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Success and Failure of Technical Trading Strategies in the Cocoa Futures Market

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Abstract. A large set of 5350 trend following technical trading rules is applied to LIFFE and CSCE cocoa futures prices, and to the Pound-Dollar exchange rate, in the period 1983:1-1997:6. We find that 72% of the trading rules generates positive profits, even when correcting for transaction and borrowing costs, when applied to the LIFFE cocoa futures prices. Moreover, a large set of trading rules exhibits statistically significant forecasting power of the LIFFE cocoa futures series. On the other hand the same set of strategies performs poor on the CSCE cocoa futures prices, with only 18% generating positive net profits and hardly any statistically significant forecasting power. The large difference in the performance of technical trading may be attributed to a combination of the demand/supply mechanism in the cocoa market and an accidental influence of the Pound-Dollar exchange rate, reinforcing trends in the LIFFE cocoa futures but weakening trends in the CSCE cocoa futures. Our case-study suggests a connection between the succes or failure of technical trading and the relative magnitudes of trend and volatility of the underlying series.

Keywords: technical trading strategies, commodity futures, exchange rate.

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1 Introduction

This paper is an attempt to answer questions raised by a financial practitioner, Guido Veenstra, employed at the leading dutch cocoa trading firm, Unicom International B.V. at Zaandam. Unicom is part of a bigger consortium that buys crops of cocoa at the Ivory Coast, where it has a plant to make some first refinements of the raw cocoa. The cocoa beans are shipped to Europe where they are transformed to cocoa-butter, cocoa-powder and cocoa-mass in plants in France and Spain. These raw cocoa products serve as production factors in the chocolate industry. The first goal of Unicom is to sell the raw cocoa beans as well as the raw cocoa products to chocolate manufacturers. A second important task of Unicom is to control the financial risks of the whole consortium. The consortium faces currency risk as well as cocoa price risk. Unicom monitors the product streams and uses cocoa futures contracts, mainly those traded at the London International Financial Futures Exchange (LIFFE), to hedge the price risk. Unicom trades cocoa futures through brokers. However, the commission fees give the brokers an incentive to contact their clients frequently and to give them sometimes unwilling advice to trade as much as possible. Brokers' advices are partly based on technical analysis.

In addition to cocoa producers, more and more speculators seem to be trading on the cocoa futures markets who use technical analysis as a forecasting tool. If a lot of speculators with a large amount of money are trading in a market, they may affect realized futures prices through their behavior. The question *'can cocoa futures prices be predicted by technical analysis?'* thus becomes important from a practitioners viewpoint. This question is not only important to cocoa producers, but in general to producers of any commodity hedging price risk. If technical analysis has forecasting power and speculators take positions in the market on the basis of technical analysis, these speculators can affect market prices. Why should a (cocoa) producer go short in the futures market to hedge his price risk exposure if he knows that a lot of speculators in the market are buying long positions driving up the price? Knowledge of the behavior of speculators in the market may be useful to adapt a producers' price hedging strategy.

Until fairly recently, the academic literature has paid little attention to technical trading strategies. Until the eighties the efficient market hypothesis (EMH) was the dominating paradigm in finance, e.g. Fama (1970) and Samuelson (1965). According to a strong form of the EMH financial time series follow a random walk and are thus inherently unpredictable. All information is discounted in the prices already and prices will only adapt if new information becomes available. Because news arrives randomly, prices will move randomly. According to the EMH financial time series are unpredictable and technical analysis is useless and can not lead to statistically significant prediction or economically significant profits.

In the last decade however, technical analysis has regained the interest of many economic researchers. Several authors have shown that financial prices and returns are forecastable to some extent, either from their own past or from some other publically available information, e.g. Fama and French (1988), Lo and MacKinley (1988, 1997, 1999) and Pesaran and Timmerman (1995, 2000). In particular, it has been shown that simple technical trading rules used in financial practice can generate positive profits and can have statistically significant forecasting power. For example Brock, Lakonishok and LeBaron (1992) (BLL hereafter) test 26 simple technical trading rules on daily data of the Dow Jones Industrial Average (DJIA) in the period 1897-1986. Each of the trading rules BLL test generates higher returns during buy days than during sell days. Further they find that returns following buy signals are less volatile than returns following sell signals. By applying bootstrap techniques they show that their results are not consistent with some popular null models like the Random Walk, the AR(1), the GARCH in Mean and the Exponential GARCH model. LeBaron (1999) performs the same analysis as BLL for the period 1988-1999 and finds that trading rules perform much worse in this period, but that volatility remains different between buy and sell periods.[1] Levich and Thomas (1993) test filter and moving average trading rules on foreign currency future prices in the period 1976-1990. Applying bootstrap techniques they conclude that the profits of the technical trading strategies can not be explained by a random walk model nor by autocorrelations in the data. LeBaron (1993) applies trading rules to exchange rates based on interest rate differentials, moving averages and volatility comparison and concludes that the trading rules tested have forecasting power.

Most papers written on the profitability of technical trading rules use daily data. But there is also some literature testing the strategies on intra-day data. Ready (1997) shows that profits of technical trading rules, applied to the largest 20% stocks of the NYSE in the period 1970-1995, disappear as price slippage and transaction costs are taken into account. Further he also finds that trading rules perform much worse in the period 1990-1995. Curcio, Goodhart, Guillaume and Payne (1997) apply technical trading rules, based on support and resistance levels, to intra daily data of foreign exchange markets. They find that no profits can be made on average when transaction costs, due to bid ask spreads, are taken into account. Price slippage and transaction costs are important themes, because they can have a negative influence on the profitability of trading rules reported in many studies.

Several authors have emphasized the danger of data snooping, meaning that if one searches long enough in a dataset, there will always appear one trading strategy that seems to work. This problem is mitigated by many authors by using only trading rules that are heavily used in financial practice or by reporting the robustness of their results across different subperiods. However, Sullivan, Timmermann and White (1998) (STW hereafter) noted that such trading strategies could be the result of survivorship bias, since the currently used trading rules in practice can be the result of a continuous search for the best strategy. Therefore they propose to use White's Reality Check bootstrap methodology (White (2000)) to correct for data snooping. STW take the results of BLL on the DJIA in the period 1897-1986 as starting point. They find that the results of BLL are robust to data

[1] Andrada-Félix, Fernández-Rodríguez and Sovilla-Rivero (1999) perform the same analysis to the General Index of the Madrid Stock Exchange in the period 1966-1997 and they find that technical trading rules have forecasting power and that there is no loss in profitability in the 1990s.

snooping in the period 1897-1986, but that in the period 1987-1997 the performance of the best trading rule is not significant when corrected for data snooping. STW show that the same results hold for a universe of 7846 trading rules and conclude that the worse performance of trading rules in the period 1987-1997 may be explained by a change of the market mechanism, e.g. an increase of market efficiency due to lower transaction costs and increased liquidity.

Some articles mentioned above found that technical trading rules have predictive power, other articles found that trading rules have no predictive power anymore after correcting for price slippage and transaction costs. In general the conclusion is that in the 1990's predictive power of technical trading rules disappears, if there was any predictive power before. Most articles about technical analysis confine themselves to stock market indices such as the DJIA, the S&P 500 or to the foreign exchange markets.

Before discussing the main contribution of the present paper, let us briefly discuss related theoretical work on *multi-agent* systems. Recently finanical markets have been viewed as evolutionary multi-agent systems, e.g. in Arthur et al. (1997), LeBaron et al. (1999), Brock and Hommes (1997,1998), Farmer (2000), Gaunersdorfer and Hommes (2000), Hommes (2000), Kirman (1991), Lux (1995) and Lux and Marchesi (1999ab); see also the related work on noise traders e.g. by Frankel and Froot (1988), De Long, Schleiffer, Summers and Waldmann (1989, 1990), Wang (1994) and Hong and Stein (1999). A common feature of these contributions is that there are two different classes of investors that can also be observed in financial practice: fundamentalist and technical analysts. Fundamentalists base their forecasts of future prices and returns upon economic fundamentals, such as dividends, interest, price-earning ratio's, macroeconomic variables, etc.. In contrast, technical analysts are looking for patterns in past prices and base their forecasts upon extrapolation of these patterns. An interesting outcome of these evolutionary heterogeneous agent systems is that the models mimic a number of stylized facts frequently observed in financial series, such as unpredictability of returns, fat tails and volatility clustering. These stylized facts may be triggered by uncertainty about economic fundamentals and are amplified by the evolutionary interaction of competing trading strategies.

The present paper is empirical and tests the profitability and predictability of trend following technical trading rules in the cocoa futures markets in the period 1983:1-1997:6. In order to avoid the problem of data snooping our approach is to test a large set of more than 5000 trading strategies, moving average, trading range break and filter rules, and to investigate the magnitude of the fraction generating positive net profits and statistically significant forecasting power. Cocoa futures contracts are traded at two different exchanges, namely at the Coffee, Sugar and Cocoa Exchange (CSCE) in New York and the London International Financial Futures Exchange (LIFFE). The results for the two cocoa futures contracts are strikingly different. When applied to the LIFFE cocoa futures prices, 72% of all trading rules generate positive profits, even when correcting for transaction and borrowing costs. Furthermore, a large set of trading rules exhibits statistically significant forecasting power of the LIFFE cocoa futures series, with e.g. 26.7% having significantly positive mean buy minus sell return; for the 5 year subperiod 1983:1-1987:12

even 47.5% of all trading rules has a significantly positive mean buy minus sell return. However, the same set of strategies performs poor on the CSCE cocoa futures prices, with only 18% generating positive net profits and hardly any statistically significant forecasting power. The large difference in the performance of technical trading is surprising, because the underlying asset in both markets is more or less the same. Our findings may be attributed to a combination of the demand/supply mechanism in the cocoa market and an accidental influence of the Pound-Dollar exchange rate. Due to a spurious relation between the level of the Pound-Dollar exchange rate and the excess demand/supply mechanism in the cocoa market, especially in the period 1983:1-1987:12, trends caused by the demand/supply mechanism were reinforced in the LIFFE cocoa futures price, but the same trends were weakened in the CSCE cocoa futures price. Many technical trading rules are able to pick up this sufficiently strong trends in the LIFFE cocoa futures but almost none of them picks up the weaker trends in the CSCE cocoa futures.

The paper is organized as follows. In section II we describe our dataset and the construction of a long, continuous time series of 15 years out of 160 different (overlapping) futures contracts of 18 months. Section III gives an overview of the 5350 trading rules we apply; the parameterizations of these rules can be found in the appendix. In section IV the performance measure, i.e. the profits net of transaction and borrowing costs generated by the trading rules, is calculated. Section V focusses on the economic performance as well as the statistical significance of the predictability of returns by technical trading rules, first under the assumption of iid returns but also after correcting for dependence in the data. In section VI a possible explanation of the large differences in the performance between CSCE and the LIFFE cocoa futures prices is given. Finally, section VII concludes.

2 Data

2.1 Data series

A commodity futures contract is an agreement between two parties to trade a certain asset at some future date. The contract specifies the quality and quantity of the good as well as the time and place of delivery. The price against which the contract is traded is called the futures price. The expiry months of cocoa futures contracts are March, May, July, September and December. The LIFFE contract specifies that at each trading day ten expiry months are available for trading. The CSCE and LIFFE cocoa futures contracts differ somewhat in their specifications. First, cocoa is grown in many regions in Africa, Asia and Latin America and therefore the crops differ in quality. In the futures contracts a benchmark is specified and the other crops are traded at premiums. The benchmark in the LIFFE contract has a higher quality than the benchmark in the CSCE contract. Therefore the benchmark in the LIFFE contract is traded at a \$160/ton[2] premium in the

[2]Contract specifications of January 26, 1998.

