An alternative approach to investigating lead-lag relationships between stock and stock index futures markets

Article

Accepted Version

Brooks, C., Garrett, I. and Hinich, M. J. (1999) An alternative approach to investigating lead-lag relationships between stock and stock index futures markets. Applied Financial Economics, 9 (6). pp. 605-613. ISSN 0960-3107 doi: https://doi.org/10.1080/096031099332050 Available at http://centaur.reading.ac.uk/35968/

Published version at: http://dx.doi.org/10.1080/096031099332050
To link to this article DOI: http://dx.doi.org/10.1080/096031099332050

Publisher: Taylor and Francis

An Alternative Approach To Investigating Lead-lag Relationships Between Stock And Stock Index Futures Markets

Chris Brooks[1]

Ian Garrett

and

Melvin J. Hinich[*]

This draft : 31 July 1998

Abstract

In the absence of market frictions, the cost of carry model of stock index futures pricing predicts that returns on the underlying stock index and the associated stock index futures contract will be perfectly contemporaneously correlated. Evidence suggests, however, that this prediction is violated with clear evidence that the stock index futures market leads the stock market. We argue that traditional tests, which assume that the underlying data generating process is constant, might be prone to overstate the lead-lag relationship. Using a new test for lead-lag relationships based on cross correlations and cross bicorrelations we find that, contrary to results from using the traditional methodology, periods where the futures market leads the cash market are few and far between and when any lead-lag relationship is detected, it does not last long. Overall, our results are consistent with the prediction of the standard cost of carry model and market efficiency.

Keywords : stock index, stock index futures, lead-lag relationships, linear causality, nonlinear causality, correlations, bicorrelations

[*] ISMA Centre, Department of Economics, The University of Reading, Whiteknights, Reading RG6 6AA, United Kingdom; Department of Accounting and Finance, University of Manchester, Manchester M13 9PL, United Kingdom; and Applied Research Laboratories and Department of Government, University of Texas at Austin, Austin, TX 78713-8029, USA respectively.

[1] Corresponding author: tel (+44) 118 931 67 68; fax (+44) 118 931 47 41;
e-mail: C.Brooks@reading.ac.uk

An Alternative Approach To Investigating Lead-lag Relationships Between Stock And Stock Index Futures Markets

1. Introduction

The lead-lag relationship between stock and stock index futures markets has been the subject of intense empirical investigation in recent years (see, for example, Kawaller, Koch and Koch (1987), Herbst, McCormack and West (1987), Stoll and Whaley (1990), Chan (1992) and Tse (1995)). In the absence of market frictions and transaction costs, the returns on a stock index and its corresponding underlying index futures contract will be perfectly positively contemporaneously correlated. In reality, however, a number of researchers have found significant evidence that there is cross autocorrelation between the returns on stock index futures and the returns on the underlying index, that is, there is a lead-lag relationship between these markets.

Whilst there seems to be a consensus on the finding that stock index futures markets lead underlying stock markets, there are problems with extant tests of lead-lag relationships and as such, these findings may be overstated. First, traditional tests of lead-lag relationships are typically carried out in the spirit of Granger (1969) and Sims (1972) linear causality tests. The problem here is that any potential nonlinearities in the data are ignored. That financial time series exhibit nonlinear behaviour is well documented in the literature (see, for example, Brooks (1996), or Hsieh (1991)) and failure to account for this could lead to biased results. In addition to the statistical evidence regarding the presence of nonlinearities, there are sound economic reasons why nonlinearities may be present in the pricing relationship between stock and stock index futures markets. Specifically, in the absence of transaction costs arbitrage between stock and stock index futures markets is based on deviations of the futures price from its fair value as given by the spot price adjusted for the cost of carrying the underlying portfolio to maturity of the futures contract. In the presence of transaction costs, however, there are bounds on such deviations within which arbitrage will not be triggered. Therefore, there will be thresholds within which the relative difference between the futures and spot price can fluctuate without triggering arbitrage. The result of this is nonlinearity in the relationship between stock and stock index futures markets and this nonlinearity may spill over into the lead-lag relationship between the markets.[1] Second, the models used to investigate lead-lag relationships typically impose the often inappropriate restriction that the parameters of such models are stable over quite long periods. The potential problem here is that changes in the nature of the lead-lag relationship over shorter periods may not be captured by these models. Alternatively, it may be the case that the lead-lag relationship is particularly strong over a short period such that the lead-lag relationship appears to be present over the whole sample when in actual fact it is not.

In this paper, we propose an alternative method for testing lead-lag relationships between stock and stock index futures markets based on Hinich (1996). The tests that we utilise are similar in spirit to the Granger-Sims causality tests used in the extant literature but have the advantage that both linear and nonlinear causality can be examined in a coherent testing environment without imposing strong restrictions on the stability of the relationship. To anticipate the findings in the paper, the results from using this alternative methodology show that the lead-lag relationship is much less pronounced than that suggested by the more traditional Granger-Sims causality tests, suggesting that the traditional testing framework has a tendency to overstate the strength of the lead-lag relationship. The rest of the paper is organised as follows. Section two briefly reviews the existing literature on lead-lag relationships. In order to facilitate comparison, section three implements tests of the lead-lag relationship using the traditionally employed methodology whilst section four discusses and implements the alternative testing methodology. Sections five and six presents the results of applying the alternative methodology and offers some concluding remarks respectively.

