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Paul Kofman* and Martin Martens**

Abstract

This paper examines the spill-overs in both returns and volatility between the London and New York stock markets during overlapping trading hours. Using high-frequency data for the FTSE 100 and S&P 500 stock index futures, we estimate the seasonal patterns in volatility using the Flexible Fourier Form specification of Gallant (1981). For both markets, volatility is estimated to be higher in the morning and late afternoon, as compared to the rest of the day. The estimated seasonals are used to adjust the returns before conducting the lead-lag analysis. The results indicate that both markets influence each other, although the impact of the US on the UK is clearly stronger.

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I. Introduction

In this paper we examine the intraday correlations in price changes and in volatility of the stock indices of London and New York during the overlapping trading hours. Previous research (e.g. Von Furstenberg and Jeon, 1989; Becker, Finnerty and Gupta, 1990; Becker, Finnerty and Tucker, 1993; Hamao, Masulis and Ng, 1990; Lin, Engle and Ito, 1994) has focussed on the overnight and daily transmission of stock index prices between several international markets, both at the level of returns and the level of volatility. Hamao, Masulis and Ng (1990), for example, look for spill-over effects in open-to-close stock returns and for the effect of open-to-close returns on the opening price of the next market to open. They find a statistically significant correlation between the London and New York open-to-close returns. This effect, however, disappears when using noon-to-close returns in New York adjusting for the overlapping trading hours. Becker, Finnerty and Tucker (1993) use futures rather than the index itself to avoid stale quotes in the morning. They find high correlation between lagged US open-to-close returns and UK close-to-open returns, and also between UK open-to-close returns and US close-to-open returns. The high correlation between daily UK open-to-close returns and US lagged close-to-open returns (using 11:00am New York time as the opening hour) is attributed to the interval of one hour and forty minutes of common trading.

In this study, we are particularly interested in the effects of overlapping trading hours in London and New York. When there is a significant effect of one market on the overnight return of the next market to open, this will be reflected in the opening prices of the latter market. Unfortunately, this does not imply profitable trading opportunities, since traders can only act upon such effects during the market's trading hours. However, if traders are able to predict future price movements during trading hours, they can take advantage by implementing various trading strategies.

To investigate the price relations between London and New York during their common trading hours, we will use index-futures contract prices. This has two major advantages as compared to the use of the stock index prices themselves. First, index values often lag actual market developments since many stocks in the index do not trade every minute. Infrequent trading combined with lower futures transaction costs are suggested as main reasons for the empirically documented lead of the futures market on the stock market (e.g. Kawaller, Koch and Koch, 1987; Stoll and Whaley, 1990; Chan, 1992; Yadav and

Pope, 1990; Abhyankar, 1995). Second, if it is possible to predict future price movements, it is cheaper to take advantage of this in the futures market than in the stock market. Instead of buying or selling a whole portfolio of stocks representing the index, traders only have to buy or sell a futures contract, involving less transaction costs and a higher leverage allowing greater debt financing of the transactions.

We propose to use high-frequency data, since we expect that 'due to the modern information technology' spill-overs between financial markets take place within very short time intervals. When using high-frequency data one has to consider some stylised facts concerning futures market transaction prices. First, we have to adjust for the negative autocorrelation in the return series caused by prices bouncing between bids and asks as indicated by Roll (1984). Second, we also have to adjust futures market returns for the seasonal patterns in volatility reported by e.g. Locke and Sayers (1993), Andersen and Bollerslev (1994) for the S&P 500 index-futures, and Abhyankar, Copeland and Wong (1995) for the FTSE 100 index-futures. This seasonality effect is characterised by higher volatility in the first and last hours of trading as compared to the central part of the trading day. We find similar evidence for our sample period.

Ignoring the intraday seasonality might have serious repercussions on a lead-lag analysis. Increasing volatility in the London market towards the end of the trading day and decreasing volatility in the New York market in the middle of the trading day would exert a negative effect on the relation between the volatilities of the two markets during their common trading interval. However, if we do adjust for these seasonal effects, the literature suggests positive spill-over effects across markets, see e.g. Eun and Shim (1989) for daily data and Becker, Finnerty and Tucker (1992) for an intradaily data application.

Our results indicate that, after adjusting for the seasonal pattern in each market individually and also for the heteroskedastic behaviour at the volatility level, there is a short lead of the US market over the UK market. This lead exists at both the return and at the volatility level. The one minute lead of New York over London is clearly statistically significant, especially for the first 30 minutes of trading in the New York market.

The next section describes our data set. In Section III we explain our estimation procedure based on a Fourier Flexible Form (FFF) to model the seasonal pattern in volatility. Section IV discusses the results of the intraday analysis of correlations between the London and New York stock markets at both the return and the volatility level, after deseasonalising the time series by the estimated FFF's. Section V explores a possible trading strategy to take advantage of the significant relations estimated at the return level. Finally, Section VI summarises our findings.

II. Data

Our data-set consists of stock index futures prices for the London and New York stock markets for a six months sample period from January through June 1993. This amounts to a total of 121 trading days and a total of 11,800 overlapping trading minutes. The data are obtained from the Futures Industry Institute (Washington, D.C.), a major source of tick-by-tick futures prices.

For the London stock index we use the futures on the Financial Times Stock Exchange (FTSE) 100 index traded at the London International Financial Futures Exchange (LIFFE). The FTSE100 futures contracts are available at four maturities with expiration on the third Friday in March, June, September, and December. LIFFE trades from 8:35 am to 4:10 pm BST based on an Open Outcry (OOC) trading system, then closes for 20 minutes, and continues trading until 5:30 pm BST based on an Automated Pit Trading (APT) system. The London Stock Exchange closes thirty minutes earlier, at 5:00 pm BST.

For the New York stock index we use the futures on the Standard & Poors (S&P) Composite 500 index traded at the Chicago Mercantile Exchange (CME). These S&P500 futures contracts also trade at four maturities with expiration dates on the third Thursday in March, June, September, and December. The CME trades from 8:30 am to 3:20 pm CST. The New York Stock Exchange (NYSE) closes twenty minutes earlier, at 3:00 pm CST.

The aforementioned times, except for the NYSE closing time, are measured in local time. For convenience we will use Chicago time (CST) from now onwards. Since our sample period includes one transition to daylight saving, we also adjust for potential differences in the exact time of transition. In the UK this transition to daylight saving time takes place on the last Sunday in March, while in the US it takes place on the first Sunday in April. The transition back to normal time takes place in September for both London and New York, and is therefore not relevant to our analysis. Therefore, except for the trading days of March, 29, 30 and 31, and April, 1 and 2 in 1993, the trading hours for LIFFE and the CME can be summarised as shown in Figure 1.

LIFFE starts trading at 2:35 am CST and closes its OOC trading system at 10:10 am CST. Since APT time is known to have low volume (and may therefore lead to spurious price movements), we will only focus on the portion of OOC trading time which overlaps with Chicago trading. Thus, we compare both markets for the time period from 8:30 am CST through 10:10 am CST, representing a 100 minute sampling interval for each trading day. The 5 trading days involving the differences in the transition to daylight saving time will, however, only have a 40 minute sampling interval.

For both futures contracts we obtained transaction prices stamped with the exact time to the nearest second. Because contracts with more than one delivery date trade simultaneously, for each day the prices of the most liquid contract are used. This is generally the contract nearest to delivery. For both the March and the June futures contracts the US traders' interest shifts towards the futures with the next nearest delivery date one week before maturity, while in the UK this occurs just one day before maturity[1]. From the tick by tick transaction prices 1-minute prices are constructed using the last available price each minute. The average lag-time relative to the exact minute-mark during the common trading interval is 7.8 seconds and 18.6 seconds for the S&P and FTSE futures, respectively. In minutes of no trading (zero transactions), the last recorded price is imputed. For the common trading period this occurs for 0.42 percent of S&P futures prices, while it occurs for 11.8 percent of FTSE futures prices. Finally, we calculate scaled 1-minute returns by multiplying the difference of the natural logs of the 1-minute futures prices by one hundred. Descriptive statistics for the returns are shown in Table 1 for the FTSE and S&P futures.

For both markets the average volatility (measured by the standard deviation) is slightly higher during common trading hours than during each markets' whole trading day, reflecting the anticipated U-shape pattern in both markets' volatility. The kurtosis measure reveals that the distribution of the returns is fat-tailed and peaked in the middle as compared to a normal distribution.

III. The Fourier Flexible Form

In this section we define the (un)adjusted return and volatility series, and we estimate a seasonal pattern for the volatility in returns of the London and New York futures markets.

III.A. Sample volatility

To investigate whether a U-shape pattern is present in the FTSE and S&P futures returns volatilities, we first have to establish a sample volatility measure. A common choice is the absolute deviation of the return from the expected daily return. However, Roll (1984) illustrates that a sequence of prices will be a random sequence of bid and ask prices. This causes returns to be negatively autocorrelated. For that reason we estimate the following autoregressive (AR) model:

$$R^{i}_{t,d} = \rho_0 + \sum_{k=1}^{L} \rho_k * R^{i}_{t-k,d} + \varepsilon^{i}_{t,d} \tag{1}$$

where $R^{i}_{t,d}$ is the (mean adjusted) return for intraday period t (t=1...T) on day d (d=1..D) for market i (i=FTSE,S&P), ρ_0 is a constant, ρ_k is an autocorrelation parameter, and L is the lag length based on inspection of the partial autocorrelation function (PACF). The model is estimated by ordinary least squares (OLS). For the FTSE returns the most appropriate specification is an AR(1) process with an estimated value of $\hat{\rho}_1$ = -0.0495. For the S&P returns an AR(2) specification turns out to be more appropriate with estimated values $\hat{\rho}_1$ = -0.0483 and $\hat{\rho}_2$ = 0.0160. Next, we define the *residual* return as

$$e^{i}_{t,d} = \hat{\varepsilon}^{i}_{t,d} \tag{2}$$

where $\hat{\varepsilon}^{i}_{t,d}$ is the estimated residual for ε in equation (1). The absolute value of this residual return will be used to measure the futures returns volatility. Averaging each 1-minute trading interval's absolute residual return over all trading days, we obtain an average sample volatility measure for each 1-minute interval as shown in Figures 2 and 3.

Both markets exhibit the anticipated 'seasonal' volatility pattern. Volatility is higher in the morning and the late afternoon as compared to the central part of the trading day. For the FTSE futures volatility, we also observe a peak at 11:30 am BST. The opening of the CME has a less pronounced impact on the FTSE futures volatility, although it seems that volatility drops just before the opening and rises immediately thereafter. This effect will be formally tested in the next subsection.

III.B. Filtering the seasonal

In comparing the FTSE and S&P futures returns and volatility levels we have to consider the observed intraday seasonal pattern. If we chose to compare the raw return volatilities in the two markets, we would ignore the fact that over the common trading interval volatility is increasing in LIFFE futures returns, while it is decreasing in the CME futures returns.

The literature proposes many alternative estimation methods to model volatility. Pagan and Schwert (1990) compare a number of them for stock returns. One of the models examined is the FFF of Gallant (1981). According to the FFF method, the variance should be specified as a sum of low-order polynomial and trigonometric terms. This is particularly appropriate, since our main concern is to fit a smooth seasonal pattern to the observed volatilities. The FFF technique has recently also been applied by Andersen and Bollerslev (1994) to the Deutschemark-USdollar exchange rate and the S&P 500 stock index-futures.

We use a similar FFF approach as proposed in the Andersen and Bollerslev study. The following equation is used to estimate the FFF by specifying the seasonal as a function of time:

$$|e_{t,d}| = \sum_{k=0}^{1} \sigma_d^k \left[\alpha_{0k} + \alpha_{1k}\frac{t}{T} + \alpha_{2k}\frac{t^2}{T^2} + \sum_{i=1}^{I} \delta_{ik} D_{i,t} + \sum_{j=1}^{J} \left(\beta_{jk}\cos\frac{2jt\pi}{T} + \gamma_{jk}\sin\frac{2jt\pi}{T} \right) \right] + \varepsilon_{t,d}$$

(3)

where the first part is a quadratic function of time t (t=1..T), the last part a linear combination of trigonometric functions of time t, σ_d is the standard deviation on day d, and $D_{i,t}$ are dummy variables equal to one if $t=t_i$ and zero elsewhere. These dummies can be used for example for the first few minutes of trading on LIFFE (where we observe a steep descent) and the peak around 11:30 am BST. We do not propose to use any dummy variables for the overlapping trading period in order to preserve the intermarket relations. The polynomial of order two will merely capture the high-low-high pattern in the volatility, while the sinoids will capture any patterns not reflected by this polynomial.

For k=1 the expression involves interactive terms with the daily level of volatility.

These levels for both markets are likely to be correlated. If that is the case, i.e. a similar daily volatility level, a cross-correlation analysis of returns might give spurious results. On the other hand, when analysing the cross-correlations in volatility, this level-filtering procedure will change the spill-overs between two markets. The daily level of volatility is part of any potential spill-over relationship in volatility. For this reason, we will also discuss the results using an estimated seasonal without the interactive term σ_d.

The results of these regressions for both futures contracts are given in Table 2. For the FTSE futures returns volatility we specify dummies for the first two minutes and for the minutes 175 through 178. Though not reported, we also conducted a regression with dummies for minutes 354 through 358, measuring the impact of New York opening at minute 356. This gives, at the 5 percent level, statistically significant negative estimates for the minutes before the opening of New York trading. Thus, volatility on LIFFE drops significantly just before the opening and rises thereafter, lending support to our observation in the previous section. These dummies are, however, not used to characterise the seasonal in order to preserve the nature of the spill-overs between the two markets. The estimated seasonal is now simply given by the estimated right-hand side of equation (3). Using this estimate we can now plot the average volatility for each minute over all trading days, see Figure 4.

Denoting the seasonal by $\sigma_{t,d}$, we can now adjust the residual return $e_{t,d}$ by dividing it by $\sigma_{t,d}$. This 'seasonally' adjusted residual return will be used to investigate return spill-overs between LIFFE and CME stock index futures during common trading. For the volatility interaction we will use the absolute value of these seasonally adjusted residuals. Using the residual of equation (3) as a volatility measure, instead of the seasonally adjusted residual of equation (2), gives similar results.

III.C. Volatility clustering

While the phenomenon of interday volatility clustering is empirically well established, there is mixed evidence with regard to intraday volatility clustering. For example, Locke and Sayers (1993) find little evidence of volatility persistence in the 1-minute returns for the S&P futures for a sample in April 1990. In contrast, Ederington and Lee (1993) do find quite strong volatility clustering effects. Their study analyses the impact of scheduled US economic news announcements on US interest rates and on the DM-$ exchange rate using intraday data from futures markets. Most of the impact these information releases have on returns disappears within one minute of the release. Not surprisingly, trading profits based on the initial reaction disappear within this period as well. Volatility, however, remains considerably higher than normal for another 15 minutes or so and slightly higher for several hours. Ederington and Lee provide two explanations. Either, trading based on the initial information persists since the implications for market prices are not immediately clear. Or, prices react to the details of the news releases as they become available. It seems logical that important public news will not immediately (being within one minute after release) be fully reflected in prices. News needs to be interpreted and traders will try to predict other traders' adjusted expectations or they will wait for the market to react to the news. Thus, one can expect that in our high frequency sample prolonged quiet periods alternate with sustained hectic periods, due to the fact that relevant news needs some time to disperse.

On the other hand, publicly available news will probably not be the only reason for any particular lead-lag structure in our two market setting. The macroeconomic announcements considered in, e.g., Ederington and Lee (Consumer Price Index, Employment and Gross National Product) are all released before the CME opens. In addition, price movements in other markets (not considered as news releases) also qualify as news. Several studies (e.g. King and Wadhwani, 1990; Lin, Engle and Ito, 1994) have tried to split intermarket relations into global effects (based on common news sources) and so-called contagion effects (based on noise spill-overs). 'Unobservables', rather than identifiable publicly available news, seems to be the common source driving world stock markets.

Volatility clustering implies positive serial correlation in the absolute (adjusted) residual return series. If we detect signs of volatility clustering in our series, then these series have to be adjusted before being used in cross-correlation estimation. For example, Pierce and Haugh (1977) show that similar autoregressive processes might lead to spurious cross-correlation estimates. Therefore, they propose to prewhiten the series before estimating the cross-correlations. This implies that, e.g. an AR(p) process is fitted to the original series, and the (white noise) residuals from these estimations are then used for further estimation of the cross-correlations.

For two reasons we prefer to filter the return series first for a seasonal, and only then (if necessary) to further prewhiten the series. First, the filtering procedure based on the FFF provides a smooth estimation of the seasonal pattern. As a result, this will change the individual and the intermarket relations only with respect to this estimated seasonal. Second, first filtering e.g. an AR(p) process will not only filter clustering effects related to news. If there is a seasonal pattern, this will induce high volatility at the beginning and at the end of the trading day. Therefore, it will also (to some extent) cause clustering in volatility of returns and hence be confused with the AR(p) process. Our approach strictly separates the two effects.

IV. Spill-overs

The previous section explained our procedure for deseasonalising the time series. The adjusted time series are next used to look at spill-overs between the London and New York markets, both at the return and volatility levels.

IV.A. Spill-overs at the return level

Once the observations have been adjusted for a seasonal and for any negative autocorrelation, we can now estimate the correlation between the two contracts' return series at different time lags. To allow comparison with the unadjusted raw returns (before deseasonalising), we also report the correlations between these series. Both sets of results are given in Table 3. The adjusted return correlations are also shown in Figure 5. The cross-correlation estimates show that each market has a statistically significant impact on the other market. The magnitude of the estimated correlations, however, indicates that the contemporaneous correlation and the 1-minute lead of the S&P futures over the FTSE futures are the largest, being 0.133 and 0.210 (second column labelled 'total' in Table 3), respectively. Thus, there is an apparent small lead at the return level of the US market over the UK market. One interpretation is that market-wide news more often has its origin in the US, and that immediately thereafter the financial markets in London receive this news (either directly, or through movements in the S&P 500). Another explanation is that some traders in the UK market just trade on the signals from the US market. The length of the significant lead, being only two minutes, indicates how quickly information disperses throughout the world's financial markets. The high estimated cross-correlation of 0.21 for the 1-minute lead of the S&P futures prices over the FTSE futures prices indicates that a profitable trading strategy could be possible, assuming futures positions can be obtained within seconds of time. This will be the subject of Section V.

It should be noted that by using the residual returns, the returns are (at least for a large part) prewhitened. Adding this to the well-known fact that cross-correlations are almost insensitive to the underlying variance of the variables, this explains the small difference between the residual returns and the adjusted residual returns. Also, deseasonalising based on an estimated seasonal without the daily volatility level σ_d in equation (3) gives similar results (not reported here).

Table 3 also reports the estimates based on a possible asymmetric reaction to positive versus negative returns in the leading market. There is, however, no leading market for the contemporaneous correlation. We therefore split this estimate into the sixth row, where we consider the sign of the UK residual, and the seventh row where the sign of the US residual is considered. The reaction of one market to movements in the other market is stronger when the residual return of the leading market is negative. This difference, however, is not statistically significant. This can be observed from the last two columns in Table 3, and formally by conducting an F-test under the assumption that the correlations are i.i.d. normal. For example, for the one minute lead of the US after a decrease in US prices, the estimated cross-correlation is 0.146 as opposed to 0.114 after an increase. Thus, traders in the UK react stronger to decreases in prices in the US than they do to increases. Hence, negative news in the US has a stronger impact on the UK than positive news. The economic significance of this effect will be tested in Section V.

IV.B. Spill-overs at the volatility level

To estimate the cross-correlations in the volatility of returns, we use the absolute value of the adjusted residual returns $|e_{t,d}/\sigma_{t,d}|$, where $\sigma_{t,d}$ is the estimated seasonal based on the regressors in equation (3). The cross-correlation results are given in Table 4 and Figure 6. The first column gives the estimates for the raw 1-minute volatility series, the unadjusted absolute residuals. Deseasonalised cross-correlation estimates are given in the second column, while prewhitened deseasonalised estimates are shown in the third column. The latter estimates indicate that only contemporaneous cross-correlation (0.0319) and the 1-minute lead of the US (0.0519) are statistically significant at the 1 percent level. When comparing Table 4 with the estimates for the returns in Table 3, it now becomes apparent that seasonal filtering and prewhitening is important. After deseasonalising the raw series, the effect of decreasing volatility in the US (at the beginning of the U-shape in Figure 3) and increasing volatility in the UK (at the end of the U-shape in Figure 2) has been eliminated. Unfortunately, however, the estimated correlations between the two markets at the daily level have been eliminated as well. The final stage (the prewhitening procedure) removes all remaining autocorrelation, only allowing a weak effect from shocks in the US market to spill-over into the UK market. Possibly, the interactive terms with the daily level of volatility in the seasonal specification have been the cause of the disappearance of the spill-overs in volatility. To check this, we also estimate a seasonal without the interactive terms involving σ_d in equation (3), which leads to somewhat different results. These are shown in the fourth column which is the analogue of the second column. The estimated cross-correlations obviously increase after deseasonalising (but, before prewhitening) the volatility series, as compared to the raw series' estimates in the first column. This reflects the importance of adjusting for the opposite patterns in the US and UK volatility series (decreasing versus increasing volatility). Prewhitening, though not reported, then yields similar estimates as those reported in the third column, a statistically significant contemporaneous spill-over, and a 1-minute and 7-minute lead (the latter is only significant at the 5 percent level in Table 4) of the US market over the UK market. Ederington and Lee (1993) report that volatility remains at a higher level, subsequent to important news releases, up to 15 minutes later. These effects are, however, not likely to be observed as spill-over effects at higher lags than the ones we found (1 and 7 minutes). The other (no news) market will already have absorbed the news in the minutes immediately after the news release. This will cause a higher level of volatility which, since it implies autocorrelation, has been filtered out in our procedure.

Next, we divide the cross-correlations into two groups, one for which the leading market's return is negative and one for which the leading market's return is positive. For the contemporaneous correlation we once again consider both possibilities of a leading market, as in Table 3. The results are given in Table 5 and in Figure 6.

In contrast with the return findings, there is a statistically significant difference in the reaction of one market to negative returns as compared to positive returns in the other market (last row Table 5). For the 1-minute lead of the US market over the UK market the cross-correlation after a negative return in the US is estimated at 0.0787 as compared to an estimate of 0.0258 after a positive return in the US. This difference is statistically significant at the 1 percent level. Apparently, traders at the LIFFE exchange react stronger to negative news from the US market than to positive news originating there.

IV.C. New York opening effect on London

Despite the absence of a pronounced New York opening effect, as revealed by the FTSE futures volatility seasonal, we observe a statistically significant negative effect on FTSE volatility immediately prior to the New York opening. It seems that at that moment traders in London wait to discover in which direction prices on Wall Street will start to move. If this is the case, then obviously the spill-overs between the two markets should be stronger at the beginning of US trading when London traders pay more attention to the US market. For this reason we also analyse the spill-overs during the first 15 respectively 30 minutes of New York trading. For the returns series we use seasonally adjusted residual returns, and for the volatility series we use prewhitened absolute deseasonalised residual returns. The combined results are presented in Table 6. The results at the return level (first two columns in the table) should be compared with the second column in Table 3. The estimated cross-correlations between the futures returns are larger for the contemporaneous spill-over and the 1-minute lead of the S&P 500 futures over the FTSE 100 futures. For the first 15 and 30 minutes the estimated 1-minute lead correlations are 0.268 and 0.257, respectively, which is significantly (at the 5 percent level) larger than the 0.210 in the total sample of 100 minutes of common trading. On the other hand, we also observe that the statistically significant 1- and 2-minute lead of the UK market over the US market for the full sample disappears for the first 15 and first 30 minutes.

It seems, therefore, that traders in London pay special attention to the US market at the beginning of its trading period, presumably to see in which direction prices move relative to the previous trading day close. Traders in the US only seem to show interest in price movements in the FTSE futures contract after the volatile opening minutes of their own market. A possible explanation is that US traders incorporate overnight news in their opening prices. That effect has been the subject of the international market studies mentioned in the introduction, for example the analysis of the returns realised during Tokyo and London stock markets' opening hours on daily opening and closing prices in the US market. After the first half hour, when volatility in the US has decreased, US traders might start to show interest in *current* price movements in London or in European news in general.

We also compare the opening minutes with our full common trading sample for volatility spill-overs. The 15 minutes, respectively 30 minutes prewhitened absolute residual series' estimates in Table 6 should be compared to the estimates in third column of Table 4. There does not seem to be a statistically significant difference between the opening minutes of New York and the total sample.

V. Profit possibilities

Given the results in Table 3, the question arises whether the coefficients are sufficiently large to enable a profitable trading strategy. To calculate exact outcomes from futures positions involved in such a strategy, we need quotes and transaction costs at every moment we want to alter an investment position. Unfortunately, these data are not readily available. Under some assumptions we can, however, get some idea whether a trading rule is profitable. We could, e.g., regard our 1-minute prices as prices against which we could trade.

To approximate a trading rule, we will focus on the 1-minute US lead over the UK documented in our empirical analysis. We therefore analyse FTSE futures returns following S&P futures price changes exceeding various high threshold levels. For different 'extreme' increases (or decreases) in the S&P futures price, the realised FTSE futures returns in the sample months are given in Table 7. The total sum of the FTSE returns for the first and the second minute after a specific S&P increase (decrease) as shown in column 1, are found in columns 4 and 5. Column 2 reflects the number of times the large S&P futures price increase or decrease actually occurred. The last column is the sum of the returns in the two minutes after a decrease (increase), given a non-zero return in the contemporaneous minute.

The results indicate that the reaction of FTSE futures prices to changes in S&P futures prices is much larger in case of decreases in the S&P futures prices. This corroborates our findings in Section III. It suggests that setting up a short position in FTSE futures after a large decrease in S&P futures prices has a better chance of being profitable. At least before transaction costs.

As noted before, the relation to real-life profits is difficult to assess since bid- and ask prices are not readily available. Under some assumptions, however, we can estimate these costs as well. First, assume the bid-ask spread is constant during the overlapping trading hours. This may not be exactly correct, but Figure 7 shows a rather constant average spread throughout the day except around lunch-time and during the APT interval. Similar conclusions are drawn in Abhyankar, Copeland and Wong (1995) for the period March 1991 to June 1993, including our sample period. Second, assume that transaction prices occur randomly at bids and asks. Then, setting up and liquidating a futures position would involve two transactions, one at the ask and one at the bid. In both cases there is a 50 percent chance that the transaction price is the correct price, and 50 percent chance that there is a mistake of exactly the size of the bid-ask spread. In addition, if transactions at the bid (ask) tend to be followed by transactions at the bid (ask), the mistake will also be the size of the spread. Thus, the estimated costs due to the spread will then be equal to the number of cases given in column 2 times the bid-ask spread. If this spread is for example 0.10 index-points, for the 28 cases in the third row ($\Delta S\&P_t \leq -0.60$) the estimated costs not already taken into account are 2.80[2].