CSCE contract. Second, the place of delivery in the CSCE contract is near New York, while the places of delivery in the LIFFE contract are nominated warehouses at different places in Europe. Third, the tick sizes of the CSCE and LIFFE contract are respectively one dollar and one pound.

Cocoa producers and farmers hedge their price risk exposure with futures contracts. This guarantees them that they buy or sell cocoa against a predetermined price. The futures price will depend on the current and expected future demand and supply. When new information becomes available the price will adapt. Normally a futures price is the derivative of the spot price and is computed by the cost of carry relationship. But in the case of soft commodities such as cocoa the spot price is not relevant, because a farmer with his crop on the land only wants to know what he can get in the future. For cocoa there is no spot price, but the spot price is in fact determined by the futures prices.

We investigate data on the settlement prices of 160 cocoa futures contracts which expire in the period January 1982 - December 1997 at the CSCE and the LIFFE[3], as well as data on the pound dollar exchange rate (WM/Reuters) and 1 month UK and US certificates of deposit (COD) interest rates in the same period.

2.2 A continuous time series of futures prices

Each futures contract covers a limited time span of approximately 18 months. So there is no continuous time series of futures prices over a couple of years. In this subsection we describe how a continuous time series can be constructed out of the prices of the separate contracts. The well known formula of the price of a futures contract at day t which expires at day T is:

$$F_t = S_t e^{(r_t^f + u_t - y_t)(T-t)}, \tag{1}$$

where S_t is the spot price of the underlying asset at time t, and r_t^f, u_t, y_t are respectively the daily risk free interest rate, storage costs and convenience yield at time t with continuous compounding. The convenience yield can be described as the utility of having the asset in stock. The term $(r_t^f + u_t - y_t)$ is called the *cost of carry* and (1) is called the cost of carry relationship. The daily return r_t^F of the futures contract, expressed as the log difference, is given by:

$$r_t^F = r_t^S + (\Delta r_t^f + \Delta u_t - \Delta y_t)\ (T-t) - (r_{t-1}^f + u_{t-1} - y_{t-1}). \tag{2}$$

This formula shows that a change in one of the factors of the cost of carry has an impact on the futures price. Otherwise, the return of a futures contract is equal to the excess return of the underlying asset over the cost of carry.

Assume that we have two future contracts, 1 and 2, with futures prices $F_t^{(1)}$ and $F_t^{(2)}$ and expiry dates $T_2 > T_1$. It follows from (2) that two futures contracts traded in the same

[3]We thank the cocoa trading firm Unicom International B.V. and ADP Financial Information Services for providing the data

period have the same trends in prices. The futures price of contract 2 can be expressed in terms of the futures price of contract 1 as

$$F_t^{(2)} = F_t^{(1)} e^{(r_t^f + u_t - y_t)(T_2 - T_1)}. \tag{3}$$

This formula shows that if, as is usual, the cost of carry is positive, the futures price of a contract 2 which expires later is higher than the futures price of contract 1 which expires earlier. But if the utility of having an asset in stock is high, e.g when there is a shortage of the commodity in the short run, then the futures price of contract 2 can be lower than the futures price of contract 1. Thus the prices of different futures contracts can move at different price levels.

A long continuous time series of futures prices will be constructed, in order to be able to test technical trading strategies with long memory. The continuous time series must be constructed out of the many price series of the different futures contracts that have the same price trends, but move at different price levels. In particular *roll over dates* must be defined at which the price movements of the different contracts are pasted together. In practice most trading occurs in the second nearest contract, that is, the futures contract that has the one but nearest expiration date. We investigated the liquidity of the cocoa futures contracts and decided to take as roll over dates the date one month before most of the practitioners switch to the next contract, so that the continuous time series always represents a high liquidity futures contract. Figure 1 exhibits graphically the roll over procedure used in this paper.

Murphy (1986) suggests to paste the prices of two successive futures contracts to study price movements over a long period of time. But the pasting of prices will introduce price jumps in the continuous time series, because the prices of two different contracts move at different levels. These price jumps can have an impact on the results and may trigger spurious trading signals if technical trading rules are tested. Therefore a continuous time series must be constructed in another way.

The holder of the long position in a futures contract pays a time premium to the holder of the short position. According to (1) the time premium paid at time t is

$$TP_t = F_t - S_t = (e^{(r_t^f + u_t - y_t)(T-t)} - 1)\ S_t. \tag{4}$$

According to (4) the time premium that must be paid will be less when the duration of the contract is shorter other things being equal. However, (4) also implies that if a continuous time series of futures prices is constructed by pasting the prices of different contracts, at each pasting date[4] a new time premium to the time series is added, because at each pasting date the time until expiration will be longer than before the pasting date. This time premium will create price jumps and therefore an upward force in the global price development. In fact, if the return of the underlying asset is not greater than the cost of carry a spurious upward trend can be observed in the continuous price series, as illustrated

[4]The pasting date is equal to the roll over date.

in figure 2, which may affect the performance of long memory trading strategies. Therefore we constructed a continuous time series of futures prices by pasting the returns of each futures contract at the roll over dates and choosing an appropriate starting value; see figure 2. For this continuous series, discontinuous price jumps and spurious trends will disappear and the trends will show the real profitability of trading positions in futures contracts.

2.3 Summary statistics

In figure 3 time series are shown of the continuation of the CSCE and LIFFE cocoa futures prices and returns as well as the pound-dollar exchange rates and returns for the period 1982:1-1997:6. The long and short term trends can be seen clearly. Each technical trading strategy needs a different time horizon of past prices to generate its first signal. Therefore the first 260 observations in each dataset will be used to initialize the trading rules, such that on January 3rd 1983 each rule advices some position in the market. All trading rules will be compared from this date. Table I shows the summary statistics of the daily returns of the sample 1983:1-1997:6 and three subperiods of five years. Returns are calculated as the natural log differences of the level of the data series.

The first subperiod, 83:1-87:12, covers the period in which the price level series exhibit first a long term upward trend and thereafter a downward trend; see figure 3. It is remarkable that the upward and downward trends of both cocoa futures series CSCE and LIFFE (accidentally) coincide with similar trends in the Pound-Dollar exchange rate series. In the second subperiod, 88:1-92:12, the cocoa series exhibit a downward trend, while the pound-dollar series is fluctuating upwards and downwards. The third subperiod, 93:1-97:6, covers a period in which the cocoa series as well as the pound-dollar series seem to show no significant long term trends anymore. From table I it can be seen that the mean returns are close to zero for all periods. The largest (absolute) mean return is negative 9.5 basis points per day, -21.2% per year, for the CSCE series in the second subperiod. The daily standard deviation of the CSCE returns series is slightly, but significantly[5] greater than the daily standard deviation of the LIFFE returns series in all periods. The daily volatility of the pound-dollar series is much smaller, by a factor more than two measured in standard deviations, than the volatility of both cocoa series in all subperiods. All data series show excess kurtosis in comparison with a normal distribution and show some sign of skewness.

Table II shows the estimated autocorrelation functions, up to order 10, for all data series over all periods. Typically autocorrelations are small with only few lags being significant.[6]

[5] $H_0 : \sigma^2_{r(csce)} = \sigma^2_{r(liffe)}$ vs $H_1 : \sigma^2_{r(csce)} \neq \sigma^2_{r(liffe)}$; $F = S^2_{r(csce)}/S^2_{r(liffe)}$;

[6] Because sample autocorrelation may be spurious in the presence of heteroscedasticity we also tested for significance by computing Hsieh (1988) heteroscedasticity consistent estimates of the standard errors, $se(k) = \sqrt{1/n}\ (1 + \gamma(x^2, k))/\sigma^4$, where n is the number of observations, $\gamma(x^2, k)$ is the k-th order sample autocovariance of the squared returns, and σ is the standard error of the returns. ***, **, * in table II then indicates if the corresponding autocorrelation is signifantly different from zero.

The CSCE series shows little autocorrelation. Only for the first subperiod the second order autocorrelation is significant at a 5% significance level. The LIFFE series shows some signs of low order autocorrelation, significant at the 10% level, in the first two subperiods. The Pound-Dollar series has a significant first order autocorrelation at a 1% significance level, mainly in the first two subperiods. The Pound-Dollar series shows also some signs of higher order autocorrelation.

3 Technical Trading Strategies

Murphy (1986) defines technical analysis as the study of past price movements with the goal to forecast future price movements, perhaps with the aid of certain quantitative summary measures of past prices such as 'momentum' indicators ('oscillators'), but without regard to any underlying economic, or 'fundamental' analysis. Another description is given by Pring (1998) who defines technical analysis as the 'art' of detecting a price trend in an early stage and maintaining a market position until there is enough weight of evidence that the trend has reversed.

There are three assumptions underlying technical analysis. The first is that all information is discounted in the prices. Through the market mechanism the expectations, hopes, dreams and believes of all investors are reflected in the prices. A technical analyst argues that the best advisor you can get is the market itself and there is no need to explore fundamental information. Second, technical analysis assumes that prices move in upward, downward or sideway trends. Therefore most technical trading techniques are trend following instruments. The third assumption is that history repeats itself. Under equal conditions investors will react the same leading to price patterns which can be recognized in the data. Technical analysts claim that if a pattern is detected in an early stage, profitable trades can be made.

In this paper we confine ourselves to *objective* trend following techniques which can be implemented by a computer. In total we test 5350 technical trading strategies divided in three different groups: moving average rules (2760), trading range break-out (also called support and resistance) rule (1990) and filter rules (600). These strategies are also described by Brock, Lakonishok and LeBaron (1992), Levich and Thomas (1993) and STW (1998). Lo, Mamaysky and Wang (2000) use non-parametric methods to implement other, geometrically based technical trading rules such as head-and-shoulder pattern formation. We use the parameterizations of STW as a starting point to construct our sets of trading rules. These parameterizations are given in Appendix A. The strategies will be computed on the continuous cocoa time series and the Pound-Dollar exchange rate. If a buy (sell) signal is generated at the end of day t, we assume that a long (short) position is taken in the market at day t against the settlement price of day t.

3.1 Moving Average Trading Rules

Moving average (ma) trading rules are the most commonly used and most commonly tested technical trading strategies. Moving averages yield insight in the underlying trend of a price series and also smooth out an otherwise volatile series. In this paper we use equally weighted moving averages:

$$ma_t^n = \frac{1}{n}\sum_{j=0}^{n-1} P_{t-j}, \tag{5}$$

where ma_t^n is the moving average (ma) at time t of the last n observed prices. Short (long) term trends can be detected by choosing n small (long). The larger n, the slower the ma adapts and the more the volatility is smoothed out. Technical analysts therefore refer to a ma with a large n as a slow ma and to a ma with a small n as a fast ma.

Ma trading rules make use of one or two moving averages. A special case is the *single crossover* ma trading rule using the price series itself and a ma of the price series. If the price crosses the ma upward (downward) this is considered as a buy (sell) signal. The *double crossover* ma trading rule on the other hand uses two moving averages, a slow one and a fast one. The slow ma represents the long run trend and the fast ma represents the short run trend. If the fast ma crosses the slow ma upward (downward) a buy (sell) signal is given. The signal generating model is given by[7]

$$\begin{array}{ll} Pos_{t+1} = 1, & \text{if } ma_t^k > ma_t^n \\ Pos_{t+1} = Pos_t, & \text{if } ma_t^k = ma_t^n \\ Pos_{t+1} = -1, & \text{if } ma_t^k < ma_t^n, \end{array} \tag{6}$$

where $k < n$ and $Pos_{t+1} = -1, 0, 1$ means taking a short, neutral resp. long position in the market in period $t + 1$.

