Linear and Nonlinear Granger Causality: Evidence from the U.K. Stock Index Futures Market

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INTRODUCTION

An important economic function of futures markets is to facilitate the process of price discovery. Empirical research has therefore been directed toward examining various aspects of the relationship between the futures and underlying asset prices. For example, the lead–lag relationship between the stock index futures returns and underlying index has received considerable attention. In theory, since both the stock index futures contract and the cash index reflect the same aggregate value of the underlying stocks and if instantaneous arbitrage is possible, index futures should neither lead nor lag cash index. Empirical research, based on linear Granger causality tests, however, suggests that the futures market generally leads the cash market with little or no feedback in the reverse direction. Another important aspect of the index futures-cash market re-

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lationship is the effect of arbitrageurs on the time path of prices in the two markets. For example, Dwyer, Locke, and Yu (1996) find strong support for a cost-of-carry model incorporating nonlinear entry costs for groups of index arbitrageurs. The main purpose of this article is to tie together these two strands of research and explore further the nature of the nonlinear causal relationship between the index futures and the cash markets.[1] This is important as it would provide additional evidence on the usefulness of models incorporating trading costs which have practical relevance for index arbitrage trading strategies.

This article contributes to the literature in two ways. First, it provides new evidence on the lead–lag relationship in the Financial Times-Stock Exchange (FT-SE) 100 index futures market using high frequency data. The results, consistent with prior work (e.g., Stoll and Whaley, 1990) based on traditional causality tests, suggest that the FT-SE 100 index futures returns tend to lead the cash index returns by about 5–15 minutes during the sample period studied. In addition, even after accounting for volatility persistence using autoregressive conditional heteroskedasticity (ARCH) filtered returns, the linear causality is unidirectional from the futures to the cash. Second, using a nonlinear causality test, based on the correlation integral, strong evidence of a bidirectional nonlinear causal relationship between the futures and cash market returns is seen. The results, in sharp contrast to those from the linear causality tests, are consistent with the possibility that a linear test captures only part of the dynamics between index futures and cash market. In addition, even after accounting for volatility persistence, there is still strong evidence of bidirectional nonlinear causality between returns from the two markets.

This article is organized as follows. The following section provides a brief review of previous empirical research in this area and the methodology used. Then the data set is described and the empirical results are outlined. Finally, conclusions are presented.

REVIEW OF PREVIOUS WORK

There is a substantial body of work on linear lead–lag relationships in the stock index futures market. A selective summary of previous research is provided in Table I. The conclusion from this work, common across many national stock index futures markets, is that the index futures returns generally lead the stock index returns with little on no feedback from the cash to the futures market. For example, in early work on the S&P 500

[1]See Brock (1991) for a survey.

TABLE I

Summary of Selected Previous Research

Author and Year	*Data Set Used*	*Results*
Fleming et al. (1996)	S&P 500 index futures and cash. S&P 100 index, and S&P 100 index options–minute returns—JAN88 to MAR91	S&P 500 index futures lead the cash by just over five minutes with no evidence of feedback. S&P index options lead cash index by about five minutes
Chung et al. (1994)	NSA futures and cash—five-minute returns—SEPT88 to SEPT91	Futures lead the cash, but some evidence of feedback; relationship affected by trading activity in the stock market, but not related to short sale constraints
Grunbichler et al. (1994)	DAX index futures and cash—minute returns—NOV90 to SEPT91	Futures lead cash by 15–20 minutes
Chan (1992)	S&P 500 index futures, MMI[a] index futures, and MMI index and component stocks—five minute returns—AUG84 to JUNE85 and JAN87 to SEPT87	Futures lead the cash and weak evidence of cash index leading the futures; futures lead during periods of market-wide information
Chan, Chan, and Karolyi (1991)	S&P index futures and cash index and MMI index futures and cash—five minute returns—AUG84 to DEC89	Intraday pattern of lead–lag examined using a bivariate GARCH model shows strong intramarket dependence and persistence in volatility of returns
Cheung and Ng (1990)	S&P 500 index futures and cash index—15-minute returns—APR82 to JUNE87	Futures lead cash consistently for at least 15 minutes with weaker evidence of cash leading the futures
Stoll and Whaley (1990)	S&P 500 index futures, MMI index futures, and cash indices	Futures tend to lead the cash by five minutes; effect not completely unidirectional with mild positive feedback from the cash to the futures
Kawaller et al. (1988)	S&P 500 index futures and cash index—one-minute returns—1984–1985	Futures lead cash by up to 45 minutes, but index futures trail behind only briefly; relationship robust to expiration days
Herbst, McCormack, and West (1987)	S&P 500 index futures and cash and value line index future and cash–FEB82 to SEPT82 to SEPT91	Futures lead cash, but some evidence of feedback, relationship affected by trading activity in the stock market, but not related to short sale constraints

[a]MMI = Major Market Index.

index futures market, Kawaller, Koch, and Koch (1988) report that the S&P 500 index futures lead the cash index by about 45 minutes. Subsequent research by Stoll and Whaley (1990) suggests that the S&P 500 index futures lead the cash by about 15–20 minutes. They also find weak evidence of feedback from the futures to the cash market. Fleming, Ostdiek, and Whaley (1996), using more recent data, however, find that the contemporaneous relationship between the S&P 500 index futures and the S&P 500 index has grown stronger over time and the feedback from the futures to the cash market has almost disappeared. They suggest that this is a sign of increased integration between the index futures and the equity market. Chung, Kang, and Rhee (1994) study the lead–lag relationship between the Nikkei Stock Average (NSA) index futures on the Osaka Stock Exchange and the underlying NSA equity index of the Tokyo Stock Exchange. They find that the futures market lead is not as dominant as in the U.S. market and that while NSA futures prices typically lead the NSA index, the cash index also has some predictive ability for futures prices. They ascribe the differences from results for the U.S. market to the specific microstructural features of the Japanese futures and equity markets. Grunbichler, Longstaff, and Schwartz (1994), who study the German index futures market, report that the Deutsche Aktien Index (DAX) index futures returns lead the cash by 15–20 minutes.

