A trading strategy based on the lead–lag relationship between the spot index and futures contract for the FTSE 100

Article

Accepted Version

Brooks, C. ORCID: https://orcid.org/0000-0002-2668-1153, Rew, A. G. and Ritson, S. (2001) A trading strategy based on the lead–lag relationship between the spot index and futures contract for the FTSE 100. International Journal of Forecasting, 17 (1). pp. 31-44. ISSN 0169-2070 doi: 10.1016/S0169-2070(00)00062-5 Available at https://centaur.reading.ac.uk/35962/

Published version at: http://dx.doi.org/10.1016/S0169-2070(00)00062-5
To link to this article DOI: http://dx.doi.org/10.1016/S0169-2070(00)00062-5

Publisher: Elsevier

A Trading Strategy based on the Lead-Lag relationship between the Spot Index and Futures Contract for the FTSE 100.

Chris Brooks, Alistair G. Rew, Stuart Ritson
ISMA Centre, Department of Economics, University of Reading
PO Box 242, Whiteknights, Reading, RG6 6BA.

Tel: (+44) 118 931 67 68
Fax: (+44) 118 931 47 41
E-mail: C.Brooks@reading.ac.uk

May 2000

A Trading Strategy based on the Lead-Lag relationship between the Spot Index and Futures Contract for the FTSE 100.

Abstract

This paper examines the lead-lag relationship between the FTSE 100 index and index futures price employing a number of time series models. Using ten-minutely observations from June 1996 – 1997, it is found that lagged changes in the futures price can help to predict changes in the spot price. The best forecasting model is of the error correction type, allowing for the theoretical difference between spot and futures prices according to the cost of carry relationship. This predictive ability is in turn utilised to derive a trading strategy which is tested under real-world conditions to search for systematic profitable trading opportunities. It is revealed that although the model forecasts produce significantly higher returns than a passive benchmark, the model was unable to outperform the benchmark after allowing for transaction costs.

Keywords: Stock index futures; FTSE 100; Error correction model; Trading rules; Forecasting accuracy; Cost of carry model.

Chris Brooks is a Reader in Financial Econometrics at the ISMA Centre, University of Reading. His research interests are in the area of financial econometrics, principally time series modelling and forecasting and risk management, where he has published widely.

Alistair Rew and Stuart Ritson are Doctoral and Masters students respectively at the ISMA Centre, University of Reading.

1. Introduction

The United Kingdom derivatives markets developed partially in response to the economic risk associated with dealing in commodities and financial instruments. Financial market deregulation together with computerisation of trading mechanisms in the 1980s have sometimes been argued to have lead to rapid fluctuation of interest rates, exchange rates and stock prices. High volatility and associated market risk have increased the demand for hedging instruments, designed to protect value by transferring risks from one party to another. One of the most important hedging instruments is a futures contract. A futures contract is a legally binding agreement to buy or sell a specific quantity of the underlying asset at a predetermined date in the future at a price agreed on today. To facilitate trading and clearing, futures contracts are standardised in all aspects apart from price. Stock index futures have a variety of attractive features for a trader who wishes to trade the share portfolio corresponding to the index. Traders frequently take coincident positions in both the cash and futures markets, which motivates the body of research investigating the relationship between the two price series. In the UK, futures contracts are traded on the London International Financial Futures and Options Exchange (LIFFE), the largest exchange of its kind in Europe.

Following Tse's (1995) investigation of the Japanese stock index and associated index futures series, this paper models empirically the temporal relationship between the price movements of the FTSE 100 futures contact and its underlying asset, the FTSE 100 stock index. By employing a number of techniques drawn from time series econometrics, we attempt to establish the model with the best forecasting ability. The issue under consideration is whether the FTSE 100 index fully reflects all available information or, conversely, whether there are systematic profitable opportunities, which could be exploited using a trading strategy.

This study is distinguished from Tse (1995) and other prior work in several ways. First, we consider high frequency (ten-minutely) data for the FTSE 100 contract. This compares with many previous papers which have used daily or at best hourly observations, or have applied their analysis to the American or Far Eastern markets. The use of very high frequency (intra-daily) data is of paramount importance for the results of a study such as this to be of value to practitioners. It is widely agreed that lead-lag relationships between spot and futures markets, if they exist at all, do not last for more than half an hour. Thus a statistical analysis using daily data is extremely unlikely to find evidence of lead-lag relationships, even if these relationships are present. Second, we extend earlier studies by placing additional emphasis on forecasting accuracy and the development of a trading strategy to assess whether any relationships that we identify can be used to generate trading profits. We consider that this represents a major step forward in the evaluation of forecasts produced by time series models. It has been argued in numerous studies (see Section 4.5 below for details and references) that the use of statistical forecast evaluation metrics often gives little guide as to the utility of employing such forecasts in a practical situation (for example, in a policy context or a financial decision). In this paper, we not only evaluate forecasts in the traditional mean squared error sense, but we also show how the forecasts can be used and thus benchmarked in a practical trading framework. We conjecture that the methodology employed in our paper could have widespread appeal and applicability for those interested in employing forecasts from time series models in practical situations. In particular, the study should be relevant for financial market practitioners who wish to test for exploitable profit opportunities derived from econometric forecasts, and for financial economists interested in testing the validity of financial market theories such as the efficient markets hypothesis. Thus study represents one of only a very small number of papers to assess forecast accuracy on this basis.