We call the single and double crossover ma rules described above, the basic ma trading rules. These basic ma rules can be extended with a %-band filter, a time delay filter, a fixed holding period and a stop loss. The %-band filter and time delay filter are developed to reduce the number of false signals. In the case of the %-band filter, a band is introduced around the slow ma. If the price or fast ma crosses the slow ma with an amount greater than the band, a signal is generated; otherwise the position in the market is maintained. This strategy will not generate trading signals as long as the fast ma is within the band around the slow ma. The extended ma model with a b*100% filter is given by:

$$\begin{array}{ll} Pos_{t+1} = 1, & \text{if } ma_t^k > (1+b)ma_t^n \\ Pos_{t+1} = Pos_t, & \text{if } (1-b)ma_t^n \leq ma_t^k <= (1+b)ma_t^n \\ Pos_{t+1} = -1, & \text{if } ma_t^k < (1-b)ma_t^n. \end{array} \tag{7}$$

According to the time delay filter a signal must hold for d consecutive days before a trade is implemented. If within these d days different signals are given, the position in

[7]Positions are unchanged until the moving averages really cross.

the market will not be changed. A ma rule with a fixed holding period holds a position in the market for a fixed number of f days after a signal is generated. This strategy tests if the market behaves different in a time period after the first crossing. All signals that are generated during the fixed holding period are ignored. The last extension is the stop loss. The stop loss is based on the popular phrase: 'Let your profits run and cut your losses short'. If a short (long) position is held in the market, the stop loss will liquidate the position if the price rises (declines) from the most recent low (high) with $x\%$. In total our group of ma rules consists of 2760 trading strategies.

3.2 Trading Range Break

Our second group of trading rules are trading range break-out (trb) strategies, also called support and resistance strategies. The trb strategy uses *support* and *resistance* levels. If during a certain period of time the price does not fall below (rise beyond) a certain price level, this price level is called a support (resistance) level. According to technical analysts, there is a 'battle between buyers and sellers' at these price levels. The market buys at the support level after a price decline and sells at the resistance level after a price rise. If the price breaks through the support (resistance) level, an important signal is generated. The sellers (buyers) have won the battle. At the support (resistance) level the market has become a nett seller (buyer). This indicates that the market will move to a subsequent lower (higher) level. The support (resistance) level will change into a resistance (support) level. To implement the trb strategy, support and resistance levels are defined as local minima and maxima of the closing prices. If the price falls (rise) through the local minima (maxima) a sell (buy) signal is generated and a short (long) position is taken in the market. If the price moves between local minima and maxima the position in the market is maintained until there is a new breakthrough. The trb strategy will also be extended with a %-band filter, a time delay filter, a fixed holding period and a stop loss. The basic trb-strategy, extended with a %-band filter, is described by

$$\begin{array}{ll} Pos_{t+1} = 1, & \text{if } P_t > (1+b)Max\{P_{t-1}, P_{t-2}, ..., P_{t-n}\} \\ Pos_{t+1} = Pos_t, & \text{if } (1-b)Min\{P_{t-1}, P_{t-2}, ..., P_{t-n}\} \leq P_t \leq (1+b)Max\{P_{t-1}, P_{t-2}, ..., P_{t-n}\} \\ Pos_{t+1} = -1, & \text{if } P_t < (1-b)Min\{P_{t-1}, P_{t-2}, ..., P_{t-n}\} \end{array} \quad (8)$$

Our group of trb-strategies consists of 1990 trading strategies.

3.3 Filter Rule

The final group of trading strategies we test is the group of filter rules. These strategies generate buy (sell) signals if the price rises (falls) by $x\%$ from a subsequent low (high). We implement the filter rule by using a so called moving stop loss. In an uptrend the stop loss is placed below the price series. If the price goes up, the stop loss will go up. If the price declines, the stop loss will not be changed. If the price falls through the stop loss, a sell signal is generated and the stop loss will be placed above the price series. If the price declines, the stop loss will decline. If the price rises, the stop loss is not changed. If the price rises through the stop loss a buy signal is generated and the stop loss is placed below the price series. The stop loss will follow the price series at a $x\%$ distance. On a buy (sell) signal a long (short) position is maintained. This strategy will be extended with a time delay filter and a fixed holding period. In total our group of filter rules consists of 600 trading strategies.

As can be seen in the appendix we can construct a total of 5350 trading strategies (2760 ma-rules, 1990 TRB-rules, 600 Filter-rules) with a limited number of values for each parameter. Each trading strategy divides the dataset of prices in three subsets, namely days on which a long (short, no) position is maintained. These subsets will be called the set of buy (sell, neutral) days.

4 Performance Measure

4.1 Cocoa Futures Prices

We assume that a trader buys or sells one contract at each signal and that there is unlimited borrowing and lending. Suppose F_t is the cocoa futures settlement price in dollars per ton (not the level of the continuous cocoa series) and W_t is the wealth of the trader at day t. In the case no interest is earned, the wealth of the trader at time t_2 who buys/sells a contract at time t_1 is equal to:

$$W_{t_2} = W_{t_1} + [\Delta(F_{t_1+1}) + \Delta(F_{t_1+2}) + ... + \Delta(F_{t_2})]\ Pos[t_1, t_2];$$

where $Pos[t_1, t_2] = -1, 0, 1$ means that a short, neutral or long position is maintained in the market in the period $[t_1, t_2]$.

We now turn to the (realistic) case that interest can be earned or paid, transaction costs must be paid and margins have to be maintained. We take as a proxy for the risk free interest rates the 1 month US and UK certificates of deposits (COD), which we recompute to daily interest rates. Money can be borrowed against an extra premium p over the interest rate. The position in the market at time t is given by Pos_t. The signals of the trading rules at day t are dependent on the level of the continuous cocoa price series of day t, but Pos_t is dependent on the signal at day $t-1$. If at day $t-1$ a signal is generated, then Pos_t will be changed. Costs will be calculated as percentage of F_{t-1}. Some strategies generate trading signals very often, others not. If a strategy does not generate trading signals very often and a position in the market is maintained for a long time, then there are also trading costs due to the limited life span of a futures contract. In particular, we assume that if a certain position in the market is maintained for 20 days after a roll over date, a trade takes place since the position has to be rolled over to the next futures contract and transaction costs must be paid. This approach leads to a fair comparison of the cost structure of strategies which generate many signals with strategies which generate only a few signals.

At the end of day t profits and losses are added and subtracted from the margin. If a signal is generated at the end of day $t-1$, we assume that a position can be taken in the market against F_{t-1} at the beginning of day t. At the beginning of day t costs are paid and money is added to or subtracted from the margin. Therefore we define the following variables:

- Mb_t is the margin at the beginning of day t;
  Me_t is the margin at the end of day t;
- Sb_t is the money on the savings account at the beginning of day t;
  Se_t is the money on the savings account at the end of day t;
- $Wb_t = Mb_t + Sb_t$ is total wealth at the beginning of day t;
  $We_t = Me_t + Se_t$ is total wealth at the end of day t;
- $We_T - Wb_1$ is the total pay-off of the strategy at time T;
- im is the initial margin as percentage of the futures price;
  mm is the maintenance margin as percentage of the futures price;
- $r_f^S(t)$, $r_f^M(t)$ is the daily risk free interest rate that can be earned on the savings account respectively the margin account at day t.

If the margin at the end of period $t-1$ is smaller than the maintenance margin, i.e. if $Me_{t-1} \leq mmF_{t-1}$, then the broker gives a margin call and money must be transferred to the margin, because otherwise the broker will liquidate the position. If on the ohter hand the margin at the end of period $t-1$ is greater than the initial margin, i.e. $Me_{t-1} > imF_{t-1}$, money can be subtracted from the margin account. The formulas which are used to compute the net profit of a technical trading strategy in the cocoa futures markets are:

$$
\begin{aligned}
We_t &= Me_t \ + \ Se_t; \\
Wb_t &= Mb_t \ + \ Sb_t; \\
Mb_t &= \begin{cases} Me_{t-1} * |Pos_t| & \text{if there is no trade and } mm\ F_{t-1} < Me_{t-1} \leq im\ F_{t-1}; \\ im\ F_{t-1} * |Pos_t| & \text{otherwise;} \end{cases} \\
Me_t &= Mb_t\ (1 + r^M_{f,t}) \ + \ (F_t - F_{t-1})\ Pos_t; \\
Costs &= \begin{cases} c\ F^o_{t-1}\ |Pos_{t-1}| \ + \ c\ F_{t-1}\ |Pos_t| & \text{if there is a trade;} \\ 0 & \text{otherwise;} \end{cases} \\
Sb_t &= Se_{t-1} \ + \ [Me_{t-1} - Mb_t] \ - \ Costs; \\
Se_t &= \begin{cases} Sb_t\ (1 + r^S_{f,t}) & \text{if } Sb_t > 0; \\ Sb_t\ (1 + r^S_{f,t} + p) & \text{if } Sb_t \leq 0, \end{cases}
\end{aligned}
$$

where F_{t-1} and F^o_{t-1} are the futures price at the end of day $t-1$ of the contract initialized and/or liquidated at day t. For example: if a short position is maintained in the March contract, and if a buy signal is generated five days after the roll over date, then a long position is taken in the May contract against F_{t-1} and the March position is liquidated against F^o_{t-1}. The following values for the parameters are used: the costs are $c = 0.1\%$ per trade, $r^S_f(t) = r^M_f(t)$, the premium against which can be borrowed is $p = 2\%$ on year basis and the initial investment is $Wb_1 = 0$ dollar or pounds.

4.2 Pound-Dollar Exchange Rate

This section describes how the pay-off of a trading rule applied to a exchange rate E_t is computed. On a buy signal the foreign currency is bought and the foreign risk free interest rate $r^F_{f,t}$ can be earned. If there is a position in the foreign currency and the trading rule gives a sell signal or advises to hold no position, then the foreign currency will be exchanged for the domestic currency and the domestic risk free interest rate $r^D_{f,t}$ can be earned. The following formula gives the return with continuous compounding r^E_t of such a strategy:

$$
r^E_t = \begin{cases} ln(\frac{E_t}{E_{t-1}}) + ln(1 + r^F_{f,t+1}) & \text{if there is a position in foreign currency;} \\ ln(1 + r^D_{t+1}) & \text{if there is a position in domestic currency;} \end{cases} +
\begin{cases} ln(\frac{1}{1+c}) & \text{if there is a buy signal;} \\ ln(1-c) & \text{if there is a sell signal;} \end{cases}
$$

The wealth at time $t+1$ is computed as $W_{t+1} = W_t e^{r^E_{t+1}}$. The total net pay-off of a strategy at time T is calculated as: $W_T - (W_0 +$ cumulative interest over $W_0)$. In this paper we assume that we start with $W_0 = 1000$ pounds and that the costs are $c = 0.1\%$ per trade. For the foreign and domestic interest rates we use as proxies the US and UK 1 month CODs.

5 Profitability and predictability of trading rules

If a large set of trading rules is tested, there will always be a strategy that generates a large profit. In practice technical traders will optimize their set of trading rules and use the best one for future forecasting. Therefore BLL and Levich and Thomas (1993) test a small set of strategies that are used in practice. In their bootstrap procedure which corrects for datasnooping STW also use only the best strategy. Instead in this paper, we look at the results of 5353 trading rules as a group. This large set consists of three subsets and each trading rule within each subset differs in the values of its parameters.

5.1 Economic significance

Cocoa Futures Series

We test for economic significance of the trading rules by looking at the distribution of the profits of a large set of strategies. The histograms in figure 4 show the distributions of the net profits of the trading rules applied to the cocoa futures prices and the Pound Dollar exchange rate. The histograms show only the results of the complete set of 5353 trading rules, but the results of the three subsets of ma, trb and filter rules are similar. In the period 83:1-97:6 the trading rules perform very well on the LIFFE cocoa futures prices, but much worse on the CSCE cocoa prices; 72% of the strategies generate a positive pay-off when applied to the LIFFE series, but only 18% generate a positive pay-off when applied to the CSCE series. This large difference is remarkable, because the underlying asset in both markets is the same, except for small differences in quality of the cocoa. The table shows that the good results for the LIFFE series mainly appear in the period 83:1-87:12, where 74% of the rules generate a profit for the LIFFE series against 18% for the CSCE series. In the second subperiod, 88:1-92:12, the trading rules seem to work equally well on both series, although the results for the LIFFE series are now weaker than in the first subperiod, with 56.8% (59.5%) of the rules generating a positive net profit for the CSCE (LIFFE) series. In the third subperiod 93:1-97:6, the trading rules perform poor on both series, since only 16.3% (30.5%) generate a positive profit for the CSCE (LIFFE) series.