A variety of factors have been put forward to explain the linear lead–lag relationship noted in the index futures and cash index returns. For example, it has been suggested that the existence of transactions costs,[2] capital requirements, and short-selling restrictions may make it optimal for some to trade in the futures market rather than the cash market. Also, as Grossman and Miller (1988) and Miller (1990) show, futures markets may provide more immediacy than the spot market. This implies that informed traders may find that they can act faster and at lower cost in the futures market than the cash, resulting in a lead–lag relationship between futures and spot prices. It also has been suggested (see Subrahmanyam, 1991; Chan, 1992) that the adverse selection costs faced by discretionary liquidity traders (i.e., liquidity traders who can choose the timing of their transactions strategically, such as large institutional traders) may be minimized by trading in the futures market rather than the spot market. This result, in the context of the Kyle (1985) and Admati and Pfleiderer (1988) models in which informed traders use the cam-

[2]In the FT-SE 100 index futures and cash markets, e.g., the comparative round-trip costs for the FT-SE 100 stock index are about 47.7 index point equivalents, while those for the index futures are 1.8 index points. These figures are based on estimates reported in the FT-SE 100 Index Futures Review, London International Financial Futures and Options Exchange (LIFFE), 2nd Quarter (1994).

ouflage provided by liquidity traders, also supports the view that informed traders may choose the futures market rather than the spot. This again implies that the transmission of information may be from the futures market to the cash market.

It also has been suggested by Grunbichler et al. (1994) that differences in liquidity between the two markets could also create a lead–lag relationship. They point out that if the average time between trades for index constituent firms is longer than that for the index futures contract, information will be incorporated, on average, more rapidly in futures prices than cash prices. Finally, Fleming et al. (1996) find that there are differential trading costs between the equity, index futures, and index options markets; in other words, the market with the lowest trading costs will react most quickly to the arrival of new information.

Recent research has also documented increasing empirical evidence of nonlinear dynamics between the futures and cash markets as well as nonlinear dependence in the individual return series of both markets. Dwyer et al. (1996), e.g., use a cost-of-carry model with nonzero transactions costs to motivate a nonlinear dynamic relationship in the S&P 500 index futures and cash basis. Their results indicate that nonlinear dynamics are important between the two markets and are related to the activities of arbitrageurs in the index futures market. Kodres and Papell (1991) also find evidence of nonlinear structure in foreign exchange futures prices which cannot be fully accounted for by the existence of daily price limits. Evidence of nonlinearity in the FT-SE 100 index futures and cash returns, using data at various frequencies from one minute to an hour, is observed in Abhyankar, Copeland, and Wong (1997). Given this overwhelming evidence of nonlinear structure between the futures and cash index returns as well as in the individual processes generating the returns, it would be of great interest to examine whether there are any nonlinear Granger causal effects between returns in the two markets using a test developed by Baek and Brock (1992a,b) to detect nonlinear Granger causality between two time series. This test is based on the correlation integral and is applied to the residuals from traditional linear causality tests in order to detect any remaining nonlinear predictive ability of one time series for another. The Baek and Brock test has been extended in Hiemstra and Jones (1994) to data showing weak dependence and applied to stock price returns and volume. It is felt that this modified Baek and Brock test would be able to provide additional insight about the appropriateness of a cost-of-carry model, incorporating transaction cost thresholds for arbitrage activity, as a realistic model of index arbitrage trading.

METHODOLOGY

This section provides brief details of the traditional linear Granger causality tests as well as of the modified Baek and Brock test. In the prior empirical work on lead–lag relationships in the stock index futures market, cited in Table I, various versions of the well-known linear tests for bivariate Granger causality have been used.[3] Here, following Fleming et al. (1996), linear causality between the index futures and the cash index returns is examined by estimating the following multivariate regression:

$$R_{c,t} = \alpha + \sum_{k=-6}^{k=+6} \beta_k R_{f,t-k} + \beta_z z_{t-1} + \varepsilon_t \tag{1}$$

where $R_{c,t}$ are the returns and $R_{f,t}$ are the index futures returns. In this regression, if the lag coefficients β_{-k} ($k = 1.6$) are significant, the futures returns lead the cash index returns; if the lead coefficients β_{+k} ($k = 1.6$) are significant, the cash index returns lead the index futures. It may be noted that eq. (1) also contains an error correction term, z_{t-1}; the first lag of the contemporaneous difference between the cash-futures price levels to account for the possibility that the futures and cash return series may be cointegrated.[4] The test statistics for the null hypothesis that the β coefficients are individually zero are calculated based on covariance matrix estimates using the Hansen (1982) generalized method of moments (GMM) approach. In addition, the null hypothesis that the lead/lag coefficients $\beta_{\pm k}$ are jointly zero is tested using a χ^2 test also based on the GMM variance matrix estimator.[5] If either of the return series shows evidence of any significant autocorrelation, then tests based on eq. (1) using the raw return series are likely to lead to spurious results regarding the direction of the causal effect. To mitigate this problem the return series is first filtered using an Autoregressive Moving Average (ARMA) specification following Stoll and Whaley (1990). The multivariate regression in eq. (1) is then run using the return innovation series as the dependent variable as follows:

$$AR_{c,t} = \alpha + \sum_{k=-6}^{k=+6} \beta_k R_{f,t-k} + \beta_z z_{t-1} + \varepsilon_t \tag{2}$$

where $AR_{c,t}$ is the relevant return innovation series.

[3]These include those suggested in Granger (1969), Sims (1972), and Pierce and Haugh (1977).

[4]If the futures and the cash series are cointegrated [in the sense of Engle and Granger (1987)], then by the Granger representation theorem, an error correction representation exists. Hamilton (1994) provides details.

[5]The GMM covariance matrix is a consistent estimator in the presence of serial correlation and heteroskedasticity of an unknown form.

The linear approach to causality testing, described above, can have low power detecting certain kinds of nonlinear causal relationships as shown in Brock (1991). Baek and Brock (1992a,b) therefore propose a nonparametric statistical method for detecting nonlinear causal relationships. Their approach uses the correlation integral, an estimator of spatial dependence across time, to detect relations between time series and to provide a statistical tool for uncovering unidirectional causal orderings between two, possibly nonlinearly related, variables. A brief description, drawing heavily on Hiemstra and Jones (1994), follows. Let $\{X_t\}$ and $\{Y_t\}$, $t = 1,2,\ldots$ be two strictly stationary and weakly dependent scalar time series. Let the m-length lead vector of X_t be denoted by X_t^m and the Lx-length lagged vector of X_t by $X_{t-Lx}^{Lx} = (X_{t-Lx}, X_{t-Lx+1}, \ldots, X_{t-1}$ and an Ly-length lagged vector of Y_t by $Y_{t-Ly}^{Ly} = (Y_{t-Ly}, Y_{t-Ly+1}, \ldots, Y_{t-1}$. Then, for given values of m, Lx and $Ly \geq 1$ and for some $e > 0$, Y is said not to strictly Granger cause X if

$$\begin{aligned} &\Pr(\|X_t^m - X_s^m\| < e \mid \|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < e) \\ &= Pr(\|X_t^m - X_s^m\| < e \mid \|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e) \end{aligned} \tag{3}$$

where $Pr(\cdot)$ denotes probability and $\|\cdot\|$ maximum norm.[6] A test based on eq. (3) can be implemented by writing it in terms of the corresponding ratios of joint probabilities:

$$\frac{c1(m + Lx, Ly, e)}{C2(Lx, Ly, e)} = \frac{C3(m + Lx, e)}{C4(Lx, e)} \tag{4}$$

where these are defined as follows:

$$\begin{aligned} C1(m + Lx, Ly, e) &\equiv Pr(\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\| \langle e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| \langle e) \\ C2(Lx, Ly, e) &\equiv Pr(\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| \langle e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| \langle e) \\ C3(m + Lx, e) &\equiv Pr(\|X_{t-Lx}^{m+Lx} - X_s^{m+Lx} - Lx\| \langle e) \\ C4(Lx, e) &\equiv Pr(\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| \langle e \end{aligned} \tag{5}$$

The strict Granger noncausality condition in eq. (3) can now be tested using correlation integral-based estimators[7] of the Ci ($i = 1, 2, 3,$ and 4) in eq. (5). These are defined as follows:

[6] $\|x\|$ denotes the maximum norm of x.