Concluding, quoted prices are needed to show that trading profit opportunities exist. In case of especially large S&P futures price decreases, even with our minute by minute prices, there are strong suggestions that potential profits are possible.

VI. Conclusion

The intraday volatility pattern of the FTSE and S&P futures returns displays in both cases a U-shape: high volatility in the morning and late afternoon, and lower volatility during the rest of the day. For the opening minutes of the NYSE this effect is less pronounced, possibly due to a drop in volatility at LIFFE a few minutes before this opening interval. We adjust for an opposite (UK versus US) seasonal volatility pattern during the common trading interval based on a Flexible Fourier Form estimation procedure.

Using index-futures, we have investigated the relationship between the S&P 500 index and the FTSE 100 index during common trading hours of the New York and London stock markets. Our results indicate that both markets' futures returns have predictive power for the other market's futures returns. However, the lead of the US market over the UK market is significantly stronger. We also analysed potential asymmetry in the sign of news on the estimated cross-correlations in returns. These correlations are (insignificantly) stronger when there is negative news (decreases in return). When focussing on a particularly volatile sub-period, we find that the US lead is stronger in the first 30 minutes after the opening of New York, while the UK lead only becomes statistically significant after this opening period. Similar results are found for the spill-overs at the volatility level. Then, however, we find a significantly stronger reaction of one market over the other in case of negative news.

We find volatility clustering in both markets at the intraday level. The clustering at the interday level is well known, reflecting sustained periods of turbulence in the financial markets. At the intraday level this fact could be interpreted as news taking some time to be fully reflected in prices.

As an extension it would be interesting to analyse price quotes and realistic transaction costs to establish the profitability of our estimated relations. Our approximate tests show promising results for taking a short FTSE futures position after a large US decrease in the previous minute. Further, it would be interesting to investigate this kind of relations between other strongly related markets sharing common trading hours. If one of these market is much larger than the other market, we expect the relations in returns and volatilities to be more uni-directional and stronger than the ones found here.

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Notes

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1 Omitting the days in the week of maturity and two days from the week before (11 through 19 March and 10 through 18 June) in our sample does not significantly change the results. Deviations are small and not systematically biased into one direction.

2 Consider a trader going short in one FTSE 100 futures contract whenever the S&P futures return is less than -0.60 index-points. For the 28 cases this occurs in our sample, it would have generated a total return of 3.70 (sum of the last two columns in Table 7) index points. Thus, except for commission costs, this trader would have gained an estimated (3.70-28*0.10=) 0.90 FTSE index-points. In practice, trades can take place within the quoted spread, which would make these profits even larger.

Appendix A: Newey-West standard errors for correlations

Newey-West (1987) standard errors are also called HAC (Heteroscedasticity and Autocorrelation Consistent) errors. The following is a method for constructing HAC errors for cross-correlations using the known method for regression models.

The relation between regression coefficients and correlation

Suppose we have two time series, y_t and x_t (with zero mean), for which we need to estimate the cross-correlation, as well as a heteroscedasticity and autocorrelation consistent standard error. Consider the following two regressions,

$$y_t = \rho_1 x_t + u_{1t} \tag{A1}$$

$$x_t = \rho_2 y_t + u_{2t}, \tag{A2}$$

In this case the OLS estimators for ρ_1 and ρ_2 are

$$\hat{\rho}_1 = \frac{\sum_{t=1}^{T} x_t y_t}{\sum_{t=1}^{T} x_t^2} = \frac{\mathrm{cov}(x_t, y_t)}{\mathrm{var}(x_t)} \tag{A3}$$

and

$$\hat{\rho}_2 = \frac{\sum_{t=1}^{T} x_t y_t}{\sum_{t=1}^{T} y_t^2} = \frac{\mathrm{cov}(x_t, y_t)}{\mathrm{var}(y_t)}, \tag{A4}$$

respectively, where T is the number of observations.

Thus, an estimator for the cross-correlation between x_t and y_t, is then

$$\hat{\rho}_{xy} = \frac{\sum_{t=1}^{T} x_t y_t}{\sqrt{\sum_{t=1}^{T} x_t^2 \sum_{t=1}^{T} y_t^2}} = \frac{\mathrm{cov}(x_t, y_t)}{\sqrt{\mathrm{var}(x_t)\,\mathrm{var}(y_t)}} = \mathrm{sign}(\mathrm{cov}(x_t, y_t))\sqrt{\hat{\rho}_1 \hat{\rho}_2}\,. \tag{A5}$$

A 'Newey-West' standard error for the cross-correlation

Based upon the above we will apply the following procedure. Regressions (A1) and (A2) will be estimated simultaneously with

$$z = \begin{pmatrix} y_1 \\ \vdots \\ y_T \\ x_1 \\ \vdots \\ x_T \end{pmatrix} = \begin{pmatrix} x_1 & 0 \\ \vdots & \vdots \\ x_T & 0 \\ 0 & y_1 \\ \vdots & \vdots \\ 0 & y_T \end{pmatrix} \begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} + \begin{pmatrix} u_{11} \\ \vdots \\ u_{1T} \\ u_{21} \\ \vdots \\ u_{2T} \end{pmatrix} = X\rho + u \, . \tag{A6}$$

If we denote the rows of matrix X with X_t (t=1 ... 2T), then the Newey-West variance-covariance matrix is equal to

$$\hat{V}[\hat{\rho}] = (X'X)^{-1} [\sum_{t=1}^{2T} \hat{u}_t^2 X_t X_t' + \sum_{j=1}^{H-1} w_j \sum_{s=j}^{2T} \hat{u}_s \hat{u}_{s-j} (X_s X_{s-j}' + X_{s-j} X_s')] (X'X)^{-1} \, , \tag{A7}$$

where $w_j = 1 - j/H$, and $E[u_t \, u_{t-j}] = 0$ for $j \geq H$ for a given value of H. For $H = 0$ this gives the White (1980) variance-covariance matrix. Using equation (A5) we can now construct a 'Newey-West' standard error for the cross-correlation applying the well-known 'delta-method' (e.g. Bishop, Fienberg and Holland, p486, 1975). Let

$$f(\rho_1,\rho_2) = \sqrt{\rho_1 \rho_2} \tag{A8}$$

then the gradient will be

$$\nabla f = \begin{pmatrix} \dfrac{\partial f}{\partial \rho_1} & \dfrac{\partial f}{\partial \rho_2} \end{pmatrix} = \begin{pmatrix} \dfrac{1}{2}\sqrt{\dfrac{\rho_2}{\rho_1}} & \dfrac{1}{2}\sqrt{\dfrac{\rho_1}{\rho_2}} \end{pmatrix} \tag{A9}$$

and (using the estimates for the parameters in (A9)) our 'Newey-West' standard error

$$\nabla \hat{f} \, \hat{V}[\hat{\rho}] \, \nabla \hat{f}' \, . \tag{A10}$$

Table 1: Statistics of the futures returns

	FTSE 100		S&P 500	
	LIFFE OOC trading	Common trading	NYSE opening hours	Common trading
mean	-0.000110	-0.000157	-0.00000432	-0.000281
standard deviation	0.0347	0.0367	0.0300	0.0348
skewness	0.314	-0.132	-0.188	-0.220
kurtosis	15.93	5.35	7.47	6.75
trading days[1]	121	121	121	121
number of observations	55,176	11,800	47,190	11,800

[1] The trading period is January 4, 1993 through June 30, 1993.

Table 2: Fourier Flexible Form estimates

	FTSE 100 Futures		S&P 500 Futures	
parameter	*1	*σ_d	*1	*σ_d
α_0	-0.0413	3.61[a]	-0.00573	1.61[a]
α_1	0.233	-16.8[a]	0.0303	-4.37
α_2	-0.231	16.3[a]	-0.0251	3.83
β_1	0.0309	-1.68[a]	0.00601	-0.313
β_2	0.00893	-0.463[a]	0.000828	-0.0671
β_3	0.00351	-0.189[b]	0.000722	-0.0631
β_4	-0.000677	-0.0317	0.000635	-0.0420
β_5	0.000149	0.0584		
γ_1	0.00173	-0.111	0.00114	-0.167[a]
γ_2	-0.00377[a]	0.0249	-0.00167	0.0139
γ_3	0.00193	-0.0639	0.00304[a]	-0.131[a]
γ_4	0.00355[a]	-0.123[a]	-0.000262	-0.000788
γ_5	0.000149	0.00526		
δ_1	-0.0406[a]	2.284[a]		
δ_2	0.0373[a]	-0.554		
δ_{175}	-0.0320[b]	1.125[a]		
δ_{176}	-0.0156	1.053[a]		
δ_{177}	-0.00749	0.476		
δ_{178}	-0.00766	0.384		
δ_{fin}	0.00860	-0.847[b]		

The model estimated is

$$|e_{t,d}| = \alpha_0 + \alpha_1\frac{t}{T} + \alpha_2\frac{t^2}{T^2} + \sum_{i=1}^{I}\delta_i D_{i,t} + \sum_{j=1}^{J}(\beta_j\cos\frac{2jt\pi}{T} + \gamma_j\sin\frac{2jt\pi}{T}) +$$
$$\sigma_d[\tilde{\alpha}_0 + \tilde{\alpha}_1\frac{t}{T} + +\tilde{\alpha}_2\frac{t^2}{T^2} + \sum_{i=1}^{I}\tilde{\delta}_i D_{i,t} + \sum_{j=1}^{J}(\tilde{\beta}_j\cos\frac{2jt\pi}{T} + \tilde{\gamma}_j\sin\frac{2jt\pi}{T})] + \varepsilon_{t,d} ,$$

where $e_{t,d}$ is the residual from a moving average representation of the original return series, t is time (t=1..T), $D_{i,t}$ are dummy variables equal to one if $t=t_i$ and zero elsewhere, and σ_d is the sample standard deviation on day d. The sample period is January through June 1993, consisting of 121 trading days with 455 trading minutes per day for the FTSE futures and 390 trading minutes per day for the S&P futures.