Pound-Dollar Exchange Rate

For the full sample the trading rules do not show much economic significant forecasting power, with only 13.6% of the trading rules generating a positive net profit. The same result is found for the first subperiod, with 13.8% generating positive profit. The trading rules seem to work better when they are applied to the Pound-Dollar exchange rate in the second subperiod, with 51.9% of the trading rules generating a positive net profit. In the third subperiod the strategies work bad and only 2.5% generate a positive profit.

Notice that, for example under the null hypothesis of a random walk, net realized profits of technical trading rules will be negative due to transaction and borrowing costs. The fact that a large set of technical trading rules generates positive net profits, especially for the LIFFE cocoa futures series, is therefore surprising and suggestive of economically significant profit opportunities. It is hard however, to evaluate the statistical significance of this observation. Therefore, in the next subsection we focus on the question whether the forecasting power of returns is statistically significant.

5.2 Statistical significance

5.2.1 Significance under the assumption of iid returns

For each trading rule the mean return and variance of the dataseries during days at which the strategy has a long, neutral or short position has been calculated. Under the assumption of iid returns we test with simple t-ratio's if the dataseries has a significant positive (negative) mean return during buy (sell) days:

$$t_m = \sqrt{N_m}\,\frac{\overline{r_m}}{S_m};$$

where m is a subscript for buy or sell days, $\overline{r_m}$ is the mean return, S_m is the estimated standard deviation and N_m gives the number of buy or sell days. Further we test with simple t-ratio's if the mean return during buy days is significantly different from the mean return during sell days:

$$t_{B-S} = \frac{\overline{r_B} - \overline{r_S}}{\sqrt{\frac{S_B^2}{N_B} + \frac{S_S^2}{N_S}}}.$$

This test statistic is not student distributed. Satterthwhaite (1946) derived an approximation for the degrees of freedom such that the critical values from the t-table can be used. If the number of observations is sufficiently large this test statistic will converge to a standard normal distribution. Next we look at the distributions of the t-ratio's of the strategy sets to see if the strategies as a group have a statistical significant forecasting power.

Table III summarizes the results. The table shows for both the LIFFE and CSCE cocoa futures series and the Pound-Dollar exchange rate series for the full sample 1983:1-1997:6 as well as for the three five year subperiods the fractions of ma, trb, filter and the complete set of trading rules for which a significantly positive (negative) mean return during buy (sell) days occurs. The table also shows the fraction of strategies for which the difference in mean return of the dataseries during buy and sell days is significantly positive. Finally, the percentage of strategies for which the dataseries at the same time has a significantly positive mean return during buy days as well as a significantly negative mean return during sell days is shown. The tables give only the results of one sided tests with a 10% significance level, the results for a 5% significance level are similar but of course weaker. For a 1% significance level most significant results disappear.

Cocoa Futures Series

For the full sample period the strategies applied to the CSCE cocoa series show hardly any statistical significant forecasting power. For example, the difference in mean return during buy and sell days is significantly positive only in 1.45% of the trading rules, whereas a significantly negative return during sell days occurs only in 5.9% of all strategies. For the LIFFE series on the other hand the results are remarkably different. For 26.7% of the strategies the mean buy-sell difference is significant. In particular, the strategies seem to forecast the sell days very well, with more than half (51.6%) of all strategies having significantly negative return during sell days. In contrast, the buy days have significantly positive returns only in 6.25% of all strategies.

For the first subperiod the trading rules show almost no statistical significant forecasting power when applied to the CSCE series. Most t-ratio's stay within the critical values. For the LIFFE series the results are totally different. All subsets of trading rules show some forecasting power. For 24.8% of the strategies the mean return of the dataseries during buy days is significantly positive, for 41.4% of the trading rules the mean return during sell days is significantly negative and for 47.5% of the strategies the Buy-Sell difference is significantly positive. Hence, for the LIFFE series the trading rules show economic as well as statistically significant forecasting power.

The second subperiod is characterized by a long term downward trend with short term upward corrections in both cocoa series. All subsets of trading rules show a significant negative mean return of the dataseries during sell days (CSCE: 45.4% $< -t_{crit}$; LIFFE: 54.8% $< -t_{crit}$), which is in line with the downward trend. The upward corrections are not predicted well by the strategies, and for many trading rules the mean return of the dataseries during buy days is even negative (CSCE: 27.3% $< -t_{crit}$; LIFFE: 33.0% $< -t_{crit}$). The results found for the second subperiod are in line with the advices of technical analysts only to trade in the direction of the main trend and not reverse the position in the market until there is enough weight of evidence that the trend has reversed. Apparently, the short term upward corrections did not last long enough to be predictable or profitable.

The third subperiod is characterized by upward and downward trends in prices.

The trading rules show no economic significance for this period and neither do they show statistical significance. For most trading rules the t-ratio's stay within the critical values. If there was any predictability in the data it has disappeared in the third subperiod.

Pound-Dollar Exchange Rate

For the full sample 83:1-97:6 the histograms show that most of the t-ratio's of the mean returns of the dataseries during buy days are positive and during sell days are negative. The histogram of the mean Buy-Sell difference has its weight on the positive side, with 31.4% significantly positive. The trading rules thus show forecasting power over the full sample.

For the first subperiod the results are very strong again (Buy: $14.7\% > t_{crit}$; Sell: $48.7 < -t_{crit}$; Buy-Sell: $49.7\% > t_{crit}$), although the sell days are forecasted better than the buy days. The trading rules as a group seem to have a statistically significant forecasting power in this period, while the economic forecasting power was poor.

In the second subperiod the strategies forecast the upward trends better than the downward trends. For 29.7% of the trading rules the Buy-Sell difference is positive. Hence, also in this subperiod there are signs of forecastability. The statistical significance found for the second subperiod is not as good as for the first subperiod, while the economic significance was strongest for the second subperiod.

In the third subperiod the Pound-Dollar exchange rate exhibits some upward and downward trends. The trading rules show hardly any signs of forecasting power in this subperiod for the Pound-Dollar exchange rate.

5.2.2 Significance after correction for dependence

In the previous subsection we showed that in the period 1983:1-1987:12 the technical trading strategies seem to have forecasting power for the LIFFE cocoa futures prices and the Pound-Dollar exchange rate. We tested on statistical significance under the assumptions of iid returns. It is well known however, that returns show dependence in the second moments (volatility clustering) and in section 2.3 we showed that our dataseries also exhibit some autocorrelation. Therefore we further explore the statistical significance found in the first subperiod by estimating for each trading rule an econometric time series model, which incorporates volatility clustering, autoregressive variables and a dummy for buy (sell) days in the regression function. We then use the histograms of the t-ratio's of the dummy coefficients, to check if the trading rules as a group show signs of forecasting power.

LIFFE Cocoa Futures Series
We estimated some econometric time series models on the daily LIFFE cocoa return series for the period 83:1-87:12 and we found that the following EGARCH-model fitted

the data best:

$$\begin{array}{lll} r_t & = \alpha + \epsilon_t; & \\ \epsilon_t & = \eta_t \sqrt{h_t}; & \eta_t \sim N(0,1); \\ ln(h_t) & = w + \theta \frac{\epsilon_t}{\sqrt{h_t}} + \gamma |\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}| + \beta ln(h_{t-1}). & \end{array}$$

Maximum likelihood estimation with Bollerslev-Wooldridge robust standard errors and covariance gives the following results with standard errors within parenthesis:

α	w	θ	γ	β
−0.000272	−0.262896	0.049451	0.130991	0.981045
(0.000323)	(0.101222)	(0.018682)	(0.042660)	(0.009190)

The coefficient θ is significant positive. This indicates that there is a positive correlation between return and volatility. On a positive shock volatility increases more than on a negative shock.

To explore the significance of the trading rules after correction for dependence the following regression function in the EGARCH-model is estimated:

$$r_t = \alpha + \delta_m \ D_m + \epsilon_t, \tag{9}$$

where $m = B$ ($m = S$) indicates that we insert a dummy for buy (sell) days, which we will refer to as the buy (sell) dummy. For every trading strategy the coefficient for a buy dummy and for a sell dummy is estimated. Table IV shows the percentage of trading rules for which the coefficient of the buy (sell) dummy is significant positive (negative) at a 10% significance level (second and third column). The fourth column shows the percentage of trading rules for which the coefficient of the buy dummy is significantly positive and the coefficient of the sell dummy is significantly negative. The results again indicate that the technical trading strategies have forecasting power in the first subperiod. The histogram of the t-ratio's of the coefficients of the buy dummy has its weight on the positive side, with 45.6% of all trading rules showing a significantly positive coefficient of the buy dummy. The histogram of the t-ratio's of the coefficients of the sell dummy has its weight on the negative side, with 33.7% of the trading rules showing a significantly negative coefficient of the sell dummy. Finally, 29.6% of all trading rules have a significant positive coefficient of the buy dummy as well as a significant negative coefficient of the sell dummy. In comparison with the tests under the assumption of iid returns, it now seems that the trading rules forecast the buy days better than the sell days, while first it was the other way around.

Pound-Dollar Exchange Rate

For the Pound-Dollar exchange rate in the period 83:1-87:12 we found that a GARCH in the mean model fitted the daily returns best:

$$\begin{array}{rl} r_t = & \alpha + \gamma\sqrt{h_t} + \phi r_{t-1} + \epsilon_t; \\ \epsilon_t = & \eta_t \sqrt{h_t}; \ \eta_t \sim N(0,1); \\ h_t = & \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}; \end{array}$$

Maximum likelihood estimation with Bollerslev-Wooldridge robust standard errors and covariance gives the following results with standard errors within parenthesis:

α	γ	ϕ	α_0	α_1	β
0.002264	-0.351023	0.077302	$8.16E-07$	0.055993	0.926976
(0.000846)	(0.133701)	(0.028809)	$(3.64E-07)$	(0.016051)	(0.019084)

All parameters are significant different from zero. The estimated coefficient for γ is significant negative, which means that an increase in volatility has a negative impact on the return.

In the regression function of the GARCH in mean model a dummy for buy or sell days is inserted and the model (9) is estimated for each trading rule to explore the significance after correction for dependence. The results are shown in table IVb. Again the results show that the trading rules as a group show forecasting power in this subperiod. The histogram of the t-ratio's of the coefficients of the buy (sell) dummy has its weight at the positive (negative) side, with 24.4% (31.5%) of the trading rules showing a significantly positive (negative) coefficient of the buy (sell) dummy and 20.0% of the trading rules showing a significantly positive coefficient of the buy dummy as well as a significantly negative coefficient of the sell dummy. The results show that sell days are better forecasted than buy days.

6 Succes and Failure of Technical Trading

The technical trading strategies show economic and statistical significant forecasting power when applied to the LIFFE cocoa series, especially in the period 1983:1-1987:12. On the other hand the same technical trading strategies show no sign of forecasting power when applied to the CSCE cocoa series in the same period. The futures contracts differ in their specification of quality, currency and place of delivery, but it is surprising that the difference in economic and statistical significance is so large. Why are these differences so pronounced?