[7] Detailed derivations of the test statistic are presented in Hiemstra and Jones (1994).

$$C1(m + Lx, Ly, e, n) \equiv \frac{2}{n(n-1)} \sum_{t<s} \sum I(x_{t-Lx}^{m+Lx}, x_{s-Lx}^{m+Lx}, e) I(y_{t-Ly}^{Lx}, y_{s-Ly}^{Lx}, e)$$

$$C2(Lx, Ly, e, n) = \frac{2}{n(n-1)} \sum_{t<s} \sum I(x_{t-Lx}^{Lx}, x_{s-Lx}^{Lx}, e) I(y_{t-Ly}^{Ly}, y_{s-Ly}^{Lx}, e)$$

$$C3(m + Lx, e, n) = \frac{2}{n(n-1)} \sum_{t<s} \sum I(x_{t-Lx}^{m+Lx}, x_{s-Lx}^{m+Ly}, e,$$

$$C4(Lx, n, e) = \frac{2}{n(n-1)} \sum_{t<s} \sum I(x_{t-Lx}^{m+Lx}, x_{s-Lx}^{m+Lx}, e)$$

$$t, s = \max(Lx, Ly) + 1, \ldots, T - m + 1,$$

$$n = T + 1 - m - \max(Lx, Ly) \tag{6}$$

where $I(\cdot)$ denotes a kernel which is equal to 1 when the two conformable vectors are within the max-norm distance e of each other and 0 otherwise. Hiemstra and Jones (1994) further show that, for given values of m, Lx, and $Ly \geq 1$ and $e > 0$, and the assumptions in Denker and Keller (1983), if Y does not strictly Granger cause X then:

$$\sqrt{n}\left[\frac{C1(m, Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} - \frac{C3(m, Lx, e, n)}{C4(Lx, e, n)}\right] \overset{asy}{\rightarrow} N\left(0, \sigma^2(m, Lx, Ly, e)\right) \tag{7}$$

In eq. (7), $\sigma^2(m, Lx, Ly, e)$ is calculated using the estimator derived in Hiemstra and Jones (1994) which allows for errors to be weakly dependent.

The intuition underlying the Baek and Brock test for nonlinear Granger causality is as follows. The expression in eq. (3) is a generalization of the traditional linear Granger causality definition; Y_t does not strictly Granger cause X_t if

$$Pr(X_t|I_t) = Pr(X_t|(I_t - Y_{t-Ly}^{Ly})), \ldots t = 1,2, \ldots$$

In other words, knowledge of past values of Y does not help linearly predict current and future values of X. The Baek and Brock approach tests for strict Granger causality from Y to X by examining whether the conditional probability that two arbitrary m-length vectors are "close," given that the corresponding Lx-length lag vectors are close, is influenced by conditioning X on the corresponding Ly-length lag vector of Y. In other words, it tests whether lagged Y has predictive power for current of future X. In practice, eq. (3) is implemented using the correlation integral, which is essentially a spatial measure of the "closeness" of two vectors to each other, i.e., it "counts" the number of occurrences where the two vectors are within some specified distance of each other.

DATA DESCRIPTION

The primary data[8] used in this study consist of intraday price histories for four FT-SE 100 index futures contracts maturing in MAR92, JUNE92, SEPT92, and DEC92 and the FT-SE 100 index recorded minute-by-minute during 1992. The FT-SE 100 index futures transactions data (unlike S&P 500 "Time and Sales" data) consist of all trade prices as well as all recorded bid–ask quotes. The FT-SE 100 equity index is a market-value weighted index of the top 100 companies (on the basis of market capitalization) quoted on the London Stock Exchange. The London Stock Exchange is a competitive dealership market, and market makers in a security are obliged to quote two-way prices valid for an exchange-determined trade size. The FT-SE 100 index is computed every minute using a price for each constituent stock based on the midpoint of the "inside" spread on each stock.

The index futures and cash price series described above are not synchronous. Since the objective of this article is to explore the lead–lag relationship between prices in the two markets, it is crucial to define and compare returns over a standardized period of time. In this study, a five-minute interval is chosen for two reasons. First, this would facilitate comparison of the results for the FT-SE 100 index futures market with those of prior research on the S&P 500, Nikkei, and DAX index futures markets. Second, a five-minute interval is adequate to detect any lead–lags which may be of practical relevance for index arbitrageurs in completing both "legs" of an actual index arbitrage transaction as described in Sofianos (1993). In creating a matched futures-cash price series, two approaches are possible. The first consists of matching the equally spaced cash index level with an index futures transaction price which is coincident in time or the "first past" that time. An alternate[9] way is to choose the last transaction price before the time that an index price is recorded. In this article,

[8]The FT-SE 100 index futures data are obtained from the London International Financial Futures and Options Exchange (LIFFE) and on the underlying index from the London Stock Exchange.
[9]Both methods are used to extract the index futures and index series from the raw data; the results are not materially different using the second method.

the futures transaction price which is "first-price" past the cash index time-stamp is used and thus any bias is in favor of the cash index. Also, in the case of the FT-SE 100 contracts, an observation is regarded as missing if in the case of the cash index there is no index level recorded or if in the case of the index futures the trade price is not available within a 30-second interval after the index time-stamp. In the data set used in this article, the futures price sampled as above lies, on average, within about 20 seconds of the time-stamp of the cash index.

The FT-SE 100 index futures market opens at 8:35 AM and closes at 4:10 PM, while the London Stock Exchange opens at 8:30 AM and closes at 16:30 PM. The matched cash-futures series for the FT-SE 100 starts at 8:35 PM in a five-minute grid till 16:10 PM. Following earlier research, prices (and returns) prior to 8:35 AM in the case of the FT-SE 100 are ignored for two reasons. First, overnight returns are not used as these are calculated over a different time interval, and second, ignoring the first five minutes of trading may mitigate to some extent the stale price problem associated with the cash index.