The remainder of this paper is organised as follows. Section 2 contains a brief discussion of the theory of futures pricing and presents a summary of the relevant literature which has sought to test these relationships empirically. Section 3 describes the data, and Section 4 considers the methodology used in forming the forecasting model and presents the results thereof. Section 5 derives a trading strategy based on the best forecasting model, and finally, Section 6 concludes.

2. The theoretical relationship between spot and futures markets

If the respective markets are free of impediments and are informationally efficient, the returns on a spot market index and the associated futures contract should be perfectly and contemporaneously correlated and not cross-correlated through time; that is, the prices of the stock index and the futures simultaneously reflect new information as it hits the market. This constraint is intuitive since otherwise arbitrage opportunities would abound. The efficient market hypothesis implies that any mispricing which arises, and associated arbitrage opportunities, should rapidly be eliminated.

The theoretical relationship between a stock index futures price and its underlying asset which gives rise to the premise above is known as the cost of carry model (see, for example, MacKinlay and Ramaswamy, 1988). It is given by

$$F_t = S_t \exp[(r-d)(T-t)] \qquad (1)$$

where F_t is the stock index price quoted at time t, S_t is the value of the underlying stock index, r gives the continuously compounded risk-free rate of return, d is the continuously compounded dividend yield, and T is the maturity date for the futures contract. If (1) is transformed into a model in log-returns rather than levels, we obtain

$$f_t = s_t + (r-d) \qquad (2)$$

where $f_t = \ln(F_t/F_{t-1})$ and $s_t = \ln(S_t/S_{t-1})$. Thus upper-case letters are used to denote the levels of the series, and lower-case letters are used to denote the log-returns. Equation (2) clearly implies that under market efficiency and in the absence of market frictions, futures and spot returns should be perfectly contemporaneously related, and in particular, one market should not lead the other.

It has been found in many studies, however, that the changes in futures price significantly lead those of the spot index. Kawaller *et al.* (1987), for example, found, using minute to minute data on the S&P 500 futures contract and the corresponding spot index, that futures price movements consistently lead the cash index movements by 20 – 45 minutes while movements in the stock index rarely affect futures price movements beyond one minute. Stoll and Whaley (1990) examined the causal relationship between the spot and futures markets, and found that S&P 500 and MM index futures returns tend to lead the stock market returns by about 5 minutes on average, but occasionally as long as 10 minutes or more, even after the stock index has been purged of infrequent trading effects. Chan (1992) argued that the futures price leads the spot to a greater extent when stock prices move together under market-wide movements rather than separately as a result of idiosyncratic movements, suggesting that the futures market is the main source of market-wide information. Ghosh (1993) also observed a similar lead-lag relationship for the US markets following the use of an error correction model.

Evidence from other markets also postulates a lead-lag relationship – Tse (1995) examines the behaviour of prices in the Nikkei index and the corresponding SIMEX traded futures contract and found that lagged changes of the futures price affect the short-term adjustments of the futures price. Tang *et al.* (1992) studied the causal relationship between stock index futures and cash index prices in Hong Kong which revealed that futures prices cause cash index prices to change in the pre-crash period but not vice versa. In the post-crash period, they found that bi-directional causality existed between the two variables.

Several papers have investigated the lead-lag relationship of the FTSE 100 index spot and futures series. Wahab and Lashgari (1993) studied daily data from January 1988 to May 1992 using error correction methodology. Their results revealed bi-directional causality between spot and futures returns. Abhyankar (1995) analysed hourly returns on the FTSE 100 from April 1986 to March 1990. It was found that there was a strong contemporaneous relationship between spot and futures returns and that futures returns led spot returns by one hour. Abhyankar then investigated the sensitivity of this result to variations in transaction costs, good or bad news (measured by the size of returns), spot volume and spot volatility. The results revealed that when transaction costs for the underlying asset fell (post 'Big Bang'), the futures lead of the spot index was reduced, implying that transaction cost differential is the major driver for the lead-lag relationship. It was found that the futures lead over spot was insensitive to variations in spot transaction volume. An AR(2)-EGARCH(1,1) model (that is, an autoregressive model of order 2 for the conditional mean, and an EGARCH model of order (1,1) for the conditional variance) was then fitted to spot and futures returns to give a time series of estimated volatilities, and it was observed that during periods of high volatility, futures markets led spot market returns. Abhyankar (1998) revisited the relationship using five-minute returns for 1992. Leads and lags were then examined by regressing spot returns on lagged spot and futures returns, and futures returns on lagged spot and futures returns using EGARCH. It was found that the futures returns led the spot returns by 15 – 20 minutes.

There is clear evidence that the futures price leads the spot price by at least a few minutes in most actively traded markets, while for lags of a day the evidence is much weaker. These 'lags' may be consistent with an absence of arbitrage opportunities if they are caused by traders choosing to exploit information in the futures market and the movement does not place it outside the arbitrage band, i.e. transaction costs are not exceeded, and because the prices at which the shares in the index basket could now trade incorporate the new information.

But why might such lead-lag relationships exist? From a practical perspective, it is generally agreed that the two phenomena of market sentiment and arbitrage trading are the major determinants linking stock index futures and the stock market. Conventional wisdom amongst professional traders suggests that movements in the futures price should reflect expected future movements in the underlying cash price. The futures price should quickly reflect all available information regarding events that may affect the underlying and respond quickly to new information. The index should respond in a similar fashion, but for the index to react to the new information completely the underlying stocks must all be revalued, i.e. every constituent stock must re-evaluate the new information and adjust accordingly. Because most stocks are not traded constantly every 10 minutes, the index will respond to new information with a lag. Consider a trader with news just arrived to the market that is bullish – the trader has two options:

1. Buy underlying stocks of the FTSE 100 index

2. Purchase FTSE 100 futures

In this scenario the futures trade can be executed immediately with little initial cash outlay, as futures are a levered instrument, compared to trading the actual underlying stocks, which would require a greater up-front investment and a probable longer implementation time because of stock selection and numerous underlying stock transactions. This transaction preference for futures may explain why the lead-lag relationship is observed in many markets. Trading futures also has the advantage of a highly liquid market, easily available short positions, low margins, leveraged positions and rapid execution. Such trading would move the futures price first then 'lead' the stock index when arbitrageurs respond to the deviations from the cost of carry relationship. Futures prices thus may provide a sentiment indicator for changes in stock prices and hence the FTSE 100 index which result when investors who are unable or unwilling to utilise futures incorporate that same information into their cash market transactions. It is also possible that cash index price changes lead changes in the futures price as the value of the index represents a subset of the information that affects futures prices. Alternatively stated – if the index were to decline or rise for whatever reason, the price change might induce a change in sentiment that would be reflected in subsequent declines or increases in the futures price. As long as the basis lies within the no arbitrage trading range, changes in market sentiment would affect both the futures price and the index in the same direction. (The ‘basis’ refers to the absolute difference between the futures and spot price and must be maintained within arbitrage bounds determined by equation (1), i.e. the futures to cash price differential normally falls within boundaries determined by financing costs and dividend yield. The relationship can be characterized for the futures price at time t (F_t) and the index price at time t (S_t) as

$$e_{L,t} < (F_t - S_t) < e_{U,t}$$

where $e_{L,t}$ = lower bound of the no arbitrage trading range at time t and $e_{U,t}$ = upper bound of the no arbitrage trading range at time t. In situations where the bound is breached, arbitrageurs would be able to make riskless profits until the prices traded back within the no-arbitrage band). To summarise, in practice the cost of carry model is often violated, and such discrepancies are usually explained by reference to transaction costs, infrequent trading of some index stocks and time delays in computing the index.

3. The data

A stock index tracks the changes in the value of a hypothetical portfolio of stocks. The percentage increase/decrease in the value of a stock index is equivalent to a weighted average change in the value of the underlying stocks over the equivalent time period, where the weights are determined by market capitalisation. The FTSE 100, or ‘Footsie’ as it is affectionately known, started trading on 31 December 1983. It comprises the 100 UK companies quoted on the London Stock Exchange with the largest market capitalisation, accounting for 73.2% of the market value of the FTSE All Share Index as at 29 December 1995 (Sutcliffe,1997). FTSE 100 futures contracts are quoted in the same units as the underlying index, except that the decimal is rounded to the nearest 0.5, the reason for this is that the minimum price movement (known as tick) for the futures contract is £12.50, i.e. a change of 0.5 in the index. The price of a futures contract (contract size) is the quoted number (measured in index points) multiplied by the contract multiplier, which is £25 for the contract. There are four delivery months: March, June, September and December. Trading takes place in the three nearest delivery months although volume in the ‘far’ contract is very small. Each contract is therefore traded for nine months. FTSE 100 futures contracts are cash-settled as opposed to physical delivery of the underlying. All contracts are marked to market on the last trading day which is the third Friday in the delivery month, and the positions are deemed to be closed. For the FTSE 100 futures contract, the settlement price on the last trading day is deemed to be an average of minutely observations between 10:10AM and 10:30AM rounded to the nearest 0.5.

The data employed in this study comprises 13,035 ten-minutely observations for all trading days of the FTSE 100 index (S_t) in the period June 1996 – 1997, provided by FTSE International. The FTSE 100 futures prices (F_t) were provided by LIFFE (covering the same sample period), and represent the closest actual transaction price preceding the spot observation, precluding any bias of the futures contract leading the spot index. Note that the FTSE 100 index is calculated every one minute but the futures transaction prices are not uniformly spaced through time. We circumvent this problem by taking an average of the last quoted bid and ask prices available during that ten-minute period. (Similarly, the FTSE index prices employed are mid-point quotes rather than transactions prices to avoid statistical anomalies associated with bid-ask bounce). The 'near' futures contract is used (for details of contract months refer to Appendix A) and is rolled over to the next contract on the tenth of the contract maturity month. The first reason for switching contracts at this point is trading volume considerations, i.e. the closest contract will generally be the most liquid contract which is essential as time series tests require the most frequent return observations possible. The second reason is slightly more complex and is determined by the converging relationship (diminishing basis) between the spot and futures price as expiry of the futures contract approaches.