The daily CSCE cocoa returns shows somewhat stronger autocorrelation in the first two lags than the LIFFE returns, which suggests more predictability. The variance of the CSCE series is slightly bigger across all subperiods than the variance of the LIFFE series, which may be an indication why trend following rules have more difficulty in predicting the CSCE cocoa series. However, it seems that this somewhat higher variance can not explain the large differences. For example, in the second subperiod, when the volatility is the strongest across all subperiods for both time series, the trading rules perform almost equally well on the CSCE and LIFFE cocoa futures prices and show forecasting power of the sell days for both series. Hence, there must be some other explanation for the differences of technical trading performance.

Figure 3 already showed that, in the period 1983:1-1987:12, the LIFFE and CSCE cocoa futures prices first exhibit an upward trend from 83:1-84:6 for CSCE in New York and from 83:1-85-2 for LIFFE in London, whereas from 85:2-87:12 both cocoa series exhibit a downward trend. The upward trend until mid 84 was due to excess demand on the cocoa market, whereas after january 1986 cocoa prices declined for several years due to excess supply. See for example the graphs of gross crops and grindings of cocoa beans from 1960-1997 in the International Cocoa Organization Annual Report 1997/1998 (see e.g. p.15, Chart I).[8] The demand-supply mechanism thus caused the upward and downward trends in cocoa future prices in the subperiod 1983:1-1987:12. Figure 3 suggests that these trends were more pronounced in London for LIFFE than in New York for CSCE.

6.1 The influence of the Pound-Dollar exchange rate

Figure 3 also showes that the Pound-Dollar exchange rate moves in similar trends in the same subperiod 83:1-87:12. More precisely, the Pound-Dollar exchange rate rises (the Pound weakened against the Dollar) from January 1983 to reach its high in February 1985. This causes an upward force on the LIFFE cocoa price in Pounds, and a downward force on the CSCE cocoa price in Dollars. The LIFFE cocoa futures price also peaked in February 1985, while the CSCE cocoa futures price reaches its high already in June 1984. After February 1985, the Pound strengthened against the Dollar until April 1988 and the Pound-Dollar exchange rate declined. This causes a downward force on the LIFFE cocoa futures price in pounds, but an upward force on the CSCE futures price in Dollars. Until January 1986 the LIFFE cocoa price declined, while the CSCE cocoa price rose slightly. After January 1986 cocoa prices fell on both exchanges for a long time, due to excess supply of cocoa beans. We therefore conclude that, by coincidence, the upward and downward trends in the cocoa prices coincide with the upward and downward trends in the Pound-Dollar exchange rate. For LIFFE at London the trends in exchange rates reinforced the trends in cocoa futures, whereas for CSCE in New York the trends in the exchange rates weakened the trends in cocoa futures prices.

Table V shows the cross-correlations between the levels of the three dataseries across all subperiods. It is well known that if two indepently generated integrated time series of the order one are regressed against each other in level, with probability one a spurious, but significant relation between the two time series will be found (Phillips 1986). Although the Pound-Dollar exchange rate should be indepently generated from the cocoa futures series, it has some impact on the price level of the cocoa series as described above. The table shows that the Pound-Dollar exchange rate is correlated strongly with the level of the LIFFE cocoa continuation series and also (although a little bit weaker) with the CSCE cocoa continuation series. In particular, in the first subperiod 83:1-87:12 the Pound-Dollar exchange rate is correlated strongly with the level of the LIFFE cocoa futures series (cross

[8] We would like to thank Guido Veenstra, employed at the dutch cocoa firm Unicom, for pointing this out to us.

correlation coefficient 0.88) and also (although a little bit weaker) with the CSCE cocoa futures series (cross correlation coefficient 0.58). In the other subperiods, there is little cross correlation between the Pound-Dollar exchange rate and the LIFFE and/or the CSCE cocoa futures series.

Apparantly, due to the accidental correlation (spurious relation) in the period 83:1-87:12 between the Pound-Dollar exchange rate movements and the demand-supply mechanism in the cocoa market, trends in the LIFFE cocoa price are reinforced and trends in the CSCE cocoa prices are weakened. Because the technical trading rules we tested are mainly trend following techniques, this gives a possible explanation for the large differences in the performance of technical trading in the LIFFE and CSCE cocoa futures.

In order to explore further the possible impact of the Pound-Dollar exchange rate on the profitability of trend following trading techniques when applied to the cocoa data series, we test the trading rules on the LIFFE cocoa price expressed in Dollars and on the CSCE cocoa price expressed in Pounds. If the LIFFE and CSCE cocoa futures prices are expressed in the other currency, than the results of testing technical trading strategies change indeed. For the full sample, 83:1-97:6, for the LIFFE cocoa series in Dollars 37.1% (versus 72% in Pounds) of all trading rules make a positive profit, while for CSCE cocoa futures in Pounds 54.3% (versus 18% in Dollars) of the trading rules make a positive profit. Especially in the first subperiod 83:1-87:12 the performance results change dramatically. For the LIFFE cocoa series in Dollars 27.9% (versus 74% in Pounds) of all trading rules make a positive profit, while for CSCE cocoa futures in Pounds 61.7% (versus 18% in Dollars) of the trading rules make a positive profit.

Table VI summarizes the results concerning the forecasting power of the trading rules applied to the LIFFE cocoa futures in Dollars and the CSCE cocoa futures in Pounds. The table shows for all periods for both dataseries the percentage of trading rules generating a significantly positive (negative) mean return during buy (sell) days. The table also shows the percentage of trading rules for which the mean Buy-Sell difference of the dataseries is significantly positive and for which buy and sell days at the same time generate significantly positive respectively negative returns. The table summarizes only the results of one sided tests with a 10% significance level. The results of table VI should be compared to the corresponding results of table III.

For the full sample, the statistical properties of the trading rules applied to the CSCE cocoa series in Pounds are only slightly better than for the CSCE cocoa series in Dollars. For example, only 2.8% (versus 1.5%) of all rules yiels a significantly positive difference between Buy-Sell returns. The sell days are predicted better, with 14.3% (versus 5.9% of the trading rules showing significantly negative mean return during sell days. For the LIFFE series in Dollars the statistical results of the trading rules are poorer than for to the LIFFE series in Pounds. The mean Buy-Sell difference is significantly positive only for 5.2% (versus 26.7%) of all trading rules. The trading rules still forecast the sell days well, with 27.0% of the trading rules having significantly negative mean return during sell days, but not nearly as good as for the LIFFE cocoa series in Pounds for which 51.6% of all rules has significantly negative mean return during sell days.

For the first subperiod the trading rules showed no statistical significant forecasting power on the CSCE series in Dollars. When applied to the CSCE series in Pounds the results are much better. For example 20.6% (versus 0.8%) of all trading rules has a significantly negative mean return during sell days. For the buy days most t-ratio's stay within the critical values and only 6.95% (versus 1.5%) has significantly positive returns. For 21.3% (versus 1.7%) of all strategies the mean Buy-Sell difference is significant. The strongly significant forecasting power of the strategies applied to the LIFFE series in Pounds totally vanishes when applied to the LIFFE series in Dollars. For most trading rules the t-ratio's of the mean return of the dataseries during buy, sell days stay within the critical values. Only 1.3% (versus 41.5%) of all trading rules has a significantly negative mean return during sell days and only only 1.6% (versus 24.8%) has significantly positive returns during buy days. The percentage of strategies for which the mean Buy-Sell difference is significant drops from 47.5% to 1.3%.

We conclude that, especially in the first subperiod, the Pound-Dollar exchange rate had a strong influence on the forecasting power of the trading rules applied to the LIFFE cocoa futures price in Pounds. There is a dramatic change in predictability when the LIFFE cocoa futures price is transformed to Dollars. On the other hand the forecasting power of the strategies on the CSCE cocoa series transformed to Pounds is not as strong as the forecasting power of the strategies applied to the LIFFE cocoa series in Pounds. The Pound-Dollar exchange rate mechanism thus provides only a partial explanation, in addition to the demand-supply mechanism on the cocoa market, of the predictability of trading rules applied to cocoa futures.

6.2 What causes succes and failure of technical trading?

An important theoretical and practical question is: what are the characteristics of financial series for which technical trading can be succesful? In order to get some insight into this general question from our case-study, it is useful to plot the price and returns series all on the same scale, as shown in figure 5. The returns series clearly show that the volatility in the Pound-Dollar exchange rate is lower than the volatility in both cocoa futures series. Furthermore, the price series on the same scale show that the trends in the LIFFE cocoa series are much stronger than in the CSCE cocoa series and the Pound-Dollar exchange rate. One might characterize the three series as follows: (i) CSCE has weak trends and high volatility; (ii) LIFFE has strong trends and high volatility, and (iii) Pound-Dollar has weak trends and low volatility.

Recall from section 5 that the performance of technical trading may be summarized as follows: (i) no forecasting power and no economic profitability for CSCE; (ii) good forecasting power and substantial net economic profitability for LIFFE, and (iii) good forecasting power but no economic profitability for Pound-Dollar. Unfortunately, economic performance of the cocoa futures series and the Pound-Dollar series can *not* be compared directly, because for both markets different net profit measures apply and have been used. In order to better compare economic profitability in these different markets, the histogram in figure 6 shows the (hypothetical) net profits of the LIFFE cocoa futures series in the period 83:1–87:12, *as if* the LIFFE series were a Pound-Dollar exchange rate series. The histogram clearly shows that most of the technical trading rules applied to the LIFFE series, in the hypothetical case that this were a Pound-Dollar exchange rate series, would generate substantial economic profits. In both performance measures, technical trading applied to the LIFFE series thus generates substantial economic net profits.

Our case-study of the cocoa futures series and the Pound-Dollar exchange rate series suggest the following connection between performance of technical trading rules and the trend and volatility of the corresponding series. When trends are weak and volatility is relatively high, as for the CSCE cocoa futures series, technical trading does not have much forecasting power and therefore also can not lead to economic profitability. Volatility is too high relative to the trends, so that technical trading is unable to uncover these trends. When trends are weak but volatility is also relatively low, as for the Pound-Dollar exchange rates, technical trading rules can have statistically significant forecasting power without economically significant profitability. In that case, because volatility is low the weak trends can still be picked up by technical trading, but the changes in returns, although predictable, are too small to account for transaction costs. Finally, when trends are strong and volatility is relatively high, as for the LIFFE cocoa futures series, a large set of technical trading rules may have statistically significant forecasting power leading to economically significant profit opportunities. In that case, the trends are strong enough to be picked up by technical trading even though volatility is high. Moreover, since volatility is high, the magnitude of the (predictable) changes in returns is large enough to cover the transaction costs.

7 Concluding remarks

In this paper the performance of a large set of 5350 technical trading rules has been tested on the prices of cocoa futures contracts traded at the CSCE and the LIFFE and on the Pound-Dollar exchange rate in the period 1983:1-1997:6. The large set of trading rules consists of three subsets: moving average (1990), trading range break-out (2760) and filter (600) strategies. The strategies perform much better on the LIFFE cocoa prices than on the CSCE cocoa prices, especially in the period 1983:1-1987:12. In this period a large group of the trading rules applied to the LIFFE cocoa futures price has statistically significant forecasting power and is economically profitable after correcting for transaction and borrowing costs. Applied to the CSCE cocoa futures series the trading rules show little forecasting power and are not profitable. The forecasting power of the strategies applied to the Pound-Dollar exchange rate in the period 1983:1-1997:6 is also statistically significant, but most trading strategies are not profitable.

The large difference in the performance of technical trading in the LIFFE or CSCE cocoa futures price may be explained by a combination of the demand/supply mechanism in the cocoa market and the Pound-Dollar exchange rate. In the period 1983:1-1987:12 the price level of the cocoa futures contracts and the level of the Pound-Dollar exchange rate were, accidently, strongly correlated. This spurious correlation reinforced upward and downward price trends of the LIFFE cocoa futures contracts in London, while weakening the trends in the CSCE cocoa futures in New York. For the LIFFE cocoa futures series the trends are strong enough to be picked up by a large class of technical trading rules; for the CSCE cocoa futures most trading rules do not pick up the trends, which are similar to the trends in the LIFFE cocoa futures but weaker. For the period 1993:1-1997:12 we find that the forecasting power of the technical trading strategies applied to the cocoa futures prices and the Pound-Dollar exchange rate is much less than in the preceding period 1983:1-1992:12. This is in line with many papers which found that forecasting power of trading strategies tends to disappear in the nineties.