The index futures price series from the nearest contract, which has the highest volume, is used in each contract period. For example, the MAR92 contract period consists of a matched cash-futures price from the date of maturity of the DEC91 contract till the day when the daily trading volume is higher for the JUNE92 (or the next-to-nearest) contract.[10] Based on the matched futures-cash price series, log returns for the index futures contract and the index are used. This procedure gives a maximum of 91 intraday returns for both the FT-SE 100 index futures and the FT-SE 100 index, respectively. Finally, since there are about 4500 observations for each of the four contracts traded during 1992, the lead–lag effect is examined for each contract separately without the need for splicing together the near and next-to-near contract series as is usually done in the literature.

EMPIRICAL RESULTS

Descriptive Statistics

The results of the preliminary analysis of the data are described first. It is seen that the FT-SE 100 index futures returns are not significantly correlated at any lag. This is similar to reported autocorrelation in S&P 500 index futures returns in many studies (e.g., see Chan, 1992) but differs from the Japanese NSA index futures series, which shows auto-

[10]This also mitigates any possible problems associated with expiration day effects.

correlation at some lags as reported by Chung et al. (1994). On the other hand, the FT-SE 100 cash index series exhibits high positive autocorrelation at the first lag in each period with statistically significant positive autocorrelations up to lags 6 during some futures contract periods. The presence of autocorrelation in the cash index returns could lead to spurious conclusions in traditional linear causality tests if not accounted for properly.

The empirical results based on both the traditional linear and nonlinear causality tests are now described. First, the results of the traditional tests for Granger causality tests on raw, ARMA filtered, and exponential generalized autoregressive conditional heteroskedasticity (EGARCH) filtered returns are reported. Next, follow the results of applying the nonparametric Baek and Brock test, to detect any remaining nonlinear Granger causality, on the residuals from the linear causality tests.

Results Based on Traditional Causality Tests

Raw, ARMA, and EGARCH Filtered Returns

Traditional Granger causality tests based on multivariate regressions such as those in eq. (1) usually use the raw return series whose causal relationship is being tested. There is, however, an important issue in tests for lead–lag relationships between the stock index futures and cash markets: the presence of significant autocorrelation in the cash index return series. This autocorrelation is induced due to market microstructure effects (e.g., stale prices, bid–ask bounce, etc.) and is likely to bias the tests for detecting lead–lags; e.g., spurious lead–lags might occur due to staleness in the index quotes which may not represent the true index level. In the previous literature (e.g., see Stoll and Whaley, 1990), this problem has been mitigated by using a suitable ARMA filter to purge the raw return series and the return innovation series then used in the causality tests for the lead–lag effects. The preliminary analysis of the data in Table II indicates there is significant autocorrelation in the raw cash index return series. An AR(2) filter was found to be adequate to whiten the cash index return series[11]; the resultant index return innovation series is used in the linear causality tests based on the multivariate regression in eq. (2).

The results of the linear Granger causality tests, based on the multivariate regressions index in eq. (1) and eq. (2), using both raw and AR

[11]In addition to the cross-correlation seen between the index futures and the cash index returns, the lag length was determined more formally by using the Akalke information criterion as well as a Ljung-Box test on the residuals.

TABLE II

Summary Statistics for FT-SE 100 Index Futures and Index Returns for Each Contract Period

	Futures				Index			
Returns (Contract)	*MAR92*	*JUNE92*	*SEPT92*	*DEC92*	*MAR92*	*JUNE92*	*SEPT92*	*DEC92*
No. of observations	5460	4641	5642	5460	5460	4641	5642	5460
Mean ($\times 10^{-4}$)	0.0602	0.1106	−0.0863	0.0880	−0.0223	0.1510	−0.0594	0.1273
Variance ($\times 10^{-7}$)	9.79	12.00	18.24	16.10	9.4129	9.9455	11.79	5.83
Skewness	1.51	18.71	1.57	4.87	8.77	33.70	11.47	1.95
Kurtosis	53.65	859.21	72.67	148.86	541.76	1820.21	486.40	149.19
Autocorrelation at lag								
1	0.0030	−0.0026	0.0149	−0.0109	0.0827[a]	0.0457[a]	0.1141[a]	0.1990[a]
2	−0.0289	0.0023	−0.0323	−0.0053	0.0078	0.0169	0.0152	0.0763[a]
3	−0.0400	−0.0078	−0.0566	−0.0103	−0.0044	0.0102	−0.0374[a]	0.0312[a]
4	0.0007	−0.0079	−0.0195	−0.0046	−0.0071	0.0172	−0.0280[a]	0.0200
5	−0.0171	0.0070	−0.0003	−0.0197	−0.0012	0.0090	0.0341[a]	0.0178
6	0.0134	0.0382	0.0530	−0.0148	−0.0028	0.0070	0.0326[a]	0.0176
7	−0.0121	0.0083	0.0224	−0.0041	−0.0097	−0.0022	0.0015	0.0051
8	0.0111	−0.0099	−0.0214	−0.0281	−0.00551	−0.0029	−0.0257	−0.0409
9	−0.0089	−0.0148	−0.0185	−0.0062	−0.0065	−0.0133	−0.0473	−0.0158
10	0.0052	−0.0310	−0.0060	0.00600	0.0058	−0.0166	−0.0268[a]	−0.0004

Notes: Returns are calculated as log relatives; the overnight and first returns of the day are excluded from the above series.
[a]Significance at the 5% level.

filtered cash index returns are presented in Tables IIIA and IIIB for the MAR92 and JUNE92 and the SEPT92 and DEC92 contract periods, respectively. The results for the AR filtered returns indicate a high degree of contemporaneous correlation (the coefficient of β_0) between the cash and the futures: 0.47, 0.72, 0.55, and 0.35 for the MAR92, JUNE92, SEPT92, and DEC92 contracts, respectively. Clearly, both markets react to information simultaneously to a considerable extent. Tables IIIA and IIIB also indicate the magnitude of the individual lead (β_{+k}) and lag (β_{-k}) coefficients and the associated t-statistic. If the lag coefficients are significant, then the futures lead the cash, and if the lead coefficients are significant then the cash is said to lead the futures. The choice of a lead and lag length of 6 used in the estimations is based, following the previous literature, on the cross-correlation pattern between the futures and cash. The reported results are, however, robust with respect to different lead/lag length specifications. For the linear tests based on the AR filtered return series, the individual β_{-k} coefficients are statistically significant and larger in size than the β_{+k} coefficients for up to 6 lags in some contract periods. The results for the raw return series are similar. In addition to the t-statistics, the results of the χ^2 test that the lead/lag coefficients are jointly zero are also reported along with their marginal significance levels; these results, in Tables IIIA and IIIB, clearly indicate that the futures lead the cash index for all contract periods in the sample. It is also noteworthy that the coefficient of the error correction term is significant in all contract periods except the MAR92 contract. The R^2 for these regressions are about 0.50 and are similar to those reported in Fleming et al. (1996). The results for the linear causal tests suggest that the FT-SE 100 index futures returns lead the cash index by about 5–15 minutes. These results are similar to those reported for the U.S. markets in the more recent research as, e.g., in Fleming et al. (1996), but differ from those in earlier research such as that reported in Kawaller et al. (1988).