2. Literature Review

If stock and stock index futures markets are functioning efficiently, then in the absence of market frictions, returns in the two markets will be perfectly contemporaneously correlated. This prediction arises directly from the cost of carry model of futures pricing which states that,

$$F_t = S_t e^{(r-d)(T-t)} \tag{1}$$

where F_t 2 is the stock index futures price quoted at time t, S_t 3 is the value of the underlying stock index, r and d are the risk free rate and the dividend yield on the underlying index respectively and $(T-t)$ 4 is the time to maturity of the futures contract. Writing this in return form we have,

$$\Delta f_t = \Delta s_t + (r-d) \tag{2}$$

where $\Delta f_t = \ln(F_t / F_{t-1})$ 6 and $\Delta s_t = \ln(S_t / S_{t-1})$ 7. Clearly, stock and stock index futures returns are perfectly contemporaneously correlated in this model and as such one market should not lead the other, that is, returns from one market should not help predict future returns in the other market. Tests of the proposition that there is no lead-lag relationship then essentially become causality tests with the model typically used being based on Sims (1972) (see, for example, Stoll and Whaley (1990), Chan (1992) and Grünbichler, Longstaff and Schwartz (1994)). The model is of the form

$$\Delta s_t = \alpha_0 + \sum_{i=-k}^{k} \beta_i \Delta f_{t+i} + u_t \qquad (3)$$

where Δs_t 9 and Δf_t 10 are as defined earlier and u_t 11 is a white noise error term. The test is then one of whether the β_i 12 are significant for $i < 0$ or $i > 0$ or both or neither. If the lags ($i < 0$) are significantly different from zero but the leads are not then the futures leads the spot. If this is true in reverse then the spot leads the futures whilst if both the lags and leads are significantly different from zero, causality is bi-directional. If none of the lags and leads are significant then there is no lead-lag relationship, a finding which is consistent with the prediction of the cost of carry model as long as there is strong positive contemporaneous correlation.

In contrast to this prediction many studies, often using intra-daily data, find significant lead-lag relationships between stock and stock index futures markets (see, amongst others, Kawaller, Koch and Koch (1987), Kipnis and Tsang, (1983), Stoll and Whaley (1990), Chan (1992) and Grünbichler, Longstaff and Schwarz (1994)). Attempts to rationalise such a relationship typically appeal to differences in market microstructure and other frictions that can disrupt the cost of carry relationship. Grossman and Miller (1988), for example, argue that lower transaction costs and greater liquidity in the futures market provides more immediacy to traders and hence traders will transact in the futures market first with the result that the futures market will lead the spot market. In an analysis of the lead-lag relation between the DAX Index and DAX Index Futures contract in Germany, Grünbichler, Longstaff and Schwarz (1994) focus on the role of different trading systems (screen versus floor trading) in explaining the lead-lag relationship and document evidence consistent with the hypothesis that the price discovery process is accelerated through screen trading in the futures market which implies that the futures will lead the spot. Stoll and Whaley (1990), on the other hand, consider the impact that nontrading and bid-ask effects may have on the lead-lag relationship[2] and find that even after adjustments for nontrading and bid-ask effects is made, the lead-lag relationship between the S&P 500 Index and Index Futures market persists. At first blush, the implication of these findings is that the lead-lag relationship is robust to any effect that might be termed institutional frictions such as stale prices in an index have and it is more an economic feature that needs to be explained. We shall argue in the following sections that there is another explanation for the apparent robustness of the lead-lag relationship, specifically that the reason why lead-lag relationships seem so pronounced is that the methodology used has a tendency to overstate the strength of the relationship.

3. Results From Using The Traditional Testing Methodology

In this section we investigate the lead-lag relationship between the FTSE 100 Index and Index Futures contract for the UK and between the S&P 500 Index and Index Futures contract for the US. Most tests of the lead-lag relationship make use of intra-daily data on stock index and stock index futures returns. One of the problems associated with tests of lead-lag relationships based on intra-daily data is the possible effect nonsynchronous trading can have on the results. Indeed, the evidence suggests that it can have a substantive impact on observed return behaviour (see Stoll and Whaley (1990) and Miller, Muthuswamy and Whaley (1994)). To minimise the possible effects of nonsynchronous trading and hence reduce the possibility of identifying a spurious lead-lag relationship whilst at the same time allowing for lead-lag relationships to genuinely exist we use daily returns on both the FTSE 100 and S&P 500 Indices and Index Futures contracts over the period January 1985 to December 1993 and January 1983 to December 1993 respectively. The FTSE 100 Index should not exhibit any nonsynchronous trading effects since it is calculated from mid-quotes that are binding, that is, market makers will trade at the quoted prices. Therefore, assuming that market makers update their quotes, nontrading effects should not be present. The S&P 500 Index is constructed on the basis of transaction prices and therefore nonsynchronous trading effects may be present and therefore may contaminate the results. Fortunately, a check to determine whether nontrading effects are present can be undertaken since if they are, from the models in Lo and MacKinlay (1990) and Miller, Muthuswamy and Whaley (1994), observed returns will follow a first order autoregressive process with a positive coefficient on lagged observed returns.[3] Therefore, a test of $\phi_1 = 0$ 13 in the regression $\Delta s_t^o = \phi_0 + \phi_1 \Delta s_{t-1}^0 + \varepsilon_t$ 14 should give some indication of whether nontrading effects are present in the data. For the whole sample, estimates of the coefficient on lagged returns are (heteroscedasticity-consistent *t*-statistics in parentheses) $\phi_1^{UK} = 0.0706(0.7993)$ 15 and $\phi_1^{US} = 0.0289(0.4299)$ 16. These terms are clearly not significantly different from zero, suggesting that nonsynchronous trading is unlikely to be a problem in the data considered here. The data are daily closing prices for both the spot and futures markets. The futures data is constructed as a rollover with the rollover taking effect in the moth prior to expiration. This avoids possible expiration month effects that might generate odd price behaviour in the series.

