

The Profitability of Intra-Day FX Trading

Using

Technical Indicators

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Technical analysis indicators are widely used by traders to predict future price levels and hence enhance trading profitability. Traders often use high frequency price (i.e. intra-day) data when calculating such indicators, which are then used as the basis for trade entry rules. Similar rules, along with standard exit rules aimed at reducing downside risk, are then used to exit these trades. In this paper we test a wide range of well known technical indicators on a set of US Dollar/British Pound Spot FX tick data from 1989-97 aggregated to various intra-day frequencies. We find that few of the rules, whether based on the well known and tested moving average crossover or on some of the more esoteric and untested indicators, are consistently profitable when traded under realistic slippage conditions. Furthermore, we vary the slippage regime to represent differences in the efficiency of trade execution e.g. between a bank trader and a small ‘hedge’ fund but still find the rules to be loss-making. When the rules are reversed, losses are still found, indicating the losses not to be economically significant – a result that supports the efficient market hypothesis.

1 Introduction

1.1 The Use of Technical Analysis

Technical analysis (TA) is the conscious and deliberate study of market price history with a view to predicting future price change and hence enhance trading profitability¹. The origins of technical analysis lie in the writings of Charles Dow in the Wall Street Journal at the start of this century. Although Dow only considered stocks, technical analysis has been extended to many other markets, including foreign exchange. Similarly, the work of Dow has been extended into what is now a much more complex doctrine.

In their surveys, Taylor and Allen (1990, 1992) found that over 90% of surveyed London foreign exchange dealers and traders use technical analysis of some sort. Furthermore, a 1995 survey of foreign exchange dealers in Hong Kong by Lui and Mole (1998) found technical analysis to be significantly more popular than fundamental analysis at shorter time horizons.

Many traders use technical analysis in a decision support capacity, where signals resulting from TA are used to ‘confirm’ the trader’s inclination to enter a trade due to some other information. In fact, many banks employ technical analysts solely to provide information on technical trading signals to its dealers and traders. Furthermore, a lot of fundamental traders rely on TA when it comes to the exact point of trade entry and trade exit. Also, it is common for traders to switch between using technical analysis and other methods, depending on what they gauge to be the strongest signal. Finally, many traders use TA alone when considering trade entry and exit.

¹ This definition is sometimes too constricting since some technical analysts also study the historical volume and open interest of a market

1.2 Review of Previous Work

Technical analysis can be split into two main categories - the study of patterns and the study of indicators. In previous work (Dempster and Jones (1999a, 1999b)), we have analysed the profitability of technical trading patterns but in this work we will study the profitability of technical indicators. Technical indicators are functions of historic market price that are used to identify current price movements in the context of past market Behaviour and hence identify potentially profitable trading opportunities. Technical indicators are generally popular with constructors of trading systems as a result of the ease with which such indicators can be expressed algebraically and objectively. For the same reasons, the majority of academic work in the field of technical analysis covers only technical indicators. A litany of practitioner literature exists, in book form, on technical indicators including Schwager (1996, 1984), Pring (1985), Murphy (1991) and Colby and Meyers (1988). However, given the wide use and coverage of technical analysis by practitioners, the amount of academic attention paid to this area is relatively low.

Although technical analysis has been used widely amongst practitioner for many years, academic opinion, until recently, has been almost unanimous in that price-based technical trading rules that can be relied on to make money consistently do not exist. Early evidence to this end by Alexander (1961, 1964) considered trading the stock market using filter rules (buy if market rises by 5%, say, and sell if market falls by the same). This study found such strategies to be unprofitable after transaction costs. Similar evidence was provided by Fama and Blume (1966) who studied filter rules on a number of US stocks. Despite some contrary evidence by Cootner (1962), who found profitability in moving average rules, most of these early (1960s) studies found no evidence of the existence of profitable technical trading rules and Fama (1970) summarised by dismissing technical analysis as a futile undertaking. This, however, did not deter practitioners.

More recently, significant excess returns from the simulated trading of technical rules in the stock markets have been found by Brock et al (1992). They analysed a variety of simple indicator-based rules, rather than just a filter. Furthermore, they addressed the

question of whether such rules could produce excess returns when tested on popular market models such as a random walk, an autoregressive model and GARCH models. Bootstrapping simulations were performed and indicated that none of the models could explain their results.

Bassembinder and Chan (1998) found similar excess returns when testing the rules of Brock et al on Asian markets although Hudson et al (1996) found that the use of technical trading rules would not allow investors to make excess returns after transaction costs in UK stock markets.

Further advances in this field have been made by Sullivan et al (1997). They apply methods introduced by White (1997) that take account of the possibility of ‘data-snooping’ – the use of data more than once in model selection. However, the analysis of Brock et al is still found to hold under this scrutiny.

In the foreign exchange markets, several studies in a similar fashion to Brock et al have documented the existence of excess returns from trading rules based on technical indicators: Dooley and Schaffer (1984), Sweeney (1986), Levich and Thomas (1993). In more recent work Allen and Karjalainen (1999) and Neely, Weller and Dittmar (1997) have used genetic programmes to ‘discover’ technical trading rules in equity and FX markets, respectively, with only the latter reporting excess returns.

Finally, intra-day data has been used by Gencay et al (1998) and Dunis et al (1998) in very specific circumstances but, up to now, the use of intra-day data when analysing technical trading rules has not been practised in any wide ranging study.

1.3 Technical Analysis and Market Efficiency

Most academic study of technical analysis is driven by the question of market efficiency. If markets are efficient then competition amongst technical analysts would ensure that

past prices could not be used to predict future price changes so, as soon as a price pattern is discovered, it would disappear. However, in a sequel to his classic survey, Fama (1991) acknowledges Grossman and Stiglitz's (1980) critique of the traditional view of market efficiency which ignored the cost of information gathering and learning. In this view, a degree of profitability in technical trading is consistent with market efficiency since such profits allow the (unmeasured) cost of learning. However, this cost is not a function of invested capital, whereas trading profitability is, resulting in traders with large enough trade size being able to produce excess returns after 'learning cost' in *liquid* markets.

Intuitively, technical trading rules will be profitable if they successfully predict market movement and signal action accordingly, suggesting a link between profitability and the ability to forecast. There is some empirical evidence that financial return series are nonlinear (Guillaume et al (1995) for example) and Neftci (1991) has argued that technical analysis may be an informal attempt by traders to exploit such nonlinearity. However, LeBaron (1992) has addressed this issue and shown that it is possible to construct linear models that match autocorrelations in foreign exchange data and produce similar technical trading rule returns, implying that nonlinearity in return series is not a necessary condition for technical trading rule profitability.

Another argument is that trading rules may be profitable because such strategies involve bearing risk and excess return simply reflects a high level of risk rather than markets being inefficient, but this has been found not to be so by Brock et al (1992) (in the stock market) and by Neely Weller and Dittmar (1997) (in foreign exchange).

1.4 The Use of Intra-Day Data

The consideration of such data is particularly of use when analysing returns of technical trading rules; many traders apply such rules at intra-day frequencies² and of those traders

² As a whole, the operations of intra-day FX traders account for 75% of FX market volume (Bank of International Settlements (1998)

who only analyse daily data for entry signals, many will use intra-day data for trade exit, especially when stops are placed in the market. As a result, the use of intra-day data when analysing trading rules adds realism.

Previous work in this area consists of testing a small range of very simple rules on daily data under a fixed slippage³ regime. This lack of usage is due to unavailability and computational difficulty. Some previous work has considered intra-day data (Gencay et al (1999), Dunis et al (1998), for example, as discussed in Section 1.2) but considers only a specific rules. In this paper, we aim to test a much wider range of rules on daily data *and* intra-day data at frequencies ranging from minutely through to 8-hourly and consider the effects of slippage on profitability. We test rules based on indicators ranging from the much tested moving average to the more complex commodity channel index. Rules are tested at a wide range of parameter values and, when rules are loss-making, the strategy is reversed. The most profitable rules based on each indicator are tested out-of-sample. Finally, to eliminate survivor bias, the most (in-sample) profitable rules for each indicator are combined to form a portfolio which itself is tested out of sample.

2 The Data

This analysis was carried out on spot foreign exchange (FX) tick⁴ data for the British Pound/US Dollar exchange rate (BPUS, or ‘spot cable’ as it is sometimes called) ranging from 6.89-12.97 inclusive.

This data was supplied by CQG Data Factory and FutureSource, two well known data providers. The CQG data, ranging from 6.89-3.96 inclusive, was gathered from a number

³ Slippage is a concept that is often alluded to but rarely specified. In this work, we take slippage to be the penalty incurred when a trade is placed as a result of differences between actual execution price and quoted mid-price combined with transaction costs. As a result, we have one penalty that covers both potential sources of slippage.

⁴ Here, a new data point, or tick, is recorded with every change in price. As a result, there are often several ticks per minute.

of FX brokers whereas the FutureSource data, stored from a live satellite feed via the Omega TradeStation utility, is the amalgamated product of major bank FX quotes and makes up the remaining part of the dataset. The fact that the dataset consists of quotes from two different source providers is not ideal, but such problems are typical with the analysis of high frequency data based on non-exchange traded instruments, since the majority of live tick data providers do not retain historical data.

The convention for quoting BPUS is to quote a five digit figure that represents the value of one British pound in US dollars (most other currencies are quoted in a style opposite to this) with an implicit decimal point after the first digit; e.g. a BPUS rate quoted 16104 means £1 = \$1.6104.

The CQG data consists of *bid* and *ask* prices – the price that the quoter would buy and sell British pounds for, respectively, if approached in the market. The difference between the bid and the ask (*bid* – *ask*) is called the *spread*. The convention, when dealing with such data, is to convert it to *midpoint* data: $\frac{1}{2}(\text{bid} + \text{ask})$ or, by definition, $(\text{bid} + \frac{1}{2} \text{spread})$ or $(\text{ask} - \frac{1}{2} \text{spread})$. In the event that bid and ask quotes are uncoupled (which sometimes occurs), the bid or ask is converted to the midpoint by respectively adding or subtracting one half of the spread calculated from the last coupled bid/ask.

The above data tends to be well checked for errors by the vendor. All the same, the data has been screened for structural breakdown and irregular quotation by sweeping it with simple, proprietary software that checks for conformity to the conventional, fixed width, comma separated ASCII format, for well-ordered temporal structure and for irregularly high or low ticks (which are more than 500 pips⁵ from the last quote). The latter has been backed up by inspection of a graphical portrayal of the data.

The data has then been aggregated to various frequencies in the standard open-high-low-close format (OHLC). Consider the set of time stamped tick data $\{(q_i, t_i) \mid 0 < i \leq K ; i, K\}$

⁵ A *pip* is the minimum allowable change in price – in this case \$0.0001.

$\in \mathbb{Z}^+$ } where K is the number of ticks in the set, q_i is the price level of the i^{th} midpoint quote and t_i is the time at which the i^{th} tick occurred (converted to be measured in minutes elapsed since the start time – 2200 – and date and so $t_1 = 0$). The ticks are ordered temporally but more than one tick may occur within the same minute and so we have the weak inequality $t_i \leq t_{i+1}$. When such multiple ticks occur, they are listed in order of occurrence.

This set is converted to sets of data aggregated to various frequencies τ , denoted as τ_{\min} frequencies; e.g. if $\tau = 1$ then frequency is minutely and denoted 1min (but 1440min is called *daily*).

The aggregation to OHLC τ_{\min} frequencies results in the following dataset:

$$\{(o_j, h_j, l_j, c_j, b_j) \mid 0 < j \leq L ; j, L \in \mathbb{Z}^+\},$$

where

$$b_j = (b_{j-1} + n\tau) \quad n := \inf\{s \mid \exists i \in [1, K] \text{ s.t. } t_i \in [b_{j-1}, b_{j-1} + s\tau), s \in \mathbb{Z}^+\} \quad j > 0$$

$$b_0 := 0$$

$$o_j = q_{i_0} \quad \text{where } i_0 := \inf\{m \mid t_m \in [b_j - \tau, b_j)\}$$

$$c_j = q_{i_c} \quad \text{where } i_c := \sup\{m \mid t_m \in [b_j - \tau, b_j)\}$$

$$h_j = \max\{q_{i_0}, q_{i_0+1}, \dots, q_{i_c}\}$$

$$l_j = \min\{q_{i_0}, q_{i_0+1}, \dots, q_{i_c}\}$$

The index j is known as the bar number and, by convention, b_j is converted from *minutes elapsed* to *time and date* format when quoted. The above, somewhat esoteric, definitions are required since the data is sometimes sparse out of peak trading times.

3 The Indicators

Below, we consider trading rules based on a number of the most popular and well known technical market indicators and exit strategies and apply them to BPUS data at the daily, 480min, 240min, 60min and 1min frequencies ranging from 1989-95 – the *sample data*.

As discussed in Section 1, previous work has tested technical trading rules in FX markets but no published work has considered some of the more complex indicators that we consider in this work. Also, we consider the realistic conditions resulting from the use of intra-day data – not before considered in the literature in the context of technical trading rules in FX markets.

We consider each rule as it stands (Strategy A) and with three different *exit strategies* (sometimes known as *cash management strategies*):

- Strategy B: exit after trading profit before slippage =100 pips
- Strategy C: 100 pip trailing stop⁶
- Strategy D: exit after trading profit before slippage =100 pips or if 100 pip trailing stop is hit.

Furthermore, when rules behave particularly badly, we consider a reversed strategy. Here, instead of taking a long position when the rule tells us we take a short position and vice versa. These strategies are suffixed ‘r’.

The best set of rules was deemed to be that which yielded the highest average slippage-adjusted profit, measured in pips per traded British Pound. For example, if I sold British Pounds at \$1.6150 and bought at \$1.6100 then my pips profit per pound traded before slippage and transaction costs would be $\$(1.6150 - 1.6100) = \$0.0050 = 50$ pips.

⁶ A *stop* is a predetermined price level at which the trader will exit the trade. A stop that is placed in such a way that a trade is exited after the price moves a set amount from the maximum price attained during the trade (and vice versa for short trades) is known as a *trailing stop* (see Schwager (1996) and James & Thomas (1998)).

As with previous work (see Dempster and Jones (1999a, 1999b)), we use the following slippage model.

A flat 10 pips per round turn are allowed for transaction costs and to compensate for discrepancies between data and actual price. In addition, the following slippage per trade (not round turn) is deducted:

trade time between 0801 and 1700 (London Market)	- 2.5 pips
trade time between 1701 and 2200 (New York Market)	- 4 pips
trade time between 2201 and 0800 (Asian Market)	- 5 pips.

The flat 10 pip addition to the variable slippage may be an overcompensation but, as we see later, as we are mainly interested in potential large profits and losses, this does not hