.034	0.064	0.333	6.020	5.168
6	0.247	0.213	0.012	5.080	0.124	0.000	0.904	0.210
7	1.007	0.346	7.589	2.044	1.443	1.527	0.029	0.199
8	0.192	1.814	0.779	0.195	0.055	0.362	0.135	2.063
9	0.387	1.029	0.314	0.480	0.038	4.591	2.041	6.249
10	0.327	0.848	1.479	0.332	0.168	0.778	0.016	0.168

Note: Each test statistic is chi-square with one degree of freedom under the null hypothesis, for which the critical value is 3.84.

[a] The asymptotic standard error for the cross-correlation at lag zero, calculated as $S = r_{uw}(0) = [\Sigma_t u_t \cdot w_t / \surd(\Sigma_t u_t^2 \cdot \Sigma_t w_t^2)]$, is $1/\surd T$.

References

Bollerslev, T., 1986, "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics* 31, 307-27.

______, 1987, "A Conditionally Heteroskedastic Time Series Model for Security Prices and Rates of Returns," *The Review of Economics and Statistics* LXIX, 542-46.

______, R. Engle, and J. Wooldridge, 1988, "A Capital Asset Pricing Model with Time Varying Covariances," *Journal of Political Economy* 96, 116-31.

Box, G.E.P., and G. Jenkins, 1970, *Time Series, Forecasting and Control,* San Francisco: Holden Day.

Cheung, Y., and L. Ng, 1989, "Tests for Causality in Variance," Working Paper, The University of Texas at Austin.

Engle, R., 1982, "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of UK Inflation," *Econometrica* 50, 987-1008.

______, T. Ito, and W. Lin, 1988, "Meteor Showers or Heat Waves? Heteroskedastic Intra-daily Volatility in the Foreign Exchange Market," Working Paper, University of California, San Diego.

Edwards, F., 1988, "Futures Trading and Cash Market Volatility: Stock Index and Interest Rate Futures," *The Journal of Futures Markets* 8, 421-39.

Fama, E., 1965, "The Behavior of Stock Market Prices," *Journal of Business* 38, 34-105.

Figlewski, S., 1984, "Hedging Performance and Basis Risk in Stock Index Futures," *Journal of Finance* 39, 657-69.

Fisher, L., 1966, "Some New Stock Market Indices," *Journal of Business* 29, 191-225.

French, K., and R. Roll, 1986, "Stock Return Variances—The Arrival of Information and the Reaction of Traders," *Journal of Financial Economics* 17, 5-26.

French, K., G. Schwert, and R. Stambaugh, 1987, "Expected Stock Returns and Volatility," *Journal of Financial Economics* 19, 3-30.

Granger, C.W.J., 1969, "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica* 37, 424-38.

______, 1980, "Testing for Causality: A Personal Viewpoint," *Journal of Economic Dynamics and Control* 2, 329-52.

______, and P. Newbold, 1977, *Forecasting Economic Time Series,* Academic Press, New York.

Granger, C.W.J., R. Robins, and R. Engle, 1986, "Wholesale and Retail Prices: Bivariate Time-series Modeling with Forecastable Error Variances," in *Model Reliability*, ed. D.A. Belsley and E. Kuh, Cambridge, MA: MIT Press.

Harris, L., 1986 "A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns," *Journal of Financial Economics* 16, 99-117.

Haugh, L., 1976, "Checking the Independence of Two Covariance Stationary Time Series: A Univariate Residual Cross-Correlation Approach," *Journal of the American Statistical Association* 76, 378-85.

Herbst, A., J. McCormack, and E. West, 1987, "Investigation of a Lead-Lag Relationship between Spot Stock Indices and Their Futures Contracts," *The Journal of Futures Markets* 7, 373-81.

Jordan, J., W. Seale, S. Dinehart, and D. Kenyon, 1988, "The Intraday Variability of Soybean Futures Prices: Information and Trading Effects," *Review of Futures Markets* 7, 97-108.

Kawaller, I., P. Koch, and T. Koch, 1987, "The Temporal Relationship between S&P 500 Futures Prices and the S&P 500 Index," *Journal of Finance* 42, 1309-29.

Laatsch, F., and T. Schwarz, 1989, "Price Discovery and Risk Transfer in Stock Index Cash and Futures Markets," *Review of Futures Markets* 7, 273-89.

Ljung, G., and G.E.P. Box, 1978, "On a Measure of Lack of Fit in Time-Series Models," *Biometrika* 65, 297-303.

MacKinlay, C., and K. Ramaswamy, 1988, "Program Trading and the Behavior of Stock Index Futures Prices," *The Review of Financial Studies* 1, 137-58.

Mandelbrot, B., 1963, "The Variation of Certain Speculative Prices," *Journal of Business* 36, 394-419.

McCurdy T., and I. Morgan, 1987, "Tests of the Martingale Hypothesis for Foreign Currency Futures with Time-Varying Volatility," *International Journal of Forecasting* 3, 131-48.

McLeod, A., and W. Li, 1983, "Diagnostic Checking ARMA Time Series Models Using Squared-Residual Autocorrelations," *Journal of Time Series Analysis* 4, 269-74.

Merton, R., 1980, "On Estimating the Expected Return on the Market: An Exploratory Investigation," *Journal of Financial Economics* 8, 323-61.

Milhoj, A., 1985, "The Moment Structure of Arch Processes," *Scandinavian Journal of Statistics* 12, 281-92.

Ng, L., 1990, "Tests of the CAPM with Time-Varying Covariances: A Multivariate GARCH Approach," Working Paper, The University of Texas at Austin.

Ng, N., 1987, "Detecting Spot Price Forecasts in Futures Prices Using Causality Tests," *The Review of Futures Markets* 6, 250-67.

Pierce, D., 1977, "Relationships—and Lack Thereof—Between Economic Time Series, with Special Reference to Money and Interest Rates," *Journal of the American Statistical Association* 72, 11-22.

———, and L. Haugh, 1977, "Causality in Temporal Systems Characterizations and a Survey," *Journal of Econometrics* 5, 265-93.

———, 1979, "The Characterization of Instantaneous Causality: A Correction," *Journal of Econometrics* 10, 257-59.

Scholes, M., and J. Williams, 1977, "Estimating Betas from Non-Synchronous Data," *Journal of Financial Economics* 5, 309-27.

Stoll, H., and R. Whaley, 1990, "The Dynamics of Stock Index and Stock Index Futures Returns," Working Paper, The Fuqua School of Business, Duke University.

Wood, R., T. McInish, and J.K. Ord, 1985, "An Investigation of Transaction Data for NYSE," *Journal of Finance* 40, 723-41.

Zeckhauser, R., and V. Niederhoffer, 1983, "The Performance of Market Index Futures Contracts," *Financial Analysts Journal*, 59-65.

Zellner, A., 1979, *Causality and Econometrics,* Carnegie-Rochester Conference Series 10, eds. K. Brunner and A.H. Meltxer, Amsterdam: North Holland, 9-54.