To provide a point of comparison for tests of the relationship based on cross correlations and cross bicorrelations, we first conduct tests of the lead-lag relationship between the respective domestic markets using equation 3. Table I reports the results from this model. In order to allow for possible changes in the nature of the lead-lag relationship, we estimate the model over the whole sample and over two sub-samples which we have termed the pre- and post-crash samples. The pre-crash sample runs from the beginning of the sample period until October 16 1987 while the post-crash sample runs from 24 October 1988 until the end of the sample. This misses out the rather volatile year that followed the crash of October 1987. The results show that at the very least the futures leads the spot market by one day in both the US and the UK, irrespective of what sample period is used to estimate the model. This appears to provide *prima facie* support for the existence of a lead-lag relationship. However, figures 1 and 2 which plot the coefficient on Δf_{t-1} 17 in (3) when (3) is estimated using rolling least squares show that there is substantial instability in the coefficient estimate and therefore the lead-lag relationship may actually be overstated if we force the data for the entire sample to be generated by the same model. We evaluate this proposition more fully in the next section.

4. An Alternative Testing Methodology

The results in the previous section clearly demonstrate that there is substantial instability in the lead-lag relationship which needs to be accounted for. Such a method that allows for this instability while at the same time allowing for the testing of a nonlinear lead-lag relationships is proposed in Hinich (1996). Assume that we have two stationary time series $\{ x(t) \}$ and $\{ y(t) \}$ of length N, both of which have been standardised to have a sample mean of zero and a unit variance. Let $C_{xy}(r)$=E[$x(t)y(t+r)$] and $C_{xxy}(r,s)$=E[$x(t)x(t+r)y(t+s)$] be the cross covariances and cross bicovariances between x and y respectively. Then under the null hypothesis of independence, $C_{xy}(r) = 0$ and $C_{xxy}(r,s) = 0$ for $r,s \neq 0$. If there is lagged dependence, then $C_{xy}(r)$ or $C_{xxy}(r,s)$ will be non-zero for at least one value of r or one pair of values for r and s respectively. In terms of the lead-lag relationship between stock and stock index futures markets, if we define Δf_t and Δs_t as $\{ x(t) \}$ and $\{ y(t) \}$ respectively, then there is no lead-lag relationship if the null hypothesis of independence is not rejected. Tests of the null hypothesis of independence are based on the cross correlation and cross bicorrelation coefficients which are respectively given by[4]

$$\rho_{xy}(r) = (N-r)^{-1} \sum_{t=1}^{N-r} x(t)y(t+r) \quad , \quad r \neq 0 \tag{4}$$

and

$$\rho_{xxy}(r,s) = (N-m)^{-1} \sum_{t=1}^{N-m} x(t)x(t+r)y(t+s) \quad , \quad m = \max(r,s) \tag{5}$$

Letting $L = N^c$ where $0 < c < 0.5$, the statistics that test the null hypothesis of zero cross correlations and zero cross bicorrelations are given by (Hinich (1996))

$$H_{xy}(N) = \sum_{r=1}^{L} (N-r)^{\frac{1}{2}} C_{xy}^{2}(r) 20 \tag{6}$$

and

$$H_{xxy}(N) = \sum_{s=1}^{L} \sum_{r=1}^{L} (N-m)^{\frac{1}{2}} C_{xxy}^{2}(r,s) \tag{7}$$

with H_{xy} and H_{xxy} being asymptotically chi squared as N, the length of the series, tends to infinity (see Theorem 1 of Hinich (1996)).

The data are split into a series of windows of length 35 observations (giving a total of 79 windows for the US data and 56 for the UK). This corresponds to approximately seven trading weeks[5], and allows analysis of relatively short-term behaviour of the market which would be unobservable in an analysis of longer periods or time. This also removes the inappropriate restriction enforced in many papers that the model parameters and therefore the data generating process remains constant throughout the entire sample period. Thus although the sample covers both the pre- and post-1987 stock market crash, the "windowing" approach used here implies that atypical patterns during this period can be observed, but will not affect the result overall. A window is defined as "significant" if either the H_{xy} , H_{xxy} or H_{yyx} statistics are significant at the 1% level. A strict criterion is used so that only the most extreme results trigger a rejection of independence. The results for H_{xxy} and H_{yyx} statistics are calculated using the standardised residuals from a VAR(2,2) fit to the returns, which is sufficient to remove any linear (cross)dependence in the series.