[a] and [b] denote significance at the 1-percent and 5-percent level, respectively.

Table 3:
Returns correlations between S&P and FTSE futures during common trading

	Residual returns: $e_{t,d}$ [i]	Adjusted residual returns: $e_{t,d}/\sigma_{t,d}$ [ii]		
		total	negative[iii]	positive[iii]
corr[$FTSE_{t-5}$, $S\&P_t$]	0.00229	0.00419	-0.0147	0.0107
	[0.0100]	[0.00958]	[0.0156]	[0.0117]
corr[$FTSE_{t-4}$, $S\&P_t$]	-0.00161	-0.00268	0.00289	0.0109
	[0.0100]	[0.00967]	[0.0160]	[0.0122]
corr[$FTSE_{t-3}$, $S\&P_t$]	-0.00423	-0.00889	0.00750	-0.0106
	[0.00998]	[0.00947]	[0.0152]	[0.0122]
corr[$FTSE_{t-2}$, $S\&P_t$]	0.0215[b]	0.0119	0.00346	0.0190
	[0.0105]	[0.00966]	[0.0155]	[0.0124]
corr[$FTSE_{t-1}$, $S\&P_t$]	0.0351[a]	0.0330[a]	0.0289	0.0196
	[0.0107]	[0.00983]	[0.0150]	[0.0124]
corr[$FTSE_t$, $S\&P_t$]	0.135[a]	0.133[a]	0.0960[a]	0.0930[a]
	[0.0100]	[0.00950]	[0.0153]	[0.0116]
corr[$FTSE_t$, $S\&P_t$]	0.135[a]	0.133[a]	0.0894[a]	0.0642[a]
	[0.0100]	[0.00950]	[0.0137]	[0.0134]
corr[$FTSE_t$, $S\&P_{t-1}$]	0.214[a]	0.210[a]	0.146[a]	0.114[a]
	[0.0100]	[0.00946]	[0.0144]	[0.0130]
corr[$FTSE_t$, $S\&P_{t-2}$]	0.0568[a]	0.0584[a]	0.0244	0.0363[a]
	[0.0103]	[0.00968]	[0.0141]	[0.0129]
corr[$FTSE_t$, $S\&P_{t-3}$]	0.0170	0.0133	0.00753	0.000490
	[0.0103]	[0.00941]	[0.0140]	[0.0132]
corr[$FTSE_t$, $S\&P_{t-4}$]	-0.000195	-0.000307	0.00785	-0.00863
	[0.00943]	[0.00911]	[0.0135]	[0.0127]
corr[$FTSE_t$, $S\&P_{t-5}$]	0.00645	0.00500	0.000103	-0.0142
	[0.00966]	[0.00953]	[0.0143]	[0.0139]
corr[$FTSE_t$, $S\&P_{t-6}$]	0.0247[b]	0.0218[b]	0.0149	0.0258
	[0.0106]	[0.00997]	[0.0148]	[0.0138]
corr[$FTSE_t$, $S\&P_{t-7}$]	0.0139	0.00554	0.0299[b]	0.0148
	[0.0109]	[0.0102]	[0.0144]	[0.0140]
corr[$FTSE_t$, $S\&P_{t-8}$]	0.00110	-0.00191	-0.0156	-0.00179
	[0.0105]	[0.00974]	[0.0149]	[0.0130]
corr[$FTSE_t$, $S\&P_{t-9}$]	0.0280[a]	0.0291[a]	0.0250	0.0191
	[0.0103]	[0.00958]	[0.0141]	[0.0135]
corr[$FTSE_t$, $S\&P_{t-10}$]	-0.00336	-0.00711	-0.00742	-0.00791
	[0.0101]	[0.00985]	[0.0138]	[0.0136]
Sum of Negative minus Positive correlations[iv]			0.0609 [0.0805]	

Spill-overs in returns between the S&P and FTSE futures during their common trading interval in the period January through June 1993 (11800 observations).

i The residual returns are estimated according to equations (1) and (2).

ii $\sigma_{t,d}$ (t=1..T, d=1..D) is the estimated seasonal volatility according to equation (3).

iii Based upon the leading market ($e_{t,d}$), the returns are divided into negative and positive returns (first six rows based upon FTSE leading, last eleven rows based upon S&P leading). The errors for these columns are White (1980) standard errors. We can not use the Newey-West errors, due to the sorting process which causes a distortion in the autocorrelations of the residuals in (A6). In Appendix A, we show how to estimate the White errors for cross correlations.

iv Assuming the correlations are i.i.d. N($\hat{\rho}$,s.e.($\hat{\rho}$)), with s.e.($\hat{\rho}$) the White standard error of $\hat{\rho}$, the sum of differences will be normally distributed as well, with corresponding mean and variance.

HAC errors (see Appendix A) are given in brackets.

[a] and [b] denote significance at the 1-percent and 5-percent level, respectively.

Table 4:
Volatility correlations between the S&P and FTSE futures during common trading

	Absolute residual returns: $\lvert e_{t,d} \rvert$ [i]	Absolute adjusted residual returns: $\lvert e_{t,d}/\sigma_{t,d} \rvert$ [ii]	Prewhitened returns series $\lvert e^{*}_{t,d}/\sigma_{t,d} \rvert$ [iii]	Absolute adjusted residual returns: $\lvert e_{t,d}/\sigma_{t,d} \rvert$ [iv]
corr[$FTSE_{t-5}$, $S\&P_t$]	0.0297[b] [0.0123]	0.0109 [0.00952]	0.00481 [0.00936]	0.0647[a] [0.0116]
corr[$FTSE_{t-4}$, $S\&P_t$]	0.0240 [0.0125]	0.00724 [0.00953]	-0.000319 [0.00953]	0.0622[a] [0.0122]
corr[$FTSE_{t-3}$, $S\&P_t$]	0.0309[b] [0.0140]	0.0115 [0.00965]	0.00344 [0.00941]	0.0672[a] [0.0120]
corr[$FTSE_{t-2}$, $S\&P_t$]	0.0353[b] [0.0145]	0.0124 [0.0102]	0.00367 [0.00975]	0.0698[a] [0.0127]
corr[$FTSE_{t-1}$, $S\&P_t$]	0.0391[a] [0.0142]	0.0211[b] [0.0100]	0.0119 [0.00966]	0.0747[a] [0.0129]
corr[$FTSE_t$, $S\&P_t$]	0.0568[a] [0.0135]	0.0401[a] [0.00998]	0.0319[a] [0.00975]	0.0950[a] [0.0127]
corr[$FTSE_t$, $S\&P_{t-1}$]	0.0719[a] [0.0124]	0.0587[a] [0.0101]	0.0519[a] [0.00976]	0.114[a] [0.0144]
corr[$FTSE_t$, $S\&P_{t-2}$]	0.0403[a] [0.0144]	0.0223[b] [0.00985]	0.0118 [0.00945]	0.0804[a] [0.0134]
corr[$FTSE_t$, $S\&P_{t-3}$]	0.0295[b] [0.0143]	0.0138 [0.00986]	0.00370 [0.00948]	0.0730[a] [0.0132]
corr[$FTSE_t$, $S\&P_{t-4}$]	0.0144 [0.0106]	0.00260 [0.00947]	-0.00744 [0.00923]	0.0498[a] [0.0121]
corr[$FTSE_t$, $S\&P_{t-5}$]	0.0262[b] [0.0129]	0.0122 [0.0101]	0.00332 [0.00984]	0.0642[a] [0.0131]
corr[$FTSE_t$, $S\&P_{t-6}$]	0.0378[a] [0.0137]	0.0201[b] [0.0101]	0.0120 [0.00997]	0.0761[a] [0.0134]
corr[$FTSE_t$, $S\&P_{t-7}$]	0.0443[a] [0.0136]	0.0285[a] [0.00998]	0.0214[b] [0.00976]	0.0923[a] [0.0143]
corr[$FTSE_t$, $S\&P_{t-8}$]	0.0352[b] [0.0150]	0.0161 [0.0103]	0.00833 [0.00964]	0.0784[a] [0.0128]
corr[$FTSE_t$, $S\&P_{t-9}$]	0.0265 [0.0164]	0.00752 [0.0102]	-0.000845 [0.00957]	0.0625[a] [0.0144]
corr[$FTSE_t$, $S\&P_{t-10}$]	0.0317[a] [0.0116]	0.0143 [0.00962]	0.00712 [0.00947]	0.0694[a] [0.0114]

Spill-overs in the volatility of returns between the S&P and FTSE futures during their common trading interval in the period January through June 1993 (11800 observations).

i The residual returns are estimated according to equations (1) and (2).

ii $\sigma_{t,d}$ (t=1..T, d=1..D) is the estimated seasonal volatility according to equation (3).

iii Prewhitening is based on an ARMA filter specification for the absolute deseasonalised residual returns.

iv $\sigma_{t,d}$ (t=1..T, d=1..D) is the estimated seasonal volatility according to equation (3), without taking account of the daily level of volatility.