The relationship considered in this paper is the long run equilibrium between S_t and F_t. By rolling over the futures contract on the tenth of the contract expiry month, the effects of the convergence will be removed. Due to the non-synchronous opening hours of the respective exchanges (the London Stock Exchange is open 8:30 – 16:30. LIFFE floor trading takes place from 8:35 – 16:10 then APT (Automated Pit Trading) continues from 16:32 – 17:30) the 16:10 (F_t) observation corresponds with 16:20 and 16:30 S_t observations. The last trade in the APT (Automated Pit Trading on LIFFE) corresponds with the 8:30 S_t observation for the following trading day. The annualised dividend yield for the FT 30 index is used as a proxy for the FTSE 100 yield. The monthly average of the three-month UK T-bill yield is used as a proxy for the risk-free rate. Both the dividend yield and UK T-bill observations are obtained from Datastream International.

4. Econometric analysis, methodology and results

4.1. Cointegration and error correction

The market efficiency arguments alluded to previously imply that the spot and futures prices should never drift too far apart, suggesting that a cointegrating relationship might be appropriate, following Ghosh (1993). In this paper, we employ the Engle–Granger (1987) single equation technique rather than the Johansen (1988) systems method due to the simplicity of the former, and the fact that there are only two stochastic variables (the spot and futures prices), and hence there could be at most one cointegrating vector. The cointegrating regression, if such a cointegrating relationship exists, would be given by

$$\ln S_t = \gamma_0 + \gamma_1 \ln F_t \qquad (3)$$

Cointegration between the stock index and index futures prices requires that both series be of the same order of nonstationarity, and that a linear combination of the two series is reduced to stationarity. We employ the standard augmented Dickey Fuller tests (Dickey and Fuller, 1979; Fuller, 1976) to test for nonstationarity. To anticipate the findings of the paper, we do indeed find, as expected, that the log-price series for the spot and the futures market are I(1). We then use the Engle–Granger two-step methodology for testing for cointegration between the log of the spot and futures prices. If cointegration exists between the two series, then the Granger representation theorem states that there is a corresponding error correction model (ECM). The ECM for the spot and futures prices can be expressed as

$$\Delta l \ln S_t = \beta_0 + \delta \hat{z}_{t-1} + \sum_{i=1}^{r} \beta_i \Delta \ln S_{t-i} + \sum_{j=1}^{s} \alpha_i \Delta \ln F_t + \varepsilon_t \tag{4}$$

where $\hat{z} = \ln S_t - \hat{\gamma}_0 - \hat{\gamma}_1 \ln F_t$ are the residuals from the first stage regression of the log-levels (the equilibrium correction term).

Table 1 presents descriptive statistics for the log-levels and log-returns of the constructed time series, together with the results of the Dickey Fuller tests. To ascertain that Ln(S_t) and Ln(F_t) are I(1) remembering that, by definition, cointegration necessitates that the variables be integrated of the same order, DF tests are performed for both log-price series. The results are detailed in panel B of Table 1. The results are highly conclusive, and as anticipated, the log-levels are I(1) and taking first differences in constructing the returns induces stationarity. This conclusion is not altered by augmentation of the test using up to 20 lags of the dependent variable. The results from these tests are not shown due to space constraints.

The next step in the Engle–Granger methodology is to estimate a regression of the log-levels, and to test its residuals for stationarity. Results from estimating the potentially cointegrating term, and equation (3) are displayed in panels A and C of Table 2 respectively. As one would expect, there is a very strong relationship between Ln(S_t) and Ln(F_t) evidenced by a slope coefficient of almost 1. In order to determine if the variables are actually cointegrated, the cointegration regression residuals ($\hat{z}_t$) are retained and tested for nonstationarity. There is clear evidence of rejection of the null hypothesis of a unit root in these residuals, and we therefore conclude that there indeed exists a cointegrating relationship (see panel B of Table 2). Next, the error correction model is fitted by using the residuals from the cointegrating regression, lagged one period, and by selecting the optimum number of lags of s_t and f_t, using Schwarz's Bayesian Criterion (denoted SBIC, Schwarz, 1978). SBIC selected one lag of each of f_t and s_t for inclusion in the ECM. (Again, the values of SBIC for each of the candidate models are not shown due to space constraints). The results of the fitted ECM are displayed in panel C of Table 2. All regressors are significant except the coefficient on the constant, indicating that changes in the spot index depend on the cointegration error as well as lagged changes in the spot index and futures price. The coefficient estimates of f_{t-1} and s_{t-1} agree in sign.