5. Results of the Alternative Testing Methodology

The cross-correlation test gives no significant windows for the US, and only one significant window for the UK. This single significant window from a total of 56 corresponds to the period 12 March 1992 - 4 May 1992 where the H_{xy} test statistic is highly significant with a p-value of 0.0048. Some statistics associated with this window are given in Table II. The largest non-contemporaneous cross-correlation coefficients contributing to the test statistic for this window have a value of -0.48 and -0.47. These are for the spot lagging the futures market by one period and for the futures lagging the spot by one period respectively. This indicates a bi-directional feedback relationship, and that the spot will move in the opposite direction to the way the futures market moved one day ago and viceversa. Thus it appears in general extremely difficult to predict one market using a simple lagged linear model of the other.

Considering the tests for nonlinear relationships, a similar result is observed. Again, only a single window is significant for the UK, occurring during a slightly later period, although still in 1992 (24 June 1992 to 11 August 1992). Interestingly, it is not the same window as caused a rejection for the simple cross-correlation, indicating that linear and nonlinear lead / lag relationships need not occur at the same time. The most significant bicorrelation for the window has a value of -0.45, for the bicorrelation $f_t f_{t-1} s_{t-2}$. Some statistics associated with that window are given in Table III. The VAR fit for this window is uncharacteristically low, indicating that the linear framework is insufficient to capture the dynamics of the series at this time. Both of these periods of linear and non-linear cross-dependence occur at around the time of exchange rate and interest rate uncertainty immediately proceeding Sterling's exit from the Exchange Rate Mechanism of the European Monetary System on September 16, 1992. The story for the U.S. is, however, very different. There are in fact 5 windows with significant H_{xxy} or H_{yyx} statistics during the sample period with all of the rejections of independence occurring around the time of fairly major changes in stock prices or interest rates. US (and world) interest rates altered during August 1983 and during July 1992, while the US stock market experienced a sharp fall in October 1989 and a full-blown crash in October 1987. Except for the stock market crash, it is always the *xxy* window which is significant.

Plots of the cross-bicorrelation test statistics, transformed to a uniform distribution for ease of interpretation, are given for the US and the UK in figures 3 and 4 respectively. The graphs show a high degree of volatility in the statistic over time. This is suggestive of the fact that any lead-lag relationship can change substantially over time since recent research has shown that the relationship binding futures and spot markets becomes stronger when the individual markets are more volatile (Kawaller *et al.*, 1993; Albert *et al.*, 1993). In the context of the analysis used here, it is straightforward to evaluate this proposition. This is achieved by calculating the correlation between the test statistics (H_{xy} , H_{xxy} or H_{yyx}) and the variances of the individual series for each window, which is used as a measure of the volatility of the series. Since contemporaneous correlations have been removed from the test statistics, if the proposition is correct (that is the markets are more closely bound together during periods of high market volatility), one would expect a large and negative correlation between the test statistics and the variances of the two individual series. Table IV shows that for the UK, this is indeed the case. The correlations between the *xy* statistics and the variances are smaller than -0.5, indicating strongly that, when the volatilities are high, the values of the test statistics will be lower, and thus that the individual markets show less evidence of feedback relationships and are therefore bound more closely together. We can test this formally using the Fisher test for significance of the correlations. The test statistic is given by

$$z = \frac{0.5 \log[(1+r)/(1-r)]}{\sqrt{\frac{1}{n-3}}} 22 \qquad (8)$$

where r is the sample correlation and n is the sample size (in this case, the number of windows). z is distributed approximately normally under the null hypothesis. The Fisher statistic shows that for the UK, the negative relationship between the cross-correlation test statistic and the variance of the series is indeed statistically significant. The correlation of the third order statistics with the variances are also fairly strong and negative for the UK (at around -0.2), although not as strong as for the linear cross-correlations, and not statistically significant. The picture for the US is very different: the correlations between the test statistics and the variances of the individual series are always positive but never significant. The important policy implication of this finding is that UK governments need not worry about the effects of large variations in futures (or spot market) prices upon the overall stability of the financial system. However, no such reassurance applies to the US.

The differences in the number of significant cross-bicorrelation windows for the US and the UK data might be attributable to either differing market microstructures, or in government policies and different macroeconomic conditions that existed in the two countries over the sample period. In the US, the primary function of market makers is to reduce volatility, while in the UK, it is to ensure that there is sufficient liquidity in the market to generate immediacy for agents who wish to buy or sell. Moreover, in the US, market makers can request that trading be temporarily suspended during times of exceptional market turbulence; market makers in the UK have no such protection. These differences in microstructure are picked up by the nonlinear rather than the linear causality tests since this is a nonlinear, volatility-related, issue.

6. Conclusions

This paper has employed a new technique for examining the extent of cross-correlations and cross-bicorrelations between stock index and stock index futures contracts. The results show that these markets do not exhibit much evidence of second or third order cross-correlations, apparently consistent with efficient market theory. Given that the data examined is, however, of daily frequency, then the mere existence of a higher proportion of significant windows than one would expect if the data were drawn from two independent white noise processes is nonetheless a surprising result. Moreover, these results cannot satisfactorily be explained with reference to the microstructure arguments of Stoll and Whaley (1990), since nonsynchronous trading and other such anomalies should not be present in daily data. It is also of interest to note the differing results of applying the same methodology to the UK and US markets. These results have implications for the degree of integration of the two markets, an issue which has been of great concern to market practitioners and politicians, as well as academics, following the publication of the report by the Brady Commission (1988). Under most market conditions, we find that the stock and stock index futures markets are operating very closely together, with price movements for both occurring on the same day and in the same direction, leading to cross-correlations and cross-bicorrelations that are not significantly different from zero.

Finally, it is also useful to observe that there is more nonlinear cross-causality than linear cross-causality between the S&P 500 spot and futures markets, so it appears that, at least at daily frequency, a linear model of the VAR type would generally be insufficient to characterise the dynamics of the relation between the series, in agreement with the conclusions of Dwyer *et al*. (1996) who undertake a very high-frequency analysis of the S&P 500 markets. Our results are also consistent with Kawaller *et al.* (1987), who find that the contemporaneous correlations typically "swamp all lag impacts in both directions" (p1329), implying that any observed lead / lag relationships are unlikely to yield significant profits if employed in an active trading strategy. Unlike Kleidon and Whaley (1992) however, we find that this integration did not break down in the UK market during October 1987, although in fact there was some evidence of a breakdown during the middle of 1992. The latter may be attributable to the effects of the ERM debacle and the ensuing interest rate uncertainty which will more directly influence the relationship between stock index and stock index futures prices than a stock market crash which should affect both markets in a similar fashion.

Acknowledgement

The authors are grateful to an anonymous referee for comments on an earlier version of this paper; the usual disclaimer applies.

References

Albert, R.L. Jr., Smaby, T.R., and Wyatt, S.B. (1993) "Did Black Monday have a Permanent Effect," *Journal of Financial Research* **16**(2), 123-138.

"Brady Commission Report" (1988) *Presidential Task Force on Market Mechanisms* U.S. Government Printing Office, Washington D.C.

Brooks, C. (1996) "Testing for Nonlinearity in Daily Pound Exchange Rates" *Applied Financial Economics* **6**, 307-317

Brooks, C. and Garrett, I. (1996) "Explaining the dynamics in stock and stock index futures markets," *Mimeo.* University of Reading and Manchester University.

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**(1), 123-152.

Dwyer, G.P. Jr., 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.

Granger, C.W.J. (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.

Grünbichler, A., Longstaff, F.A. and Schwartz, E.S. (1994) "Electronic screen trading and the transmission of information : an empirical examination," *Journal of Financial Intermediation* **3**, 166-187.

Harris, L.H. (1989) "The October 1987 S&P 500 Stock-Futures Basis," *Journal of Finance* **44**, 77-99.

Herbst, A.F., McCormack, J.P., and West, E.N. (1987) "Investigation of a Lead-Lag Relationship between Spot Stock Indices and Their Futures Contracts," *Journal of Futures Markets* **7**(4), 373-381.

Hinich, M.J. (1996) “Testing for Dependence in the Input to a Linear Time Series Model,” *Journal of Nonparametric Statistics* **6**, 205-221.

Hsieh, D.A. (1991) “Chaos and nonlinear dynamics : applications to financial markets,” *Journal of Finance* **46,** 1839-1877.

Kawaller, I.G., Koch, P.D. and Koch, T.W. (1993) “Intraday Market Behaviour and the Extent of Feedback Between the S&P 500 Futures Prices and the S&P 500 Index,” *Journal of Financial Research* **16**(2), 107-121.

Kawaller, I.G., Koch, P.D. and Koch, T.W. (1987) “The Temporal Price Relationship between S&P 500 Futures and the S&P 500 Index,” *Journal of Finance* **42**(5), 1309-1329.

Kipnis, G., and Tsang, S. (1983) “Index Futures Track Each Other Better than Indexes,” *Commodities* February: 50-52.

Kleidon, A.W. and Whaley, R.E. (1992) “One Market? Stocks, Futures, and Options During October 1987,” *Journal of Finance* **42**(3), 851-877.

Lo, A.W. and MacKinlay, A.C. (1990) “An Econometric Analysis of Nonsynchronous Trading,” *Journal of Econometrics* **45**, 181-211.

Miller, M.H., Muthuswamy, J. and Whaley, R.E. (1994) “Mean reversion of Standard & Poor's 500 Index basis changes : arbitrage-induced or statistical illusion?” *Journal of Finance* **49**, 479-513.

Sims, C.A. (1972) “Money, Income and Causality,” *American Economic Review* **62**, 450-552.

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**(4), 441-468.

Tse, Y.K. (1995) “Lead-Lag Relationship Between Spot Index and Futures Price of the Nikkei Stock Average,” *Journal of Forecasting* **14**, 553-563.

Yadav, P.K., Pope, P.F. and Paudyal, K. (1994) “Threshold autoregressive modelling in finance : the price difference of equivalent assets,” *Mathematical Finance* **4**, 205-221.