Baek and Brock (1992a) point out that their test might yield spurious rejections of the null hypothesis of Granger noncausality due to neglected nonstationarities associated with structural breaks and heteroskedasticity. In the case of the data used in this article, the latter, i.e., volatility persistence, is likely to be an issue. To account for this, the raw returns are first filtered using univariate EGARCH models. For each series, AR(n)-EGARCH (p, q) models were fitted and the final order of the model was based on tests for whiteness of the residual series; however, in all cases, an EGARCH (1,1) model was found to be adequate. The EGARCH filtered returns were then used in linear causality tests based on eq. (2). In

TABLE IIIA

Results of Linear Causality Tests between Cash Index and Futures Returns MAR92 and JUNE92 Contracts

	Observed Index Returns		*Index Return Innovations*		*Observed Index Returns*		*Index Return Innovations*	
Coefficient	*Estimate*	*t-Statistic*	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*
α ($\times 10^{-4}$)	−0.5687	−1.69[a]	−0.4963	−1.47	−0.4952	−3.06[c]	−0.6056	−3.77[c]
β_{-6}	0.0211	2.14[b]	0.0196	1.99[b]	0.0194	2.03[a]	0.0189	2.32[b]
β_{-5}	0.0177	1.87[a]	0.0173	1.83[b]	0.0121	0.92	0.0108	0.85
β_{-4}	0.0057	0.50	0.0009	0.08	0.0266	2.24[b]	0.0245	2.14[b]
β_{-3}	0.0587	5.17[c]	0.0498	4.50[c]	0.0452	2.50[b]	0.0423	2.57[c]
β_{-2}	0.1060	−0.01	0.0932	5.94[c]	0.0626	1.41	0.0592	1.39
β_{-1}	0.1577	9.58[c]	0.1191	6.24[c]	0.0766	1.90[a]	0.0438	0.91
β_{0}	0.4662	7.68[c]	0.4676	7.71[c]	0.7177	4.44[c]	0.7183	4.45
β_{+1}	−0.0166	−1.17	−0.0147	−1.03	−0.0122	−1.05	−0.0118	−1.03
β_{+2}	−0.0239	−2.13	−0.0229	−2.02[b]	−0.0088	−1.25	−0.0080	−1.12
β_{+3}	−0.0132	−0.97	−0.0139	−1.02	−0.0182	−2.24[b]	−0.0181	−2.23
β_{+4}	−0.0081	0.96	0.0075	0.90	−0.0010	−0.15	−0.0011	−0.16
β_{+5}	0.0073	0.75	0.0072	0.75	0.0023	0.23	0.0035	0.35
β_{+6}	0.0013	0.14	0.0007	0.08	−0.0253	−0.23	−0.0249	−2.40
β_{z}	0.0068	−0.03	0.0062	1.39	0.0064	3.47[c]	0.0060	3.30
χ^2_{LEAD}	13.46		11.94		10.90		10.51	
(p-value)	(0.036)		(0.063)		(0.090)		(0.105)	
χ^2_{LAG}	1556.0		86.64		15.78		13.14	
(p-value)	(0.000)		(0.000)		(0.015)		(0.041)	
R^2	0.27		0.25		0.64		0.64	
No. of observations	5433		5433		4614		4614	

Notes: The results are reported for the following regressions: FT-SE 100 index returns on lead, contemporaneous, and lagged FT-SE 100 index futures returns and an error correction term, z_{t-1}, $r_{c,t} = \alpha + \Sigma_{k=-6}^{+6} \beta_f r_{f,t-k} + \beta_z z_{t-1} + \varepsilon_t$ and FT-SE 100 index return innovations from an AR(2) model on the FT-SE 100 cash index returns on lead, contemporaneous, and lagged FT-SE 100 index futures returns and an error correction term, z_{t-1}, $ar_{c,t} = \alpha + \Sigma_{k=-6}^{+6} \beta_f r_{f,t-k} + \beta_z z_{t-1} + e_t$. In both cases, z_{t-1} is the first lag of the difference between contemporaneous cash and futures levels. The reported t-statistics correspond to the null hypothesis that the parameter estimate equals zero and are calculated based on the Hansen and Singleton (1982) autocorrelation and heteroskedasticity consistent covariance matrix with a maximum lag length of 6. The χ^2_{LEAD} and the χ^2_{LAG} statistics test the null hypothesis that the lead and lag coefficients are jointly zero; thus a rejection here of the null hypothesis that the χ^2_{LAG} coefficients are jointly zero implies that the futures returns lead the cash returns.

[a]Significance at the 10% level.
[b]Significance at the 5% level.
[c]Significance at the 1% level.

TABLE IIIB

Results of Linear Causality Tests between Cash Index and Futures Returns: SEPT92 and DEC92 Contracts

	Observed Index Returns		*Index Return Innovations*		*Observed Index Returns*		*Index Return Innovations*	
Coefficient	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*
$\alpha\,(\times 10^{-4})$	−0.8986	−4.07[c]	−0.7196	−3.34[c]	−0.4460	−3.21[c]	−0.4561	3.22[c]
β_{-6}	0.0234	2.50[b]	0.0200	2.10[b]	0.0107	1.30	0.0049	0.56
β_{-5}	0.0298	3.47[c]	0.0276	2.97[c]	0.0262	3.41[c]	0.0211	2.77[c]
β_{-4}	0.0199	1.28	0.0161	1.06	0.0180	2.06[b]	0.0065	0.82
β_{-3}	0.0344	3.22[c]	0.0223	2.20[b]	0.0434	4.07[c]	0.0215	2.29[b]
β_{-2}	0.1058	5.57[c]	0.0881	5.21[c]	0.0792	5.25[c]	0.0332	2.70[b]
β_{-1}	0.1642	6.05[c]	0.1019	2.84[c]	0.1754	6.53[c]	0.1097	3.91[c]
β_0	0.5451	6.67[c]	0.5468	6.72[c]	0.3463	8.22[c]	0.3456	8.11[c]
β_{+1}	−0.0157	0.01	−0.0151	−1.21	0.0019	0.18	0.0006	0.06
β_{+2}	−0.0048	−0.48	−0.0024	−0.24	0.0079	1.03	0.0089	1.12
β_{+3}	−0.0202	−1.88[a]	−0.0213	−1.95[a]	−0.005	−0.65	−0.0054	−0.68
β_{+4}	0.0099	1.13	0.0092	1.02	0.0006	0.08	−0.0011	−0.13
β_{+5}	0.0068	0.78	0.0086	0.96	0.0080	1.16	0.0075	1.06
β_{+6}	−0.0161	−1.63	−0.0146	−1.43	0.0023	0.19	0.0025	0.20
β_z	0.0142	5.17[c]	0.0122	4.61[c]	0.0047	3.00[c]	0.0039	2.40[c]
χ^2_{LEAD}	3.47		3.21		6.38		t6.70	
(p-value)	(0.748)		(0.782)		(0.382)		(0.350)	
χ^2_{LAG}	96.25		31.90		75.67		39.31	
(p-value)	(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.53		0.50		0.44		0.38	
No. of observations	5615		5615		5433		5433	