Although the present paper only documents the economic and statistical performance of technical trading rules applied to a single commodity market, some general conclusions which may be useful for other financial series as well are suggested by our case-study. First, in order to asses the succes or failure of technical trading it is useful to test a large class of trading rules, as done in this paper. A necessary condition for reliable succes of technical trading seems to be that a large class of trading rules, not just a few, should work well. If only a few trading rules are succesfull this may simply be due to 'chance' or to data snooping. It should also be emphasized that even if a large class of trading rules has statistically significant forecasting power this is *not* a sufficient condition for economic significant trading profits after correcting for transaction costs. An example is the Pound-Dollar exchange rate, for which a large fraction of trading rules exhibits statistically significant forecasting power but these trading rules hardly generate economic net profitability.

Our case-study of the cocoa futures series and the Pound-Dollar exchange rate series suggest a connection between the succes or failure of technical trading rules and the trend and volatility of the corresponding series. When trends are weak and volatility is relatively high technical trading does not have much forecasting power and therefore also can not lead to economic profitability. Technical trading is unable to uncover these trends, because volatility is too high. When trends are weak but volatility is relatively low, technical trading rules can have statistically significant forecasting power without economically significant profitability. In that case, because volatility is low the weak trends can still be picked up by technical trading, but the changes in returns, although predictable, are too small to account for transaction costs. Finally, when trends are strong and volatility is relatively high a large set of technical trading rules may have statistically significant forecasting power leading to economically significant profit opportunities. In that case, even though volatility is high the trends are strong enough to be picked up by technical trading. Moreover, since volatility is high, the magnitude of the (predictable) changes in returns is large enough to cover the transaction costs. We emphasize that this connection between predictive and economic performance of technical trading is suggestive and only documented by the market studied here. Further research, of interest from a theoretical as well as a practical viewpoint, is needed to uncover whether the succes and failure of technical trading is explained by the relative magnitudes of trend and volatility.

Technical analysis may pick up sufficiently strong trends in asset prices, without knowing or understanding the economic forces behind these trends. It seems wise however that a technical analyst does not trust his charts only, but also tries to trace economic fundamentals which may cause or reinforce detected trends. For the LIFFE cocoa futures series the trends were caused by two forces, the supply-demand mechanism in the cocoa market and the exchange rate movements. If both the technical charts and fundamental indicators point in the same direction technical trading can be succesfull; otherwise failure seems a real possibility.

A Parameters of Technical Trading Strategies

In this appendix we give the values of the parameters of our technical trading strategies. Most parameter values are equal to those used by STW. Each basic trading strategy can be extended by a %-band filter (band), time delay filter (delay), fixed holding period (fhp) and a stop loss (sl). Out total set consists of 5353 different trading rules, including the strategies that are always short, neutral or long.

A.1 Moving Average Rules

n	=number of days over which the price must be averaged
band	=%-band filter
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period
sl	=%-rise (%-fall) from a subsequent low (high) to liquidate a short (long) position

n	=[1, 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250]
band	=[0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05]
delay	=[2, 3, 4, 5]
fhp	=[5, 10, 25, 50]
sl	=[0.02, 0.03, 0.04, 0.05, 0.075, 0.10]

With the 16 values of n we can construct $\binom{16}{2} = 120$ basic ma-strategies. We extend these strategies with %-band filters, time delay filters, fixed holding period and a stop loss. The values chosen above will give us in total:
$120 + 120 * 8 + 120 * 4 + 120 * 4 + 120 * 6 = 2760$ ma strategies.

A.2 Trading Range Break Rules

n	= length of the period to find local minima (support) and maxima (resistance)
band	=%-band filter
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period
sl	=%-rise (%-fall) from a subsequent low (high) to liquidate a short (long) position

n	=[5, 10, 15, 20, 25, 50 ,100, 150, 200, 250]
band	=[0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05]
delay	=[2, 3, 4, 5]
fhp	=[5, 10, 25, 50]
sl	=[0.02, 0.03, 0.04, 0.05, 0.075, 0.10]

With the parameters and values given above we construct the following trb-strategies:

basic trb-strategies:	10*1	=10
trb with %-band filter:	10*8	=80
trb with time delay filter:	10*4	=40
trb with fixed holding period:	10*4	=40
trb with stop loss:	10*6	=60
trb with %-band and time delay filter:	10*8*4	=320
trb with %-band and fixed holding:	10*8*4	=320
trb with %-band and stop loss:	10*8*6	=480
trb with time delay and fixed holding:	10*4*4	=160
trb with time delay and stop loss:	10*4*6	=240
trb with fixed holding and stop loss:	10*4*6	=240

This will give in total 1990 trb-strategies.

A.3 Filter Rules

filt	= %-rise (%-fall) from a subsequent low (high) to generate a buy (sell) signal
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period

filt	=[0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, 0.5]
delay	=[2, 3, 4, 5]
fhp	=[5, 10, 25, 50]

With the parameters and values given above we construct the following filter-rules:

basic Filter-rule:	24*1	=24
Filter-rule with time delay:	24*4	=96
Filter-rule with fixed holding:	24*4	=96
Filter-rule with time delay and fixed holding:	24*4*4	=384

This will give in total 600 Filter-strategies.

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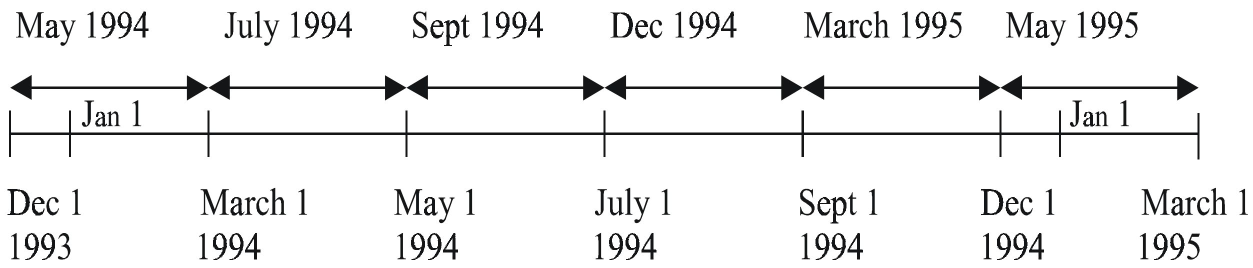

Figure 1: *Roll over scheme. The time axis shows the roll over dates from Dec. 1, 1993 until March 1, 1995. The arrows above the time axis show in which period which futures contract is used in constructing the continuous futures price series.*

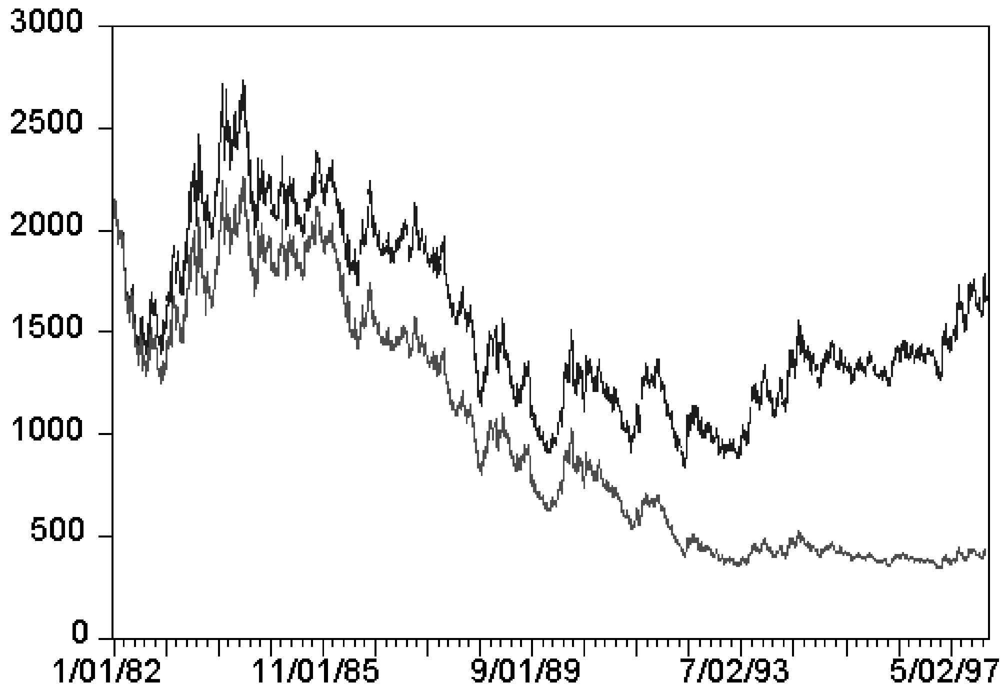

Figure 2: *Two continuous time series of CSCE cocoa futures prices in the period 82:1-97:6. The upper time series is constructed by pasting the futures* prices *at the roll over dates. The time premium of a futures contract leads to price jumps and spurious trends. In this paper we use the lower continuous time series, constructed by pasting the* returns *of the futures prices at the roll over dates and by choosing as starting value the futures price of the May contract at 1/3/1983. Any trends that are present in the lower series reflect real profitability of trading positions.*

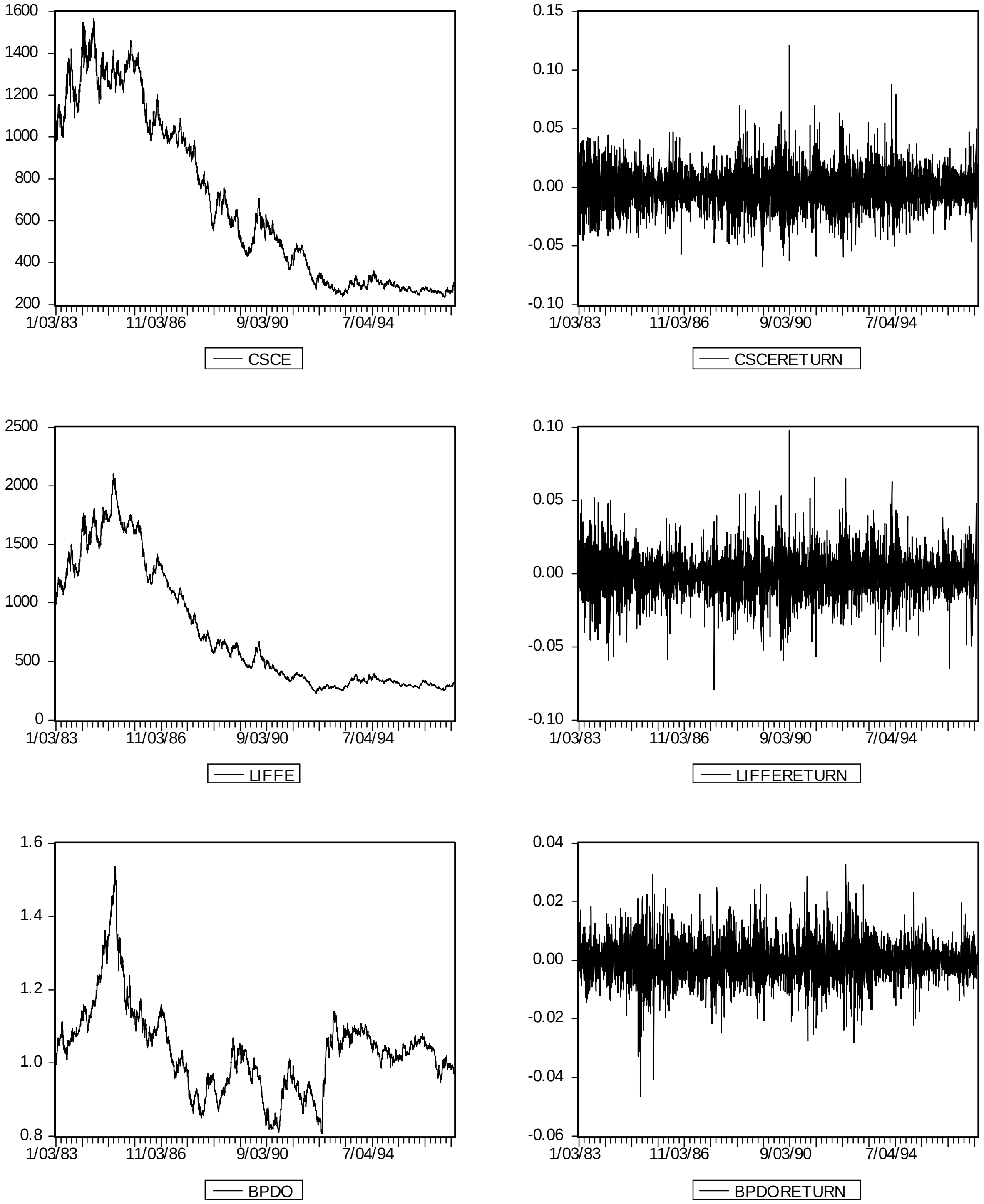

Figure 3: *Time series, over the period 1983:1-1997:6, of CSCE (top left) and LIFFE (middle left) cocoa futures prices, the Pound-Dollar exchange rate (bottom left) and corresponding returns series (right).*