HAC errors (see Appendix A) are given in brackets.

[a] and [b] denote significance at the 1-percent and 5-percent level, respectively.

Table 5:

Volatility correlations between the S&P and FTSE futures during common trading: negative and positive news effects

	Prewhitened Absolute Adjusted residual returns	
	$e_{t,d}\leq 0$[i]	$e_{t,d}>0$[i]
corr[$FTSE_{t-5}$, $S\&P_t$]	0.00849 [0.0156]	-0.00229 [0.0116]
corr[$FTSE_{t-4}$, $S\&P_t$]	-0.0124 [0.0161]	0.00737 [0.0120]
corr[$FTSE_{t-3}$, $S\&P_t$]	0.00633 [0.0149]	0.00193 [0.0120]
corr[$FTSE_{t-2}$, $S\&P_t$]	0.00996 [0.0156]	-0.00168 [0.0123]
corr[$FTSE_{t-1}$, $S\&P_t$]	0.00587 [0.0152]	0.0107 [0.0125]
corr[$FTSE_t$, $S\&P_t$]	0.0410[a] [0.0158]	0.0207 [0.0119]
corr[$FTSE_t$, $S\&P_t$]	0.0392[a] [0.0140]	0.0244 [0.0131]
corr[$FTSE_t$, $S\&P_{t-1}$]	0.0787[a] [0.0146]	0.0258[b] [0.0132]
corr[$FTSE_t$, $S\&P_{t-2}$]	0.0342[b] [0.0135]	-0.0104 [0.0129]
corr[$FTSE_t$, $S\&P_{t-3}$]	-0.00399 [0.0139]	0.0113 [0.0129]
corr[$FTSE_t$, $S\&P_{t-4}$]	0.00545 [0.0134]	-0.0195 [0.0127]
corr[$FTSE_t$, $S\&P_{t-5}$]	0.0108 [0.0141]	-0.00281 [0.0139]
corr[$FTSE_t$, $S\&P_{t-6}$]	0.0155 [0.0149]	0.00874 [0.0139]
corr[$FTSE_t$, $S\&P_{t-7}$]	0.0329[b] [0.0142]	0.00977 [0.0139]
corr[$FTSE_t$, $S\&P_{t-8}$]	0.0233 [0.0143]	-0.00639 [0.0126]
corr[$FTSE_t$, $S\&P_{t-9}$]	0.000790 [0.0140]	-0.00212 [0.0132]
corr[$FTSE_t$, $S\&P_{t-10}$]	0.0120 [0.0136]	0.00170 [0.0135]
Sum of Negative minus Positive correlations	0.231[a] [0.0802]	

i Based upon the leading market, the returns are divided into negative and positive returns (first six rows based upon FTSE leading, last eleven rows based upon S&P leading). The given errors in brackets are White errors (consult Appendix A).

ii Assuming the correlations are i.i.d. $N(\hat{\rho}, s.e.(\hat{\rho}))$, with $s.e.(\hat{\rho})$ the White standard error of $\hat{\rho}$, the sum of differences will be normally distributed as well, with corresponding mean and variance.

HAC errors (see Appendix A) are given in brackets.

[a] and [b] denote significance at the 1-percent and 5-percent level, respectively.

Table 6:

Spill-overs during the first 15 and 30 minutes of trading in New York

	(Prewhitened absolute) adjusted residual returns			
	returns $e_{t,d}/\sigma_{t,d}$ [i]		volatility $\lvert e^{*}_{t,d}/\sigma_{t,d}\rvert$ [ii]	
	15 min	30 min	15 min	30 min
corr[$FTSE_{t-5}$, $S\&P_t$]	0.0439 [0.0259]	0.0161 [0.0177]	-0.0184 [0.0274]	-0.00746 [0.0174]
corr[$FTSE_{t-4}$, $S\&P_t$]	0.000187 [0.0270]	-0.00626 [0.0183]	-0.0157 [0.0264]	-0.00703 [0.0180]
corr[$FTSE_{t-3}$, $S\&P_t$]	-0.0439 [0.0264]	-0.0329 [0.0177]	-0.0148 [0.0270]	-0.00239 [0.0175]
corr[$FTSE_{t-2}$, $S\&P_t$]	0.00139 [0.0260]	-0.00673 [0.0180]	0.0242 [0.0260]	0.0152 [0.0177]
corr[$FTSE_{t-1}$, $S\&P_t$]	-0.00240 [0.0235]	0.000905 [0.0175]	0.00173 [0.0266]	0.0141 [0.0181]
corr[$FTSE_t$, $S\&P_t$]	0.180[a] [0.0248]	0.166[a] [0.0172]	0.0570[b] [0.0254]	0.0438[b] [0.0175]
corr[$FTSE_t$, $S\&P_{t-1}$]	0.268[a] [0.0233]	0.257[a] [0.0171]	0.0454 [0.0251]	0.0614[a] [0.0179]
corr[$FTSE_t$, $S\&P_{t-2}$]	0.0606[b] [0.0252]	0.0668[a] [0.0185]	0.0497 [0.0253]	0.0325 [0.0184]
corr[$FTSE_t$, $S\&P_{t-3}$]	-0.0269 [0.0256]	0.00950 [0.0181]	0.00627 [0.0251]	0.0286 [0.0176]
corr[$FTSE_t$, $S\&P_{t-4}$]	-0.00210 [0.0277]	-0.0148 [0.0180]	0.0191 [0.0254]	0.0152 [0.0172]
corr[$FTSE_t$, $S\&P_{t-5}$]	0.0171 [0.0265]	0.0182 [0.0177]	-0.0273 [0.0293]	-0.00126 [0.0179]
corr[$FTSE_t$, $S\&P_{t-6}$]	-0.0386 [0.0307]	0.00425 [0.0194]	0.00937 [0.0320]	0.0217 [0.0193]
corr[$FTSE_t$, $S\&P_{t-7}$]	-0.00252 [0.0340]	0.0131 [0.0207]	0.0264 [0.0339]	0.0349 [0.0206]
corr[$FTSE_t$, $S\&P_{t-8}$]	0.0352 [0.0351]	-0.00328 [0.0197]	0.0384 [0.0330]	0.0173 [0.0185]
corr[$FTSE_t$, $S\&P_{t-9}$]	0.00286 [0.0376]	0.0370 [0.0200]	0.0221 [0.0368]	0.00402 [0.0206]
corr[$FTSE_t$, $S\&P_{t-10}$]	0.0121 [0.0440]	0.000594 [0.0209]	0.0594 [0.0401]	0.0366 [0.0194]

Spill-overs in returns and volatility for the first 15 and 30 minutes after the opening of the New York market. The sample period covers January through June 1993, yielding 1815 observations for the first 15 minutes and 3630 observations for the first 30 minutes of common trading.

[i] The residual returns, $e_{t,d}$, are estimated according to equations (1) and (2), and $\sigma_{t,d}$ (t=1..T, d=1..D) is the estimated seasonal volatility according to equation (3).

[ii] Prewhitening is based on an ARMA filter specification for the absolute deseasonalised residual returns.

HAC errors (consult Appendix A) are given in brackets.

[a] and [b] denote significance at the 1-percent and 5-percent level, respectively.

Table 7:
FTSE futures returns after a large increase/decrease of S&P futures prices

$\Delta S\&P_t$ [i]	# cases	$\Delta FTSE_t$ [ii]	$\Delta FTSE_{t+1}$ [ii]	$\Delta FTSE_{t+2}$ [ii]
-0.70	13	-1.10	-1.20	-0.70
-0.65	17	-1.10	-1.80	-0.80
-0.60	28	-2.20	-1.90	-1.80
-0.55	41	-2.85	-3.45	-1.30
-0.50	73	-3.45	-5.45	-0.90
-0.45	78	-3.25	-5.85	-1.10
-0.40	115	-5.00	-8.35	-0.60
-0.35	211	-10.15	-14.50	0.35
0.35	194	5.80	9.75	0.85
0.40	107	2.85	6.05	0.50
0.45	63	0.90	3.65	0.50
0.50	52	1.10	2.95	0.90
0.55	26	0.65	1.45	-0.15
0.60	18	-0.35	1.15	-0.05
0.65	10	-0.40	0.50	-0.15
0.70	5	-0.20	0.30	0.15

Columns 4 and 5 give cumulative FTSE futures returns from holding a futures position (a short position after a U.S. decrease and a long position after a U.S. increase) for the two trading minutes immediately following a large change in the S&P futures price. The sample period covers the common trading interval in the period January through June 1993 (121 trading days, and 11800 observations).

i For example -0.70 denotes the observations for which $\Delta S\&P_t \leq -0.70$. Returns are based upon market observed prices (no transformation has been applied).

ii The numbers denote the sum of the market observed returns $\Delta FTSE$ in the corresponding minutes in which the U.S. return surpassed one of the thresholds in column 1.