Notes: The results are reported for the following regressions: FT-SE 100 index returns on lead, contemporaneous, and lagged FT-SE 100 index futures returns and an error correction term, z_{t-1}, $r_{c,t} = \alpha + \Sigma_{k=-6}^{+6} \beta_i r_{f,t-k} + \beta_z z_{t-1} + \varepsilon_t$ and FT-SE 100 index return innovations from an AR(2) model on the FT-SE 100 cash index returns on lead, contemporaneous, and lagged FT-SE 100 index futures returns and an error correction term, z_{t-1}, $ar_{c,t} = \alpha + \Sigma_{k=-6}^{+6} \beta_i r_{f,t-k} + \beta_z z_{t-1} + \varepsilon_t$. In both cases, z_{t-1} is the first lag of the difference between contemporaneous cash and futures levels. The reported t-statistics correspond to the null hypothesis that the parameter estimate equals zero and are calculated based on the Hansen and Singleton (1982) autocorrelation and heteroskedasticity consistent covariance matrix with a maximum lag length of 6. The χ^2_{LEAD} and the χ^2_{LAG} statistics test the null hypothesis that the lead and lag coefficients are jointly zero; thus a rejection here of the null hypothesis that the χ^2_{LAG} coefficients are jointly zero implies that the futures returns lead the cash returns.

[a]Significance at the 10% level.
[b]Significance at the 5% level.
[c]Significance at the 1% level.

TABLE IV

Results of Linear Causality Tests between EGARCH Filtered Cash Index and Futures Returns: MAR92, JUNE92, SEPT92, and DEC92 Contracts

	EGARCH Filtered Index Returns MAR92		*GARCH Filtered Index Returns: JUNE92*		*GARCH Filtered Index Returns SEPT92*		*GARCH Filtered Index Returns: DEC92*	
Coefficient	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*	*Estimate*	*t-Statistics*
α ($\times 10^{-2}$)	−0.8800	−0.76	−0.8195	−0.65	−0.8784	−0.79	0.0780	0.07
β_{-6}	0.0142	1.13	0.0363	2.75[c]	0.0106	0.92	0.0233	2.06[a]
β_{-5}	0.0185	1.57	−0.0003	−0.03	0.0295	2.77[c]	0.0369	3.39[c]
β_{-4}	−0.0010	−0.84	−0.0007	−0.05	0.0342	3.05[c]	0.0154	1.41
β_{-3}	0.0233	1.88[a]	0.0153	1.17	0.0180	1.51	0.0014	0.13
β_{-2}	0.0672	5.23[c]	0.0955	0.02	0.0622	5.25[c]	0.0267	2.06[a]
β_{-1}	0.2961	20.74[c]	0.2848	15.55[c]	0.2920	17.00[c]	0.2652	16.30[c]
β_0	0.3981	21.50[c]	0.3883	21.51[c]	0.4426	15.71[a]	0.4348	18.64[c]
β_{+1}	−0.0095	−0.77	0.0073	0.54	0.0181	1.24	0.0176	1.25
β_{+2}	−0.268	−1.91[a]	0.0134	0.93	0.0168	1.53	0.0237	1.83[a]
β_{+3}	0.0009	0.07	0.0023	−0.18	−0.0035	−0.34	0.0140	1.15
β_{+4}	0.0090	0.76	−0.0070	−0.44	−0.0031	−0.28	0.0094	0.71
β_{+5}	−0.0081	−0.69	0.0101	0.79	0.0090	0.83	0.0069	0.59
β_{+6}	−0.0042	−0.37	−0.0012	−0.10	0.0045	0.42	0.0066	0.53
χ^2_{LEAD}	5.02		2.11		5.72		10.75	
(p-value)	(0.541)		(0.909)		(0.456)		(0.096)	
χ^2_{LAG}	455.52		278.19		329.65		296.38	
(p-value)	(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.25			0.25	0.29		0.27	
No. of observations	5493		4704		5705		5523	

Notes: The results are reported for the following regression: univariate EGARCH(1,1) models were fitted to the raw FT-SE 100 index futures and cash index returns. The standardized residuals from these cash index returns were regressed on lead, contemporaneous, and lagged residuals from the EGARCH model fitted to the FT-SE 100 index futures returns; $egar_{c,t} = \alpha + \Sigma_{k=-6}^{+6} \beta_t egar_{f,t-k_{t-1}} + \varepsilon_t$. *The reported t*-statistics correspond to the null hypothesis that the parameter estimate equals zero and are calculated based on the Hansen and Singleton (1982) autocorrelation and heteroskedasticity consistent covariance matrix with a maximum lag length of 6. The χ^2_{LEAD} and the χ^2_{LAG} statistics test the null hypothesis that the lead and lag coefficients are jointly zero; thus a rejection of the null hypothesis that the χ^2_{LAG} coefficients are jointly zero here implies that the futures returns lead the cash returns.

[a]Significance at the 10% level.

[b]Significance at the 5% level.

[c]Significance at the 1% level.

Table IV, the results of these tests are reported. These results show that even after using an EGARCH filter, the contemporaneous correlation between the index futures and the cash index is high: 0.40, 0.39, 0.44, and 0.43 for the MAR92, JUNE92, SEPT92 and DEC92 contract periods, respectively. The lag coefficients β_{-k} are significant up to 2 or 3 lags suggesting strongly that the futures lead the cash index by about 5–15 minutes. Further, none of the coefficients β_{+k} is significant, suggesting the cash index does not lead the futures. In addition, the χ^2 test clearly falls to reject the null hypothesis that the futures lag the cash index. Thus the evidence, even after adjusting for volatility persistence, supports the hypothesis that the FT-SE 100 index futures returns lead the cash index.