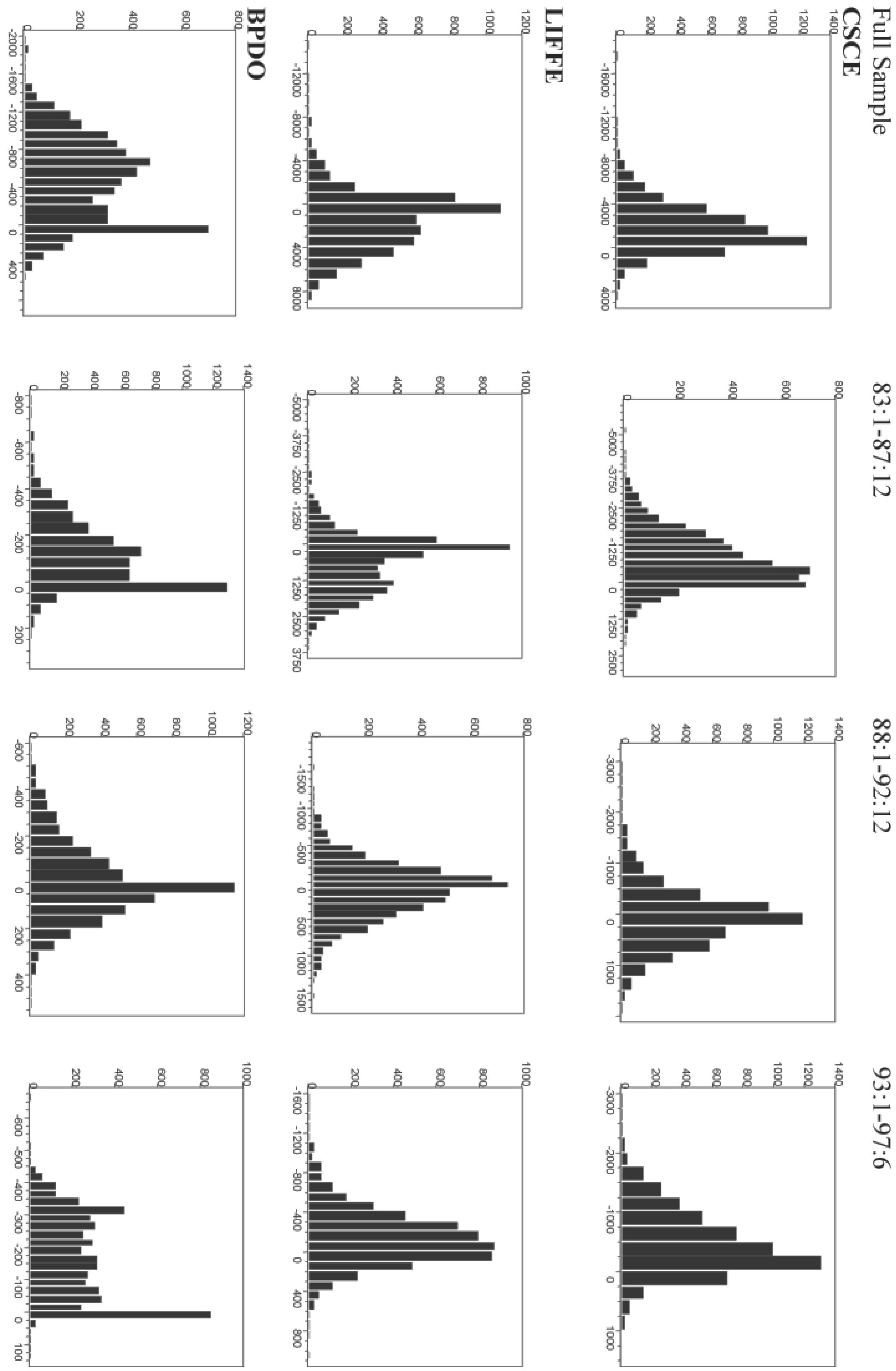

Figure 4: *Histograms of the net pay-offs of 5353 trading rules applied to the CSCE and LIFFE cocoa continuation series and the Pound-Dollar exchange rate, for the full sample 1983:1-1997:6 and the three subperiods 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.*

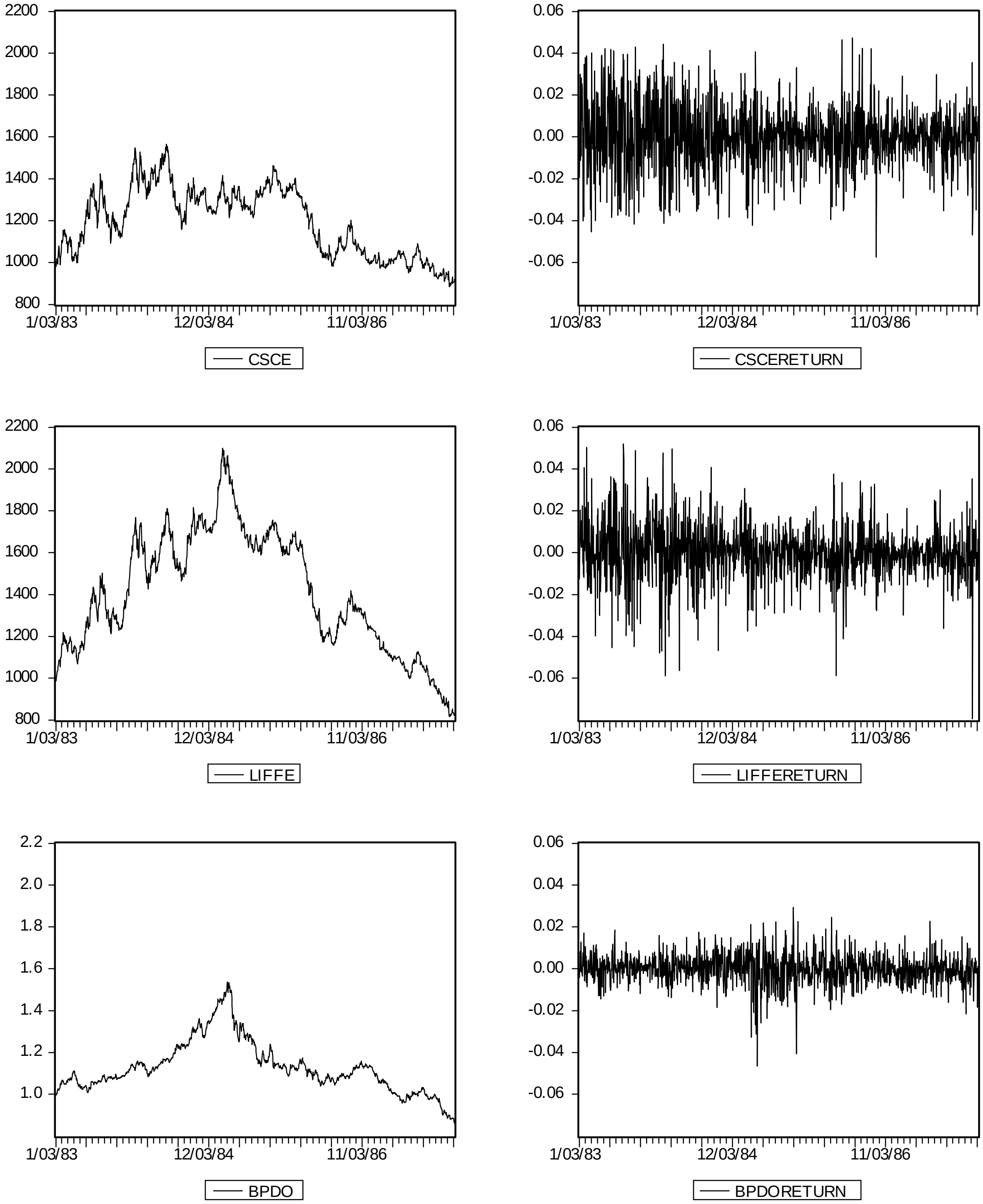

Figure 5: *Time series, over the period 1983:1-1987:12, of CSCE (top left) and LIFFE (middle left) cocoa futures prices on the same scale 800–2200, the Pound-Dollar exchange rate on scale 0.8–2.2 (bottom left) and corresponding returns series (right) all on the same scale -0.08–0.06.*

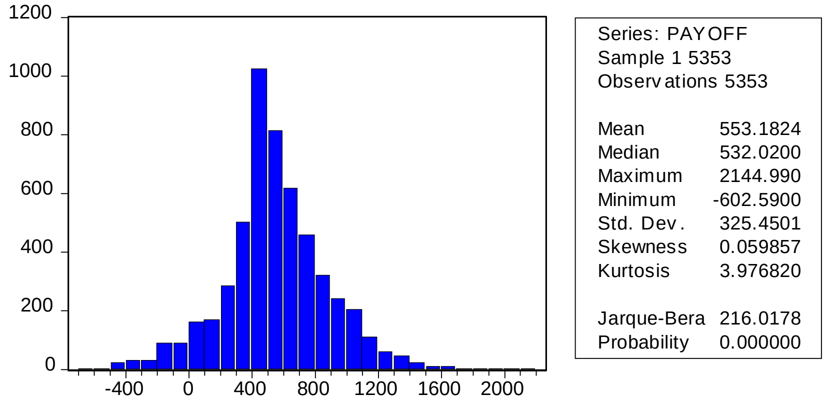

Figure 6: *Histogram of the hypothetical net profits of 5353 technical trading rules applied to the LIFFE cocoa futures series in the period 83:1–87:12, as if the LIFFE series were a Pound-Dollar exchange rate series.*

Table I: **Summary statistics for daily returns**

Results are presented for the full sample and for three subperiods. Returns are calculated as the log differences of the prices.