The positive coefficient on f_{t-1} implies that the spot index moves in the direction of the previous movement of the futures price, underlining the price discovery role of the futures market for the spot market. This result confirms Abhyankar's (1998) finding of a lead-lag relationship between FTSE 100 spot and futures of 5 to 20 minutes, detailed previously in the literature review. For a higher number of lags of f_t and s_t the coefficients on the regressors were all negative for $s_{t-k,}$ and positive and of an approximately equal size for f_{t-k}. This suggests that the two are effectively cancelling each other out and that the extra lags might be spurious. The coefficient on $\hat{z}_{t-1}$ is negative, suggesting that if s_t

is large relative to the equilibrium relationship at time t-1, then it is expected to adjust downwards during the next period.

4.2. ECM-COC –The cost of carry theory model

Following Tse (1995), a second ECM is formed utilising the cost of carry relationship. As detailed in equation (1), the futures price is given by the spot index plus the cost of carry compounded continuously. The estimated cointegrating relationship is now given by

$$\hat{z}_t = \ln S_t - \hat{\gamma}_0 - \hat{\gamma}_1 \ln F_t - \hat{\gamma}_2 (r-d)(T-t) \tag{5}$$

with equation (4) still constituting the full error correction model. $\hat{z}_t$ is tested for nonstationarity and the ECM is fitted as previously. The advantage of this cointegrating equation over the standard one is that it makes use of the theoretical relationship which might lead the spot and futures price to diverge from one another. The results from estimating this cointegrating relationship are given in Table 3. As can be seen, the coefficient estimates are extremely similar to those observed in the previous case, and the cointegrating regression residuals are indeed stationary. The cost of carry term is significant in the cointegrating regression, and the coefficient values in the cointegrating regression are slightly modified when we allow for the expense involved in financing a spot position in the asset.

4.3. An ARMA model

In order to form a benchmark for comparison to the ECM models estimated previously, an ARMA model is estimated (with s_t as the dependent variable since prediction of the spot series is the modelling motivation). An ARIMA(p,q) model is a univariate time series modelling technique, where p denotes the number of autoregressive terms, q the number of moving average terms. The ARMA model is expressed as

$$s_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i s_{t-i} + \sum_{j=1}^{q} \beta_j u_{t-j} + u_t \tag{6}$$

Again the SBIC criterion (Schwarz, 1978) is utilised and suggests that only one autoregressive lag and no moving average lags are optimal. For completeness, the results are reported in Table 4.

4.4. VAR model

An unrestricted vector autoregressive model (VAR) is also estimated for the spot and futures prices, the purpose being to consider the additional explanatory and forecasting power of the cointegrating term in the ECM. The equation of the VAR which has the spot returns as dependent variables may be expressed as

$$s_t = \theta_0 + \sum_{i=1}^{p} \theta_i s_{t-i} + \sum_{j=1}^{q} \phi_j f_{t-j} + v_t \tag{7}$$

A multivariate extension of SBIC (see, for example, Enders, 1995, p.315) is used to determine the appropriate number of lags, and this once again selects a lag length of one for the variables. The coefficient estimates and their associated t-ratios are given in Table 5.

4.5. Out of sample forecasting accuracy

One step ahead forecasts for the returns on the spot index s_t are created utilising the 1040 ten-minutely observations for May 1997 which were not included in the original sample. (Since the out of sample period used covers a historically very "bullish" month, with prices rising during that month by more than average, the use of a longer run of data out of sample would be desirable. However, this would impose very considerable extra computational burdens. In any case, since we are not interested in the performance of our trading rules *per se*, but rather in their performance relative to a passive benchmark, the use of a bullish out of sample month should not bias the results in favour of our models. In fact, if anything, since the passive strategy involves being long the index for the whole period, and our trading strategies imply being out of the index for a part of the time, a rising market would represent a harsher relative test for our rules than a static or falling one). These forecasts are then compared to the actual returns, with the forecast accuracies being evaluated on the standard statistical criteria of root mean squared error (RMSE), and mean absolute error (MAE). (For a description of these forecast evaluation metrics and their relative merits, see Brooks (1997)). The results illustrate that all the models perform reasonably well, with no single model being substantially more accurate than another, although interestingly, all three statistical criteria give the same ordering of model accuracies. The ARMA model is the least accurate followed by the VAR, which has two implications. First, forecasting accuracy can be improved by using the lead-lag relationship between the spot and futures markets rather than simply using information contained in the univariate spot series alone. Second, forecast accuracy can be further improved by making use of the long-term relationship between the spot and futures market in an error correction model, rather than using a model in pure first differences (ARMA and VAR), which by definition will lose any long-term properties of the data. (Another possible approach to modelling long range dependencies in asset returns is via fractionally integrated (ARFIMA) models (see, for example, Hosking, 1981)). The star performer is ECM-COC: the error correction model based on the cost of carry theory. It predicts the correct direction of movements of the spot index 68.75% of the time and minimises both the RMSE and MAE. The direction forecasts are of particular interest in this case, since it has been suggested (Gerlow *et al.*, 1993) that the accuracy of forecasts according to traditional statistical criteria may give little guide to the potential profitability of employing those forecasts in a market trading strategy, so that models which perform poorly on statistical grounds may still yield a profit if used for trading, and vice-versa. Models which can accurately forecast the sign of future returns, or can predict turning points in a series have been found to be more profitable (Leitch and Tanner, 1991). Therefore in the next section, we attempt to derive a profitable trading strategy utilising the ECM-COC model, which provided the highest proportion of correct direction forecasts.