Nonlinear Granger Causality Using the Modified Baek and Brock Test

The nonparametric test of Baek and Brock is useful for detecting any remaining nonlinear causality after the linear causal effect has been accounted for. It is implemented by using the residuals from the regressions based on eq. (3) estimated earlier. The modified Baek and Brock test [see eq. (7)] requires a subjective choice of values for the lead length m, the lag lengths Lx and Ly, and the scale parameter e to be chosen, and there are no guidelines in the literature for a choice of optimal values. Based on the Monte Carlo results in Hiemstra and Jones (1992), however, the lead length is set at $m = 1$ and $Lx = Ly$, using common lag lengths of 1–4 lags. Also, in all cases, the test was applied to the standardized series using a common scale parameter[12] of $e = 1.5\sigma$, where $\sigma = 1$ denotes the standard deviation of the standardized time series.

Table VA presents the results of the modified Baek and Brock test applied to the residuals obtained after estimating eq. (2) separately using the cash index return innovations for the four FT-SE 100 futures contract sample periods. In Table VA, CS and TVAL respectively denote the difference between the two conditional probabilities in eq. (4) and the standardized test statistic in eq. (7). As indicated earlier, under the null hypothesis of nonlinear Granger causality, the test statistic CS is distributed as $N(0,1)$. The smallest value of the CS test statistic, in Table VA, is 2.559, providing clear evidence of nonlinear bidirectional effects from the futures to the cash and vice versa for all contract periods. These results are in sharp contrast to those of the linear Granger causality test. These results hold for all the common lag lengths used in conducting the test.

[12]There is no material difference in the results when $e = 0.5\sigma$ and 1.0σ were used.

TABLE VA

Results of Nonlinear Granger Causality Tests on Residuals of Linear Granger Causality Tests on FT-SE 100 Index Futures and Cash ARMA Filtered Returns

	Futures Do Not Cause Cash		Returns Cash Do Not Cause Futures	
H_0	CS	TVAL	CS	TVAL
		MAR92 Contract		
Lu = Lv				
1	0.0733	17.757[c]	0.0244	9.331[c]
2	0.1169	18.364[c]	0.0375	8.685[c]
3	0.1395	16.322[c]	0.0540	8.567[c]
4	0.14670	13.36[c]	0.06530	7.633[c]
		JUNE92 Contract		
Lu = Lv				
1	0.0670	14.555[c]	0.0117	4.992[c]
2	0.06080	14.529[c]	0.0249	5.632[c]
3	0.1387	11.617[c]	0.0190	2.747[c]
4	0.1383	6.885[c]	0.0319	2.559[c]
		SEPT92 Contract		
Lu = Lv				
1	0.0773	17.757[c]	0.0244	9.331[c]
2	0.11630	21.515[c]	0.0371	10.013[c]
3	0.1331	19.773[c]	0.0496	10.038[c]
4	0.1441	117.957[c]	0.0589	9.600[c]
		DEC92 Contract		
Lu = Lv				
1	0.0762	18.820[c]	0.267	9.887[c]
2	0.1117	18.874[c]	0.04220	9.775[c]
3	0.1272	16.684[c]	0.0439	7.687[c]
4	0.1409	15.694[c]	0.0474	6.686[c]

Notes: Modified Baek and Brock nonlinear Granger causality test results using VAR residuals of the linear granger causality tests on ARMA filtered returns. Lu and Lv denote the number of lags in the residual series used in the test. In all cases, the lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, $N(0,1)$.
[a]Significance at the 10% nominal level for a one sided test.
[b]Significance at the 5% nominal level for a one-sided test.
[c]Signifiance at the 1% nominal level for a one-sided test.

To examine whether the nonlinear causal relationship observed between the residuals of the ARMA filtered linear regression tests is due to the effect of persistence in the variance, the following procedure is followed. Standardized EGARCH filtered residuals are first used in a linear Granger causality test based on eq. (2). In Table VB, the results of the modified Baek and Brock test applied to these residuals are presented. It is clear that the bidirectional feedback effect is still strong and the TVAL statistic is highly significant at all conventional levels. Again these results

TABLE VB

Results of Nonlinear Granger Causality Tests on Residuals of Linear Granger Causality Tests on FT-SE 100 Index Futures and Cash EGARCH Filtered Returns

	Futures Do Not Cause Cash		*Cash Do Not Cause Futures*	
H_0	*CS*	*TVAL*	*CS*	*TVAL*
		MAR92 Contract		
Lu = Lv				
1	0.0325	9.621[c]	0.0059	2.980[c]
2	0.0531	8.841[c]	0.0050	1.422
3	0.0685	7.537[c]	0.0133	2.297[c]
4	0.0670	4.781[c]	0.0269	2.698[c]
		JUNE92 Contract		
Lu = Lv				
1	0.0369	10.721[c]	0.0064	3.309[c]
2	0.0668	9.995[c]	0.0172	4.160[c]
3	0.0775	7.239[c]	0.0177	2.529[c]
4	0.0824	4.500[c]	0.0374	2.853[c]
		SEPT92 Contract		
Lu = Lv				
1	0.0484	13.654[c]	0.0035	1.947[a]
2	0.0738	13.336[c]	0.0059	1.934[a]
3	0.0877	11.324[c]	0.0096	2.085[b]
4	0.0900	8.511[c]	0.0199	2.630[c]
		DEC92 Contract		
Lu = Lv				
1	0.0490	13.563[c]	0.0031	1.721[a]
2	0.0751	13.240[a]	0.0051	1.788[a]
3	0.0212	11.027[c]	0.0101	2.120[c]
4	0.0857	7.773[c]	0.0194	2.471[c]

Notes: Modified Baek and Brock nonlinear Granger causality test results using VAR residuals of the linear Granger causality tests on EGARCH filtered returns. Lu and Lv denote the number of lags in the residual series used in the test. In all cases, the lead length, m is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, $N(0,1)$.

[a]Significance at the 10% nominal level for a one-sided test.

[b]Significance at the 5% nominal level for a one-sided test.

[c]Signifiance at the 1% nominal level for a one-sided test.

are in contrast to those of the linear Granger causality test. It is also useful to compare the results in Tables VA and VB. The size and significance of the bidirectional nonlinear causal effect are slightly lower after an EGARCH filter is applied but are still significant.

The results in Tables VA and VB indicate that there is evidence of a bidirectional causation from futures to the cash and vice versa in the stock index futures market. It appears that after the linear lead of the futures market is accounted for, both of the returns have nonlinear predictive power for each other. These results, given the nature of the Baek-Brock test, do not detract from the importance of the empirical finding that the futures market leads or reacts to information faster than the cash market. However, they suggest that there are significant nonlinear effects in the dynamics between the index futures and the cash market returns. This provides support for index arbitrage models such as those of Dwyer et al. (1996), who model the activities of real-world index arbitrageurs by having groups of traders who can enter the market at different levels of entry-related transactions costs. The activities of such groups of arbitrageurs affect the dynamic relationship between the two markets which Dwyer et al. (1996) represent by a threshold autoregressive model which also accounts for both cointegration and heteroskedasticity in the futures-cash price series. The model generates entry thresholds for different classes of index arbitrageurs which are realistic and have practical implications for index arbitrage activity. The presence of nonlinear Granger causal effects between the futures and cash price series thus provides additional evidence underlining the importance of transactions costs in realistic models of the futures-cash basis.