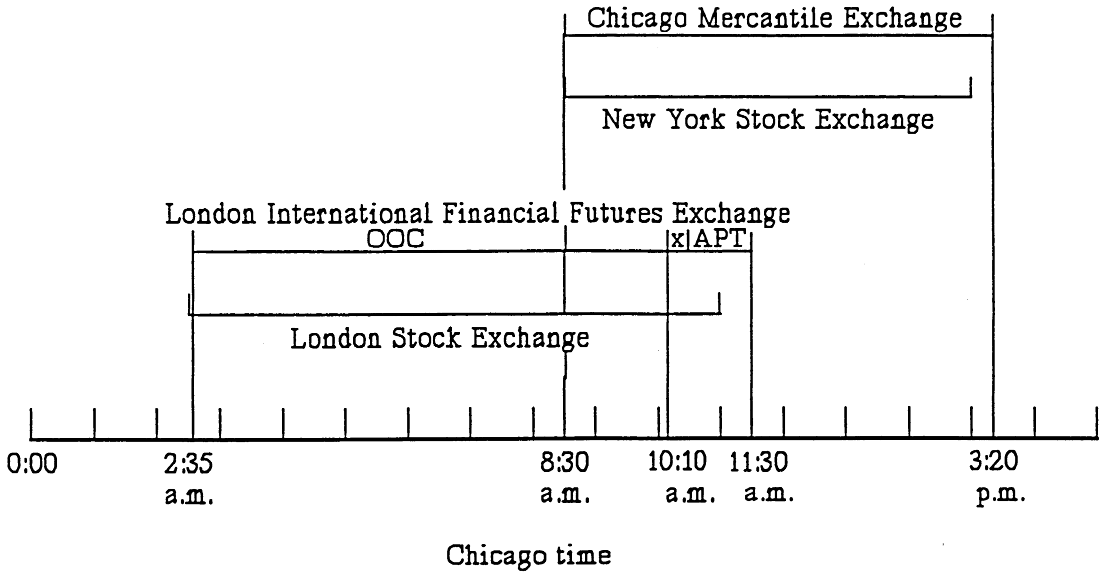

Figure 1:

Trading hours London International Financial Futures Exchange (LIFFE) divided between Open Outcry (OOC) and Automated Pit Trading (APT), London Stock Exchange, Chicago Mercantile Exchange, and the New York Stock Exchange.

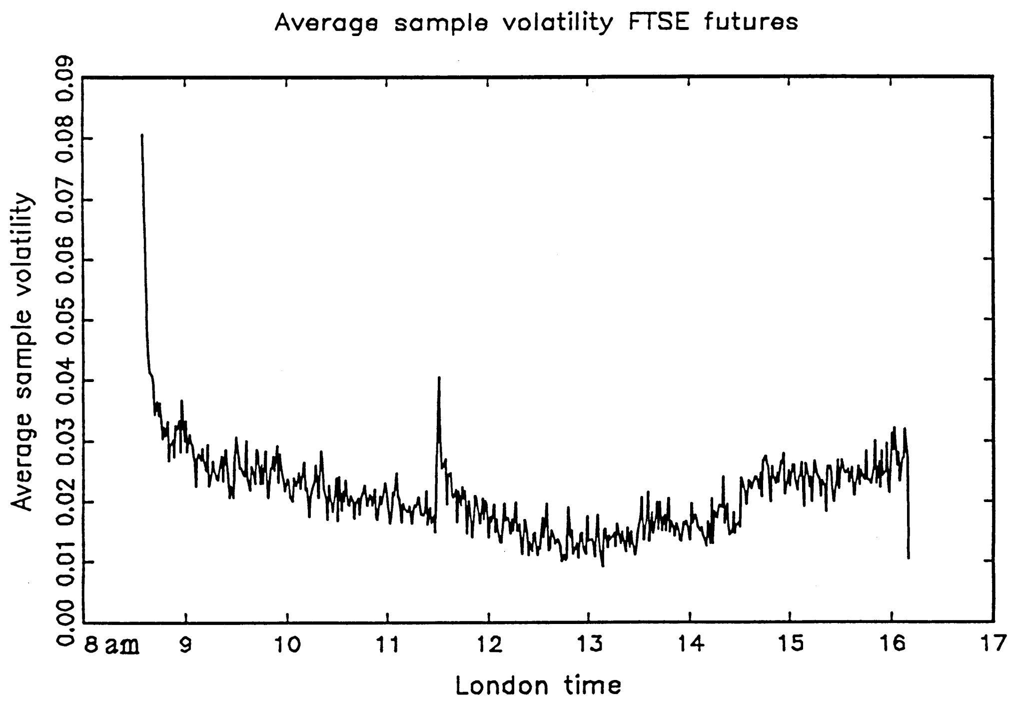

Figure 2:

Average sample volatility of FTSE futures returns during OOC trading at LIFFE, January 1993 until June 1993. The sample volatility used is the absolute value of the residual from an AR(1) process for the FTSE futures returns. The average is taken with respect to each trading interval across trading days.

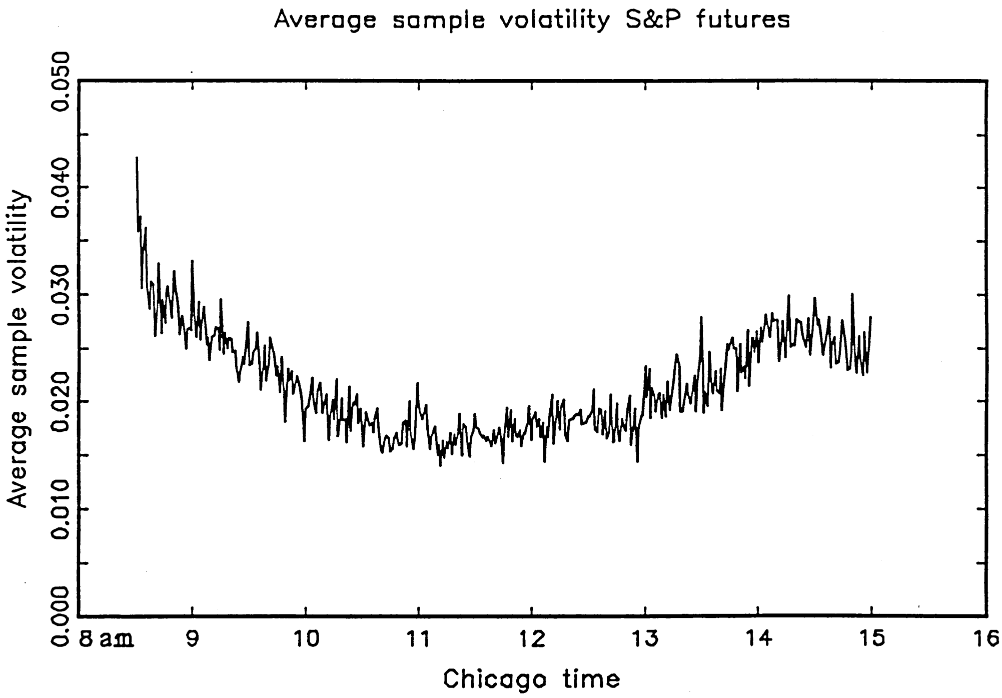

Figure 3:

Average sample volatility of S&P futures returns during trading at CME (until the close of the NYSE at 3:00pm), January 1993 until June 1993. The sample volatility used is the absolute value of the residual from an AR(2) process for the S&P futures returns. The average is taken with respect to each trading interval across trading days.