5. Forming a trading strategy based on statistical forecasts

As previously outlined, one motivation for this study is to develop a profitable trading strategy based on the best of the models estimated above: ECM-COC. The model is used in a variety of trading strategies and compared to a passive investment in the FTSE 100 index. The trading strategies will be stress-tested by considering the size of transactions costs and the effect of their inclusion.

5.1. Strategy description

The trading period is the same as the forecasting period used above, i.e. from May 1 – May 30 1997. The ECM-COC model yields ten-minutely one step ahead forecasts. The trading strategy involves analysing the forecast for the spot return, and incorporating the decision dictated by the trading rule. It is assumed that the original investment is £1000. The returns are cumulative, and if the holding in the index is zero, the investment earns the risk free rate, and the amount invested in both the index and the risk free rate increases or decreases with total wealth.

5.1.1. Liquid trading strategy

This trading strategy involves trading on the basis of every positive predicted return and making a round trip trade, i.e. a purchase and sale of the FTSE 100 stocks every ten minutes that the return was predicted to be positive by the model. If the return was predicted to be negative by the model, no trade was executed and the investment earns the risk-free rate. (Although we are imposing the restriction that all transactions are neutral or long the index so that no short sales are permitted, this is not unrealistic since short positions in equities are expensive to maintain).

5.1.2. Buy and hold strategy

This strategy attempts to reduce the amount of transaction costs by allowing the trader to continue holding the index if the return at the next predicted investment period is positive. Rather than make a round trip transaction for each period, the trader leaves the position open until the returns are predicted to become negative.

5.1.3. Filter strategy – Better predicted return than average

This strategy involves purchasing the index only if the predicted returns are greater than the average predicted positive return (there is no trade for negative returns therefore the average is only taken of the positive returns). This strategy differentiates itself from the previous rules in the sense that the trader has become more selective in which trades he/she executes, i.e. a filter rule is utilised. This strategy has a filter of 0.000956%, which is the average ten-minutely in-sample return. If the trader trades on the basis that the predicted return is greater than the filter, the trader will continue to hold the index until the predicted return is negative, i.e. the buy and hold strategy introduced previously is used.

5.1.4. Filter strategy – Better predicted return than first decile

This strategy is essentially identical to the above trading strategy, but the difference is that rather than utilize the average as previously, only the predicted returns in the first decile are traded on. In this scenario, the filter is 0.0026%.

5.1.5. Filter strategy – High arbitrary cut off

An arbitrary filter is imposed of 0.0075%, which will only flag returns that are predicted to be extremely large.

5.2. Risk adjustment

The incremental risk adjustment incurred by making additional trades is almost non-existent and relates to counterparty or transaction risk. Because the alternative or control strategy involves investing passively in FTSE 100 index (rather than investing in a bond), the inherent risk of holding the security is approximately equal. One may even argue that the trading strategies have slightly less risk because for some portion of the time the holding of the risky asset (FTSE 100 index) is zero.

5.3. Transaction costs

Typical transaction costs for a round trip (purchase and sale) of the FTSE 100 index are detailed in Table 7. As one would expect, transacting in the futures market is considerably cheaper than in the spot market, since the index itself does not exist as an entity but rather one must buy and sell the components of the index individually.

5.4. The trading profits: Champagne or Cola?

The returns for the trading strategies detailed above are illustrated in Table 8. Examining the results reveals that the model can generate significant profits in the absence of transaction costs. May 1997 was an extremely bullish month for the FTSE 100 evidenced by the high returns even from a passive investment. The most profitable trading method is the ‘liquid trading strategy’ which yields a 15.62% return for the month compared with 4.09% benchmark passive strategy. If transaction costs are included in the returns, none of the active trading strategies can outperform the benchmark passive strategy. With maximum returns of 0.25% per transaction observed using the ‘filter III’ trading strategy, compared with transaction costs of 1.7% (total transaction cost for purchasing and subsequent selling of the underlying stocks of the FTSE 100 index) make the trading rules ineffective. In fact, all of the trading rules except the passive buy-and-hold make substantial losses due to the transactions costs involved in the large number of trades. However, as the major bias in the forecast period is positive returns, the model may outperform the index in a bear market when timing of trades is equally important.

To add an additional touch of reality to the analysis, we allow for 10 minutes of “slippage” time. This term is used to indicate that, if a forecast is made now, it will typically take at least a few minutes for a resulting buy/sell signal to be executable in the markets. So a trading signal derived from the model is assumed to be executed 10 minutes later, and the return calculated over the following 10 minutes. The trading profits allowing for slippage are also given in Table 8. The clear picture emerging is that the profitability of the rules is further eroded after allowing time for transactions to be executed; this is entirely plausible for it is likely that the value of exploiting short-term deviations of the spot and futures prices from their long-term equilibrium values will not last long.