		Full Sample	83:1-87:12	88:1-92:12	93:1-97:6
CSCE	N	3655	1255	1263	1137
	Mean	-0.000322	-5.54E-05	-0.000944	7.47E-05
	Std. Dev.	0.016616	0.015786	0.018837	0.014768
	Skewness	0.243401	-0.050605	0.340136	0.479069
	Kurtosis	4.971974	3.395177	5.204299	5.503939
LIFFE	N	3674	1261	1265	1148
	Mean	-0.000308	-0.000154	-0.000860	0.000130
	Std. Dev.	0.014056	0.013537	0.015526	0.012851
	Skewness	0.081589	-0.248155	0.351550	0.038300
	Kurtosis	5.798391	5.852688	5.557818	5.723061
BPDO	N	3781	1304	1304	1171
	Mean	-7.54E-06	-0.000115	0.000165	-8.08E-05
	Std. Dev.	0.006566	0.007053	0.007174	0.005150
	Skewness	-0.021903	-0.449268	0.392087	-0.086694
	Kurtosis	6.137171	6.497238	4.842740	6.367524

Table II: **Autocorrelation functions of daily returns**

For every dataseries the estimated autocorrelations $\rho(i)$ are given up to order 10. a, b, c means that the corresponding autocorrelation is significant at a 1%, 5%, 10% significance level with Bartlett standard errors. ***, **, * means that the corresponding autocorrelation is significant at a 1%, 5%, 10% significance level with Hsieh (1988) heteroscedasticity consistent standard errors.

CSCE	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	$\rho(6)$	$\rho(7)$	$\rho(8)$	$\rho(9)$	$\rho(10)$	N
83:1-97:6	-0,0032	-0,0457a**	0,0007	-0,0003	0,0149	-0,0212	-0,0168	0,0107	-0,0045	0,0143	3655
83:1-87:12	0,0311	-0,0620b**	0,0037	-0,0069	-0,0130	-0,0048	-0,0289	-0,0429	0,0086	-0,0250	1255
88:1-92:12	-0,0130	-0,0440	0,0040	0,0140	0,0230	-0,0220	-0,0180	0,0330	-0,0150	0,0460	1263
93:1-97:6	-0,0300	-0,0330	-0,0140	-0,0220	0,0340	-0,0420	-0,0030	0,0360	-0,0030	0,0020	1137
LIFFE											
83:1-97:6	0,0341b*	-0,0359b*	0,0045	0,0349b	0,0131	-0,0261	-0,0098	0,0267	0,0044	0,0280c	3674
83:1-87:12	0,0030	-0,0180	0,0540c*	0,0020	0,0380	0,0090	-0,0200	0,0000	0,0140	-0,0110	1261
88:1-92:12	0,0610b**	-0,0370	-0,0120	0,0620b*	-0,0040	-0,0320	-0,0380	0,0470c	0,0150	0,0430	1265
93:1-97:6	0,0267	-0,0596b	-0,0320	0,0271	0,0096	-0,0602b*	0,0436	0,0260	-0,0237	0,0485	1148
BPDO											
83:1-97:6	0,0833a***	0,0241	-0,0158	0,0016	0,0343b	-0,0034	-0,0303c	0,0280c	0,0121	-0,0048	3781
83:1-87:12	0,1025a**	0,0201	-0,0099	-0,0313	0,0266	0,0286	-0,0081	0,0479c	-0,0221	-0,0570b	1304
88:1-92:12	0,1085a***	0,0165	-0,0192	0,0359	0,0958a**	-0,0135	-0,0598b*	0,0250	0,0357	0,0414	1304
93:1-97:6	-0,0132	0,0477	-0,0151	-0,0029	-0,0605b	-0,0411	-0,0220	-0,0074	0,0299	0,0158	1171

Table III: **Table of statistical significance under iid returns.**

The table shows for all groups of trading rules (ma, trb, filter, all) for the full sample and for each of the three subperiods (1, 2, and 3) the percentage for which a significantly positive (negative) mean return during buy (sell) days occurs. The table also shows the percentage of strategies for which the difference in mean return of the dataseries during buy and sell days is significant positive. Finally the percentage of strategies for which the dataseries has a significantly positive mean return during buy days as well as a significantly negative mean return during sell days is given. The table only summarizes the results of one sided tests with a 10% significance level.

CSCE

Mean Buy: % t-ratio's>t_{crit}(10%)					Mean Sell: % t-ratio's<-t_{crit}(10%)					Mean Buy-Sell: % t-ratio's>t_{crit}(10%)					Buy and Sell				
	Period					Period					Period					Period			
Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full
ma	1.25	0.07	0.52	0.15	ma	0.04	59.53	0.67	6.40	ma	9.6	1.17	0.78	1.10	ma	0.07	0	0	0.07
trb	1.62	1.15	0.52	1.25	trb	0.93	28.4	0.34	3.55	trb	1.5	1.81	0.87	0.55	trb	0	0.05	0	0
filter	2.09	0.67	3.97	1.05	filter	2.26	32.5	1.04	10.95	filter	4.35	7.17	2.59	6.10	filter	0	0	0.17	0.17
all	1.49	5.23	0.92	0.65	all	0.79	45.41	0.60	5.90	all	1.65	2.07	1.04	1.45	all	0.04	0.02	0.02	0.06

LIFFE

Mean Buy: % t-ratio's>t_{crit}(10%)					Mean Sell: % t-ratio's<-t_{crit}(10%)					Mean Buy-Sell: % t-ratio's>t_{crit}(10%)					Buy and Sell				
	Period					Period					Period					Period			
Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full
ma	24.46	0.66	2.20	4.25	ma	51.79	65.96	1.10	65.50	ma	53.63	7.91	2.64	31.50	ma	17.93	0.48	0.07	2.74
trb	26.61	0.56	8.04	6.95	trb	32.51	41.45	0.56	38.35	trb	43.14	5.36	4.13	21.30	trb	12.34	0.28	0.22	1.53
filter	20.36	2.67	5.19	13.40	filter	20.36	43.67	0.74	29.90	filter	31.61	18.50	3.52	21.90	filter	5.54	1.66	0.36	3.50
all	24.77	0.86	4.58	6.25	all	41.45	54.83	0.87	51.60	all	47.46	8.27	3.26	26.70	all	14.57	0.55	0.16	2.39

BPDO

Mean Buy: % t-ratio's>t_{crit}(10%)					Mean Sell: % t-ratio's<-t_{crit}(10%)					Mean Buy-Sell: % t-ratio's>t_{crit}(10%)					Buy and Sell				
	Period					Period					Period					Period			
Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full
ma	17.06	27.41	0.70	11.83	ma	58.72	10.23	0.74	19.89	ma	62.36	28.55	0.78	31.69	ma	12.40	5.55	0	8.89
trb	12.83	36.82	0.52	20.06	trb	34.50	7.47	4.36	18.40	trb	35.87	33.18	1.18	34.05	trb	6.69	4.02	0.28	7.85
filter	6.27	35.62	0.27	8.70	filter	34.70	5.33	5.95	13.22	filter	18.07	25.14	1.35	15.65	filter	5.94	2.09	0	0.87
all	14.70	31.40	0.61	14.19	all	48.68	8.78	2.33	19.04	all	49.72	29.68	0.96	31.42	all	9.95	4.67	0.09	7.59

Table IV: **Tables of significance after correction for dependence**

a. This table shows for all sets of trading rules applied to the LIFFE cocoa series in the period 83:1-87:12 the percentage of trading rules for which the estimated buy (sell) dummy in the regression function of the EGARCH model is significantly positive (negative) at a 10% significance level (second and third column). The fourth column shows the percentage of trading rules for which the dummy for buy days is significantly positive and the dummy of sell days is significantly negative.

LIFFE 83:1-87:12

Rule	Buy Dummy	Sell Dummy	Buy and Sell Dummy
ma	47.1	41.6	38.4
trb	44.8	25.7	20.8
filter	40.7	23.0	15.7
all	45.6	33.7	29.6

b. This table shows for all sets of trading rules applied to the Pound-Dollar exchange rate in the period 83:1-87:12 the percentage of trading rules for which the estimated buy (sell) dummy in the regression function of the GARCH in mean model is significantly positive (negative) at a 10% significance level (second and third column). The fourth column shows the percentage of trading rules for which the dummy for buy days is significantly positive and the dummy of sell days is significantly negative.

BPDO 83:1-87:12

Rule	Buy Dummy	Sell Dummy	Buy and Sell Dummy
ma	30.0	38.8	26.2
trb	16.3	24.4	10.7
filter	15.7	18.6	13.5
all	24.2	31.5	20.0

Table V: **Cross-correlations**

The tables show the cross-correlation between the LIFFE and CSCE continuation cocoa series, and the Pound-Dollar exchange rate for the periods 83:1-87:12, 88:1-92:12 and 93:1-97:6.

83:1-97:6

Corr	LIFFE	CSCE	BPDO
LIFFE	1.00		
CSCE	0.98	1.00	
BPDO	0.66	0.51	1.00

83:1-87:12

Corr	LIFFE	CSCE	BPDO
LIFFE	1.00		
CSCE	0.87	1.00	
BPDO	0.88	0.58	1.00

88:1-92:12

Corr	LIFFE	CSCE	BPDO
LIFFE	1.00		
CSCE	0.97	1.00	
BPDO	0.08	-0.13	1.00

93:1-97:6

Corr	LIFFE	CSCE	BPDO
LIFFE	1.00		
CSCE	0.93	1.00	
BPDO	0.26	0.16	1.00

Table VI: **Significance under iid returns, cocoa series in other currency**

The table shows for all periods (1, 2, 3, full) the percentage of strategies (ma, trb, filter, all) for which the LIFFE cocoa series expressed in Dollars and the CSCE cocoa series expressed in Pounds have a significant positive (negative) mean return during buy (sell) days. The table also shows the percentage of strategies for which the difference in mean return of the dataseries during buy and sell days is significant positive. Further is shown the percentage of strategies for which the dataseries has a significant positive mean return during buy days and a significant negative mean return during sell days. The table summarizes the results of one sided tests with a 10% significance level. This table should be compared with table III.

CSCE in Pounds

Mean Buy: % t-ratio's>t_{crit}(10%)					Mean Sell: % t-ratio's<-t_{crit}(10%)					Mean Buy-Sell: % t-ratio's>t_{crit}(10%)					Buy and Sell				
	Period					Period					Period					Period			
Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full
ma	5.82	0.62	0.37	0.62	ma	29.04	20.80	1.14	18.45	ma	27.90	3.00	0.77	2.85	ma	1.00	0.11	0.04	0.11
trb	6.99	0.50	0.44	0.53	trb	12.60	16.00	0.27	8.72	trb	13.80	2.51	0.27	1.63	trb	0.23	0.06	0	0.05
filter	12.32	1.00	3.23	5.67	filter	4.82	19.83	2.66	13.17	filter	12.50	6.00	5.89	6.17	filter	0.18	0	0.55	0.17
all	6.95	0.62	0.69	1.16	all	20.62	19.00	0.99	14.30	all	21.28	3.18	1.13	2.78	all	0.64	0.08	0.08	0.10

LIFFE in Dollars

Mean Buy: % t-ratio's>t_{crit}(10%)					Mean Sell: % t-ratio's<-t_{crit}(10%)					Mean Buy-Sell: % t-ratio's>t_{crit}(10%)					Buy and Sell				
	Period					Period					Period					Period			
Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full	Rule	1	2	3	Full
ma	1.36	0.47	2.82	0.84	ma	1.07	81.23	0.73	32.74	ma	1.76	14.86	2.27	5.47	ma	0.15	0.07	0.18	0.22
trb	1.83	3.31	5.25	1.36	trb	1.31	55.00	0.11	21.21	trb	2.45	13.82	2.17	3.32	trb	0	2.08	0	0.27
filter	1.80	4.67	8.47	4.83	filter	2.16	46.67	1.08	18.83	filter	3.24	23.17	6.13	9.83	filter	0.36	0.83	0.72	1.17
all	1.57	1.94	4.29	1.49	all	1.27	68.13	0.56	27.04	all	2.17	15.48	2.66	5.22	all	0.12	0.86	0.18	0.35