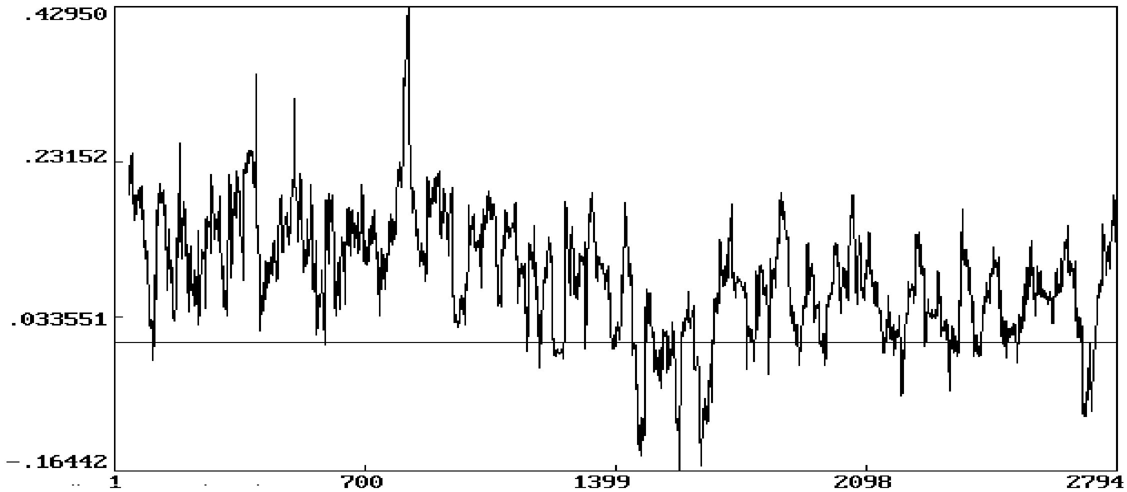
Table I
Parameter Estimates From Regression of Stock Index Returns on Lagged, Contemporaneous and Leading Futures Returns

$$\Delta s_t = \alpha_0 + \sum_{i=-k}^{k} \beta_i \Delta f_{t+i} + u_t$$

	FTSE 100			S&P 500		
	Whole Sample	Pre-crash Sample	Post-crash Sample	Whole Sample	Pre-crash Sample	Post - crash Sample
β_{-4}	0.0201** (3.0097)	0.0177 (1.7926)	0.0117** (2.9622)	-0.0003 (-0.0489)	0.0019 (0.2362)	-0.0199* (-2.2647)
β_{-3}	-0.0025 (-0.7461)	0.0026 (0.4012)	0.0025 (0.3892)	0.0018 (0.3841)	0.0076 (0.8046)	0.0017 (0.1812)
β_{-2}	-0.0042 (-0.0946)	0.0052 (0.5630)	0.0093 (1.4945)	0.0503* (2.5482)	-0.0069 (-0.5587)	0.0150** (3.8300)
β_{-1}	0.0893** (10.855)	0.0615* (2.5363)	0.0752** (9.5992)	0.0585** (2.6412)	0.1434** (17.220)	0.0550** (12.662)
β_0	0.7808** (52.621)	0.7898** (21.511)	0.7662** (31.670)	0.7681** (30.507)	0.7559** (33.374)	0.8782** (35.180)
β_1	-0.0111 (-0.8965)	0.0304 (1.9588)	0.0060 (0.6547)	0.0294** (6.0458)	0.0094 (0.6960)	0.0153 (1.8102)
β_2	0.0175** (2.5753)	0.0119 (0.9634)	-0.0090 (-1.2472)	0.0252** (6.7813)	0.0296* (2.2488)	0.0176* (2.1691)
β_3	0.0054 (0.5715)	0.0167 (0.6897)	0.0192* (2.0329)	0.0013 (0.6694)	0.0067 (1.0488)	-0.0076* (-2.1079)
β_4	0.0024 (0.7184)	-0.0173 (-1.2998)	0.0034 (0.5752)	-0.0127* (-2.1046)	0.0020 (0.1310)	0.0012 (0.5622)
H_{lag}	183.14**	17.340**	84.912**	188.63**	161.70**	63.892**
H_{lead}	9.9324*	7.1651	7.1332	56.355**	7.6148	10.516*