CONCLUSIONS

The study contributes to the literature on lead–lag relationships between the index futures and the cash markets in several ways. First, it provides evidence that the FT-SE 100 index futures tend to lead the cash index by about 5–15 minutes, confirming a similar pattern seen in the U.S., German, and Japanese stock index futures markets. Second, it also suggests that the linear lead–lag relationship persists even after the return series are adjusted for persistence in volatility. Finally, the results imply, in sharp contrast to the linear tests, that if nonlinear effects are accounted for, neither market leads or lags the other. The strong evidence for nonlinear causality provides support for models of index arbitrage which seek to include transaction cost thresholds to model the activities of index arbitrageurs. An issue for future research could be to see if the strong nonlinear causal effects are robust to changes in market conditions, e.g., in periods of high and low volume and volatility and during periods of "good" and "bad" news.

BIBLIOGRAPHY

Abhyankar, A., Copeland, L. S., and Wong, W. (1997): "Uncovering Nonlinear Structure in Real-Time Stock Market Indices: The S&P 500, the DAX, the

Nikkei 225 and the FT-SE 100," *Journal of Business and Economic Statistics,* 15(1):1–14.

Admati, A. R., and Pfleiderer, P. (1988): "A Theory of Intraday Patterns: Volume and Price Variability," *Review of Financial Studies,* 1:3–40.

Baek, E., and Brock, W. (1992a): "A General Test for Nonlinear Granger Causality: Bivariate Model." Working paper, Departments of Economics, Iowa State University, Ames, and University of Wisconsin, Madison.

Baek, E., and Brock, W. (1992b): "A Nonparametric Test for Independence of a Multivariate Time Series," *Statistica Sinica,* 2(1):137–156.

Brock, W. (1991): "Causality, Chaos, Explanation and Prediction in Economics and Finance," in *Beyond Belief: Randomness, Prediction and Explanation in Science,* page 230–279, Casti, J., and Karlquist, A. (eds.). Boca Raton, FL: CRC Press.

Chan, K. (1992): "A Further Analysis of the Lead–Lag Relationship between the Cash Market and Stock Index Futures Market," *Review of Financial Studies,* 5:123–152.

Chan, K., Chan, K. C., and Karolyi, G. A. (1991): "Intraday Volatility in the Stock Index and the Stock Index Futures Markets," *Review of Financial Studies,* 4(4):657–684.

Cheung, Y.-W., and Ng, N. (1990): "The Dynamics of S&P 500 Index and Index Futures Intraday Price Volatilities," *Review of Futures Markets,* 9(2):458–486.

Chung, Y. P., Kang, J.-K., and Rhee, S. G. (1994): "The Lead–Lag Relationship between the Stock Market and the Stock Index Futures Market in Japan." Working paper, Pacific Basin Capital Markets Research Center, University of Rhode Island, Kingston.

Denker, M., and Keller, G. (1983): "On U-Statistics and von Mises Statistics for Weakly Dependent Processes," *Zeitschrift fur Wahrscheinlichkeitstheode und Verwandte Gabiete,* 64:505–522.

Dwyer, G. P., Locke, P., and Yu, W. (1996): "Index Arbitrage and Nonlinear Dynamics between the S&P 500 Futures and Cash," *Review of Financial Studies,* 9(1):301–332.

Engle, R., and Granger, C. W. J. (1987): "Co-Integration and Error Correction: Representation, Estimation and Testing," *Econometrica,* 50:978–1008.

Fleming, J., Ostdiek, B., and Whaley, R. (1996): "Trading Costs and the Relative Rates of Price Discovery in Stock, Futures and Options Markets," *The Journal of Futures Markets,* 16:353–387.

FT-SE 100 Index Futures Review, London International Financial Futures and Options Exchange, LIFFE, 2nd Quarter, 1994.

Granger, C. (1969): "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica,* 37:424–438.

Grossman, S. J., and Miller, M. H. (1988): "Liquidity and Market Structure," *Journal of Finance,* 43:617–633.

Grunbichler, A., Longstaff, F., and Schwartz, E. (1994): "Electronic Screen Trading and the Transmission of Information: An Empirical Examination," *Journal of Financial Intermediation,* 3:166–187.

Hamilton, J. (1994): *Time Series Analysis,* Princeton, NJ: Princeton University Press.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Method of Moment Estimators," *Econometrica,* 50:1029–1051.

Hansen, L. P., and Singleton, K. (1982): "Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models," *Econometrica,* 50:1269–1286.

Herbst, A., McCormack, J., and West, E. (1987): "Investigation of a Lead–Lag Relationship between Spot Indices and Their Futures Contracts," *The Journal of Futures Markets,* 7:373–382.

Hiemstra, C., and Jones, J. (1992): "Monte Carlo Result for a Modified Version of the Baek and Brock Nonlinear Granger Causality Test." Department of Economics, Loyola College, and U.S. Securities and Exchange Commission.

Hiemstra, C., and Jones, J. (1994): "Testing for Linear and Nonlinear Granger Causality in the Stock Price Volume Relationship," *Journal of Finance,* 49(5):1639–1664.

Kawaller, I., Koch, P., and Koch, T. (1988): "The Relationship between the S&P 500 Index and S&P 500 Index Futures Prices," *Economic Review,* 73(3):2–10.

Kodres, L. E., and Papell, D. H. (1991): "Nonlinear Dynamics in the Foreign Exchange Futures Market." Working paper, Department of Finance, University of Michigan, Ann Arbor.

Kyle, A. S. (1985): "Continuous Auctions and Insider Trading," *Econometrica,* 53:1315–1335.

Miller, M. H. (1990): "International Competitiveness of U.S. Futures Exchanges," *Journal of Financial Services Research,* 4:387–408.

Pierce, D. A., and Haugh, L. D. (1977): "Causality in Temporal Systems: Characterizations and a Survey," *Journal of Econometrics,* 5:265–293.

Sims, C. (1972): "Money, Income and Causality," *American Economic Review,* 62:540–552.

Sofianos, G. (1993): "Index Arbitrage Profitability," *Journal of Derivatives,* 1:6–20.

Stoll, H. R., and Whaley, R. E. (1990): "The Dynamics of Stock Index and Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis,* 25:441–468.

Subrahmanyam, A. (1991): "A Theory of Trading in Stock Index Futures," *Review of Financial Studies,* 4:17–71.