To summarise, the forecasting model proves to be good at predicting the returns of the FTSE 100 index, but cannot generate excess returns net of transactions costs and after allowing for reasonable slippage time. But could the model still have a useful application in the financial markets? We would argue “yes” for the following reasons. First, major investment banks that are active equity market makers in the FTSE 100 would have significantly lower transaction costs. Referring to the transaction costs outlined above, a market maker has the potential to reduce transaction costs to 0.5%. This may enable the development of viable trading strategies utilising the models constructed in this paper. Second, the model provides a very good indicator for entry times into the market for traders interested in high frequency transacting. (A complicating factor, however, is that optimal entry timing for each individual stock which comprises the FTSE 100 is likely to be different. It could be possible to generate new results in a similar fashion for individual stocks which have traded futures contracts, but simply employing our timing rules on the individual stocks, where the rules were generated for the index, could lead to sub-optimal timing decisions for a large number of the components). Third, transaction costs are continuously under pressure - there may be a time in the future when the model is able to generate average returns in excess of transaction costs. (Although, of course, lower transactions costs would imply that index arbitrageurs would have more opportunities to trade profitably, implying that such arbitrage opportunities would quickly disappear). Fourthly, although the FTSE 100 consists of 100 stocks, the actual index movers are the larger capitalised stocks and it may therefore be possible to form a reasonable proxy for the index comprising, say, ten of the largest stocks (an index "tracker"), thereby reducing transaction costs by approximately 90%. Finally, as markets for the largest stocks become ever more liquid, and trading mechanisms become increasingly automated, it is possible that slippage times will be reduced, enabling the trading rules to be actioned sooner after they are determined.

6. Conclusions

This paper has investigated the lead-lag relationship between the FTSE 100 index and futures prices, and has attempted to derive a profitable strategy from this relationship. It was confirmed, as one might expect, that the futures returns lead the spot returns. The predictive power of futures returns supports the hypothesis that new market-wide information disseminates in the futures market before the spot market with arbitrageurs trading across both markets to maintain the cost of carry relationship. This is intuitive as a consequence of the reduced transaction costs and other associated benefits of trading in the futures market as opposed to the spot.

The best model in terms of predictive ability is the cost of carry error correction model (ECM-COC), which predicts the correct direction of the spot returns 68.75% of the time. In the absence of transaction costs, and using the ‘buy and hold’ strategy derived from this model, a monthly return of 15.62% is obtained compared with a monthly return of 4.09% for the passive benchmark. However, ECM-COC is unable to outperform the benchmark after the introduction of transaction costs. Although transaction costs and slippage times preclude a viable trading rule based on the model at the present time, there are potential circumstances for utilising the results such as optimum timing for trades or by a trader with significantly lower transaction costs such as a market maker.

Acknowledgments

The authors are grateful to an Associate Editor and to two anonymous referees of this journal for useful comments on an earlier version of this paper. We would also like to thank FTSE International and to LIFFE for providing the necessary data; the usual disclaimer applies.

References

Abhyankar, A. (1998). Linear and nonlinear Granger causality: Evidence from the UK stock index futures market, *Journal of Futures Markets,* 18(5), 519-540.

Abhyankar, A. (1995). Return and volatility dynamics in the FTSE-100 stock index and stock index futures markets, *Journal of Futures Markets,* 15(4), 457-488.

Brooks, C. (1997). Linear and nonlinear (non-) forecastability of daily sterling exchange rates, *Journal of Forecasting*, 16, 125-145.

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.

Dickey, D.A., & Fuller, W.A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root, *Econometrica,* 49(4), 1057-1072.

Enders, W. (1995). *Applied Econometric Time Series*, New York: John Wiley & Sons.

Engle, R.F., & Granger, C.W.E. (1987). Cointegration and error correction: Representation, estimation and testing, *Econometrica*, 55, 251-76.

Fuller, W.A. (1976). *Introduction to Statistical Time Series,* New York: John Wiley &Sons.

Gerlow, M.E., Irwin, S.H., & Liu, T-R. (1993). Economic evaluation of commodity price forecasting models, *International Journal of Forecasting,* 9, 387-397.

Ghosh, A. (1993). Cointegration and error correction models: Intertemporal causality between index and futures prices, *Journal of Futures Markets,* 13, 193-198.

Hosking, J.R.M. (1981). Fractional differencing, *Biometrika,* 68, 165-176.

Johansen, S. (1988). Statistical analysis of cointegration vectors, *Journal of Economic Dynamics and Control*, 12, 231-254.

Kawaller, I.G., Koch, P.D., & 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.

Leitch, G., & Tanner, J.E. (1991). Economic forecast evaluation: Profit versus the conventional error measures, *American Economic Review,* 81(3), 580-590.

MacKinlay, A.C., & Ramaswamy, K. (1988). Index-futures arbitrage and the behaviour of stock index futures prices, *Review of Financial Studies,* 1, 137-158.