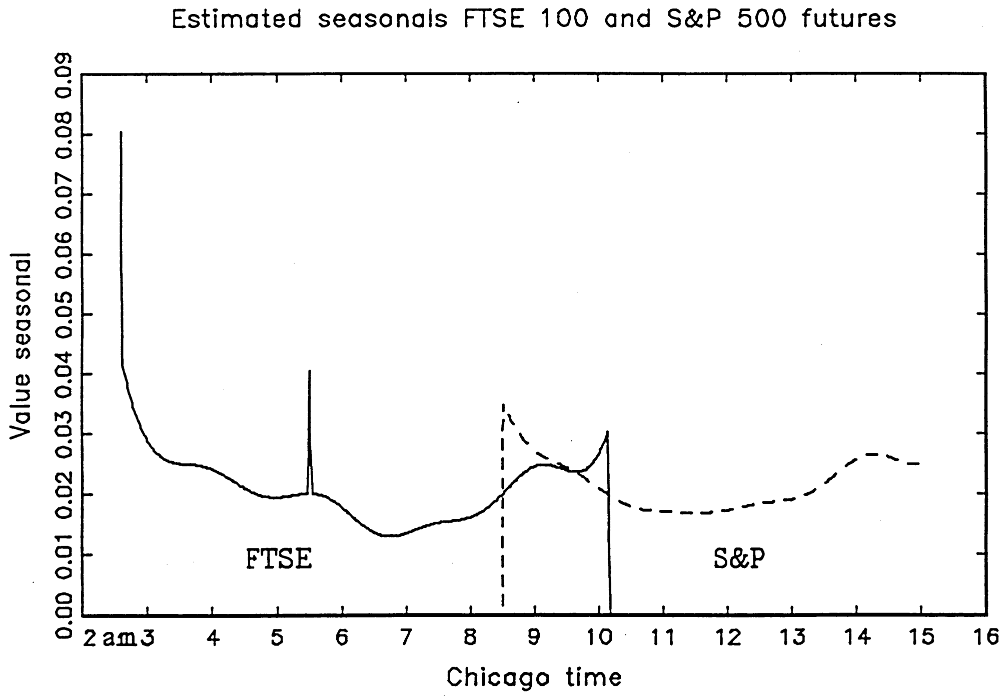

Figure 4:

The estimated Fourier Flexible Form for the average sample volatility of the FTSE and S&P futures returns given in Figures 2 and 3, respectively.

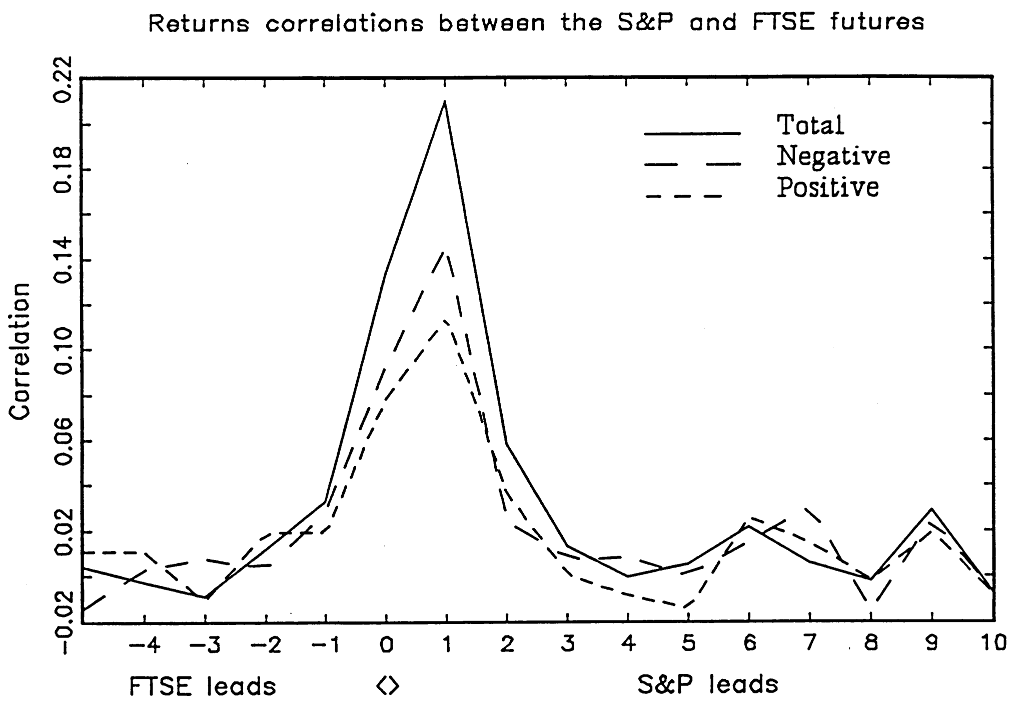

Figure 5:

Return spill-overs between the S&P and FTSE futures returns during common trading minutes for the January-June 1993 period. The cross-correlations are estimated for the adjusted residual returns. The exact estimates are given in the last three columns of Table 3.

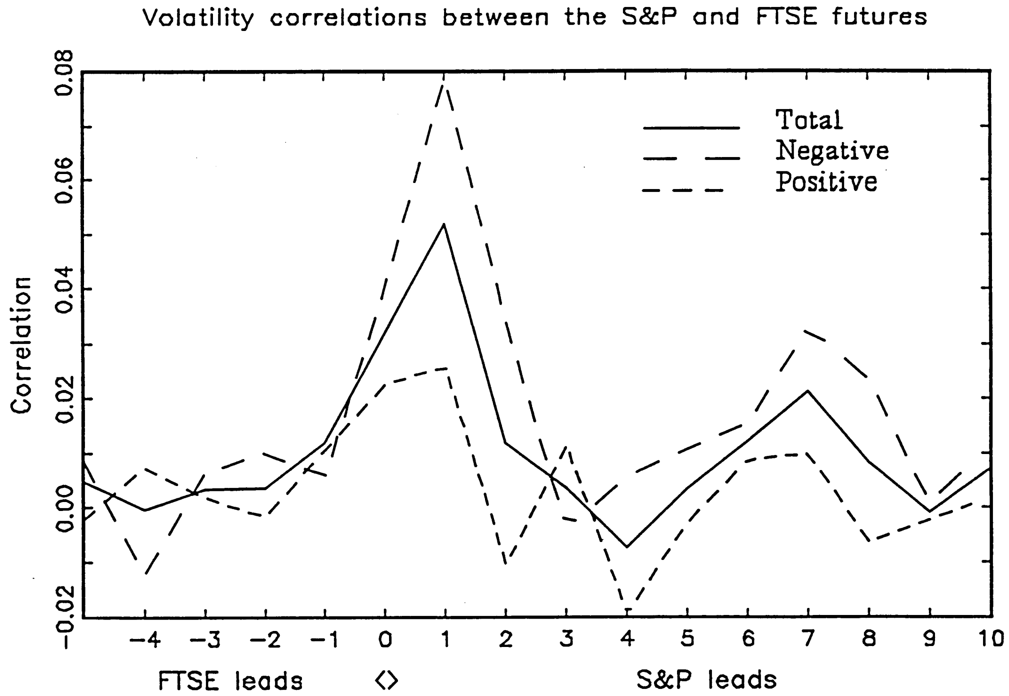

Figure 6:

Volatility spill-overs between the S&P and FTSE futures returns during common trading minutes for the January-June 1993 period. The cross-correlations are estimated for the prewhitened absolute adjusted residual returns. The exact estimates are given in the third column of Table 4 and Table 5.

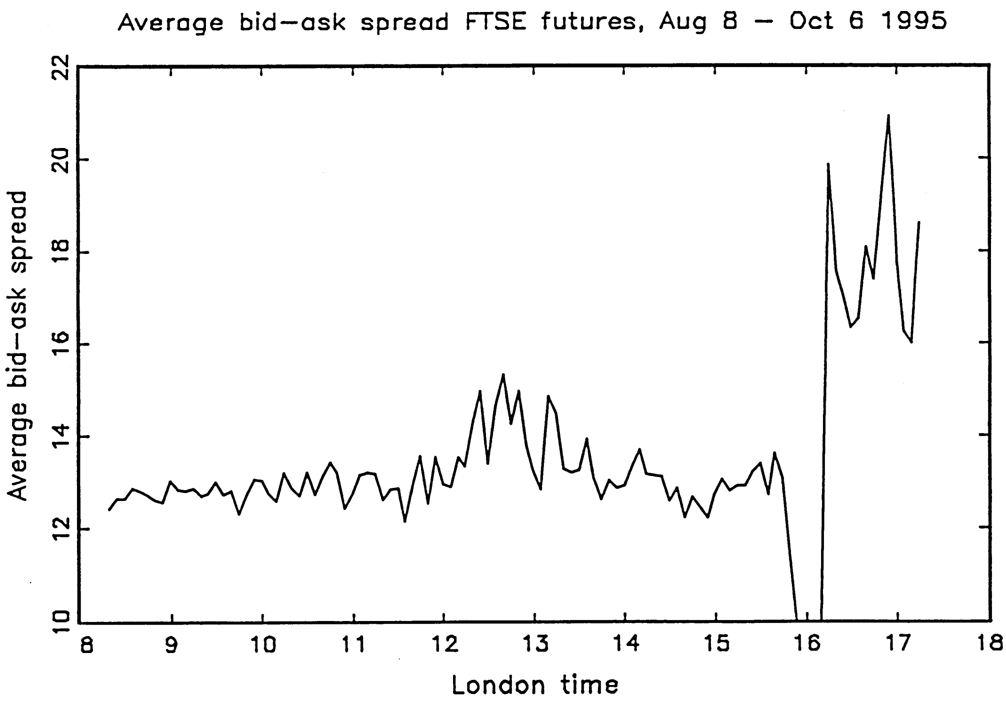

Figure 7:

Average bid-ask spread for each 5-minute interval of FTSE futures trading, period August 8 until October 6, 1995. Spreads less than or equal to zero and spreads larger than 0.50 have been filtered. This resulted in 30,915 observations, of which more than 68 percent were equal to 0.10 and more than 27 percent were equal to 0.20. The larger spreads typically occur during lunch-time and APT time.