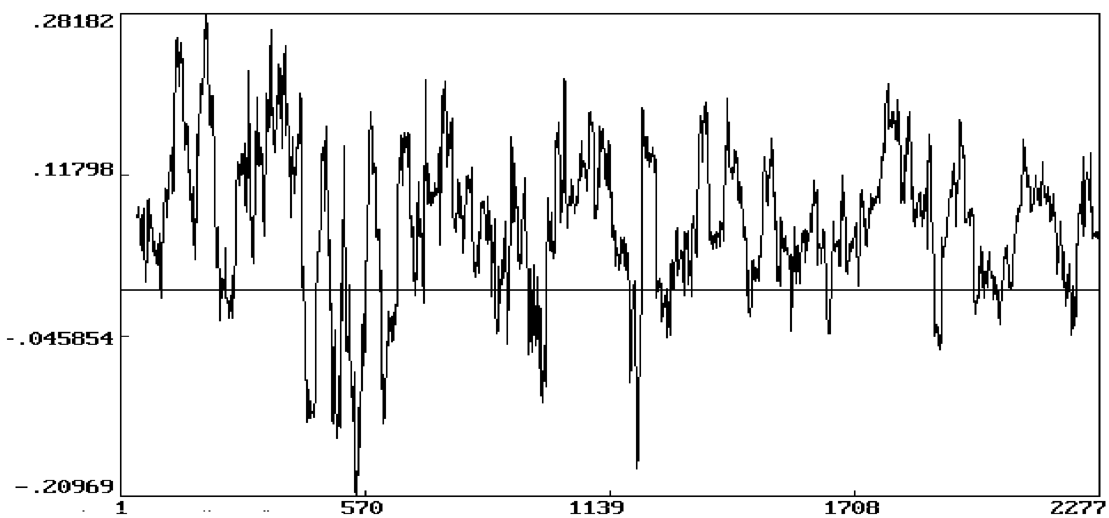
Notes : Figures in parentheses are *t* statistics calculated using the Newey and West (1987) variance-covariance matrix. H_{lag} and H_{lead} are Wald tests of the joint significance of lag and lead terms respectively and are distributed $\chi^2(4)$ under the null hypothesis that the relevant coefficients are zero. * and ** denote significance at the 5% and 1% levels respectively.

Figure 1
Coefficient on Δf_{t-1} 24 for the S&P 500, Estimated by Rolling Least Squares



1

Figure 2
Coefficient on Δf_{t-1} 25 for the FTSE 100, Estimated by Rolling Least Squares



2

Table II

Results of The Cross-Correlation Test for the Significant Windows for the US and UK

Dates Covered By Window	*p*-Values of Test Statistics *xy*	*xxy*	*yyx*	Significant Correlations (at lag)	R^2 for VAR Fit
US					
No significant window					
UK					
12/3/92-4/5/92	0.0048	0.9092	0.7323	-0.47 (-1) -0.48 (1)	0.740

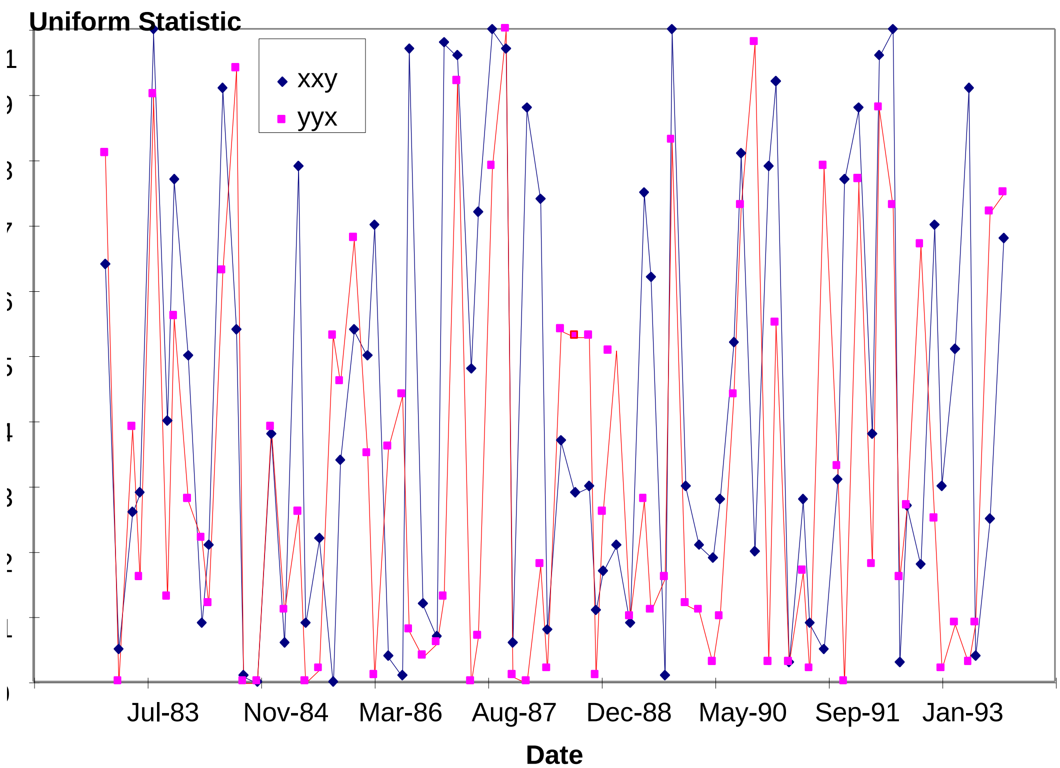
Note: Futures market leads for positive lags, spot market leads for negative lags.

Table III

Results of the Cross-Bicorrelation Test for the Single Significant Window using Residuals from a BVAR(2,2) Fit

Dates Covered By Window	*p*-Values of Test Statistics *xy*	*xxy*	*yyx*	Most Significant Bicorrelation (at lag)	R^2 for VAR Fit
US					
22/7/83-9/9/83	0.0040	0.1011	0.8685	0.43(1,-1)	0.571
28/7/87-15/9/87	0.0001	0.2134	0.9817	-0.48(1,1)	0.516
16/9/87-3/11/87	0.0316	0.0020	0.6525	-0.39(1,1)	0.717
11/10/87-28/11/89	0.0000	0.1713	0.9378	-0.60(1,-2)	0.749
1/6/92-17/7/92	0.0002	0.2673	0.7909	-0.66(1,1)	0.602
UK					
24/6/92-11/8/92	0.9931	0.0073	0.0220	-0.45 (1,2)	0.616

Figure 3
The Transformed Uniform Cross-Bicorrelation Test Statistics for the US



3

Figure 4
The Transformed Uniform Cross-Bicorrelation Test Statistics for the UK

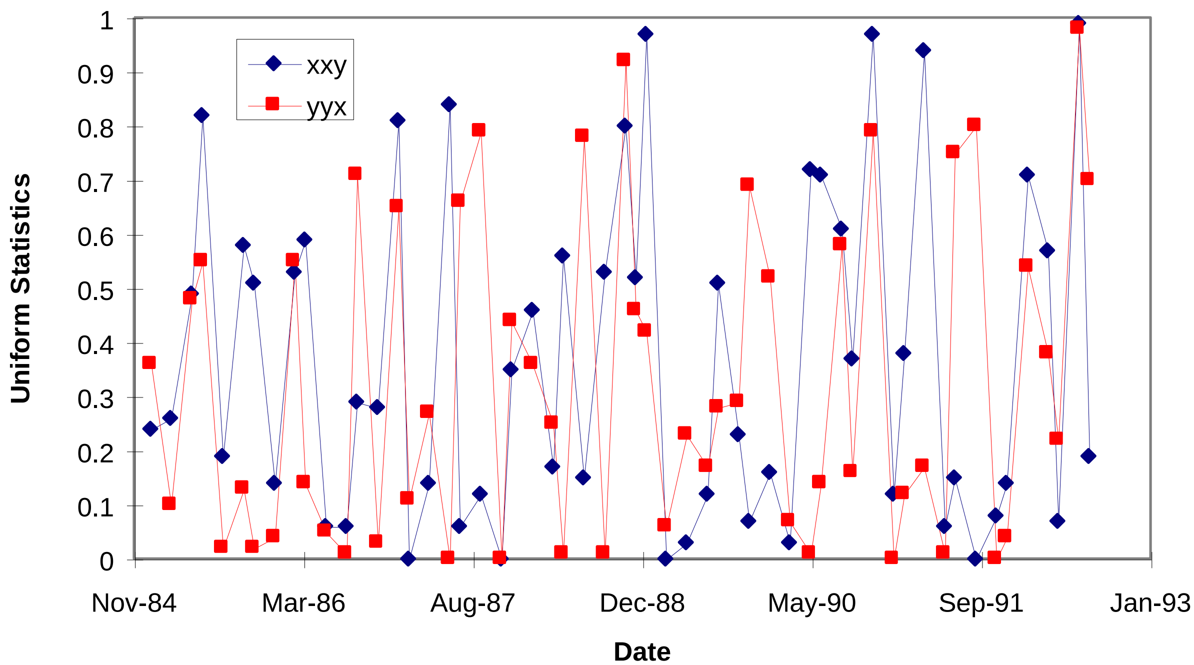


Table IV
Correlations of the Cross-Correlation and Cross-Bicorrelations Test Statistics with the Individual Variances for the US and the UK

Correlation Between	*xy, Var(X)*	*xy, Var(Y)*	*xxy, Var(X)*	*xxy, Var(Y)*	*yyx, Var (X)*	*yyx, Var(Y)*
US						
Value	0.20	0.19	0.02	0.24	0.06	0.24
Fisher	0.768	0.728	0.080	0.927	0.227	0.927
UK						
Value	-0.55	-0.52	-0.22	-0.21	-0.19	-0.18
Fisher	-2.115**	-1.971*	0.765	-0.729	-0.658	-0.622

Notes: Value denotes the value of the correlation coefficient and "Fisher" denotes the value of the Fisher test that the true value of that coefficient is zero. * and ** denote significance at the 5% and 1% levels respectively.

[1] For more on threshold nonlinearity see Yadav, Pope and Paudyal (1994) and Dwyer, Locke and Yu (1996) for evidence relating to the US and Brooks and Garrett (1996) for evidence relating to the UK.

[2] The importance of this is that if factors such as nontrading are present then they may induce a spurious lead-lag relationship because in the case of nontrading the index will contain stale prices and thus the futures will appear to lead the spot for no other reason than the effect of stale prices on the index. Note also that technically, we can distinguish between nontrading and nonsynchronous trading. Nonsynchronous trading is the situation where securities trade at least once every time interval but not necessarily at the end of the interval, whereas nontrading is the situation where securities do not trade for several time intervals. However, since the effect of both of these is to induce autocorrelation in stock returns, we will use the two interchangeably here.

[3] If all of the stocks within the portfolio have the same probability of nontrading then the coefficient on lagged observed returns in the AR(1) model provides an estimate of that nontrading probability.

[4] Notice that the summations in (4) and (5) exclude contemporaneous terms. This is to avoid rejection of the null hypothesis of independence because of the strong contemporaneous correlations that we would expect to exist between spot and futures returns.

[5] The results are not, however, sensitive to fairly large changes in this parameter.