Schwarz, G. (1978). Estimating the dimension of a model, *Annals of Statistics,* 6, 461-464.

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

Sutcliffe, S. (1997). *Stock Index Futures: Theories and International Evidence,* second edition, London: Thomson Business Press.

Tang, Y. N., Mak, S. C., & Choi, D. F. S. (1992). The causal relationship between stock index futures and cash index prices in Hong Kong, *Applied Financial Economics,* 2, 187-190.

Tse, Y.K. (1995). Lead-lag relationships between spot index and futures price of the Nikkei stock average, *Journal of Forecasting,* 14, 553-563.

Wahab, M., & Lashgari, M. (1993). Price dynamics and error correction in stock index and stock index futures markets: A cointegration approach, *Journal of Futures Markets*, 13, 711-742.

Appendix - Empirical results

Table 1: Descriptive statistics and DF tests for nonstationarity.

Panel A: Summary statistics for log-price data		
	Ln F_t	**Ln S_t**
Observations	11995	11995
Sample mean	8.299	8.302
Variance	0.003	0.003
Skewness	0.008	-0.059
Kurtosis	-1.158	-1.082
Panel B: Test for non-stationarity on log-price series		
Dickey Fuller statistic	-0.133	-0.734
Panel C: Summary statistics for returns data		
	s_t	F_t
Observations	11994	11994
Sample mean	1.400e-05	1.500e-05
Variance	4.805e-07	1.032e-06
Skewness	-5.159	-1.430
Kurtosis	191.019	37.720
Panel D: Test for nonstationarity on returns data		
Dickey Fuller statistic	-84.997	-114.180

Table 2: Tests for cointegration and the fitted ECM for s_t

Panel A: Cointegrating regression		
Coefficient estimated	**Coefficient value**	**t-ratio**
$\hat{\gamma}_0$	0.135	26.374
$\hat{\gamma}_1$	0.983	1600.165
Panel B: DF test of cointegration errors		
Dickey Fuller statistic -14.7303		
Panel C: Estimated error correction model		
Coefficient estimated	**Coefficient value**	**t-ratio**
$\hat{\beta}_0$	9.671e-06	1.608
$\hat{\delta}$	-8.339e-01	-5.130
$\hat{\beta}_1$	0.180	19.289
$\hat{\alpha}_1$	0.131	20.495

Table 3: Tests for cointegration and fitted ECM for s_t

Panel A: Cointegrating regression		
Coefficient estimated	**Coefficient value**	**t-ratio**
$\hat{\gamma}_0$	0.109	20.803
$\hat{\gamma}_1$	0.933	1298.127
$\hat{\gamma}_2$	0.010	10.389
Panel B: DF test of cointegration errors		
Dickey Fuller statistic -14.9627		
Panel C: Estimated error correction model		
Coefficient estimated	**Coefficient value**	**t-ratio**
$\hat{\beta}_0$	1.278e-05	1.608
$\hat{\delta}$	-7.207e-03	-4.361
$\hat{\beta}_1$	0.169	16.940
$\hat{\alpha}_1$	0.138	21.030

Table 4: Fitted ARMA model for s_t

Coefficient estimated	Coefficient value	t-ratio
$\hat{\alpha}_0$	8.635e-06	0.057
$\hat{\alpha}_1$	0.249	28.095

Table 5: Coefficient estimates for unrestricted VAR

Coefficient estimated	Coefficient value	t-ratio
$\hat{\theta}_0$	9.663e-06	1.605
$\hat{\theta}_1$	0.176	18.945
$\hat{\phi}_1$	0.136	21.321

Table 6: Comparison of out of sample forecasting accuracy

	ECM	ECM-COC	ARIMA	VAR
% correct direction	67.690%	68.750%	64.360%	66.800%
RMSE	4.382e-04	4.350e-04	4.531e-04	4.510e-04
MAE	0.426	0.426	0.438	0.438

Table 7: Estimated round trip transaction costs

	Asset FTSE100	
	Spot (%)	**Futures (%)**
Bid-ask spread	0.80	0.083
Stamp duty	0.50	0.000
Commission (twice)	0.40	0.033
Total cost	1.70	0.116

Source: Sutcliffe (1997)

Table 8: Trading strategy returns based on ECM-COC forecasts

Trading strategy	**Return (£)**	**Monthly return (%) {annualised}**	**Return (£) with slippage**	**Monthly return (%) {annualised} with slippage**	**Number of trades**
Passive investment	1040.920	4.090 {49.080}	1040.920	4.090 {49.080}	1
Liquid trading	1156.210	15.620 {187.440}	1056.380	5.640 {67.680}	583
Buy and hold	1156.210	15.620 {187.440}	1055.770	5.580 {66.960}	383
Filter I	1144.510	14.450 {173.400}	1123.570	12.360 {148.320}	135
Filter II	1100.010	10.000 {120.000}	1046.170	4.620 {55.440}	65
Filter III	1019.820	1.980 {23.760}	1003.230	0.320 {3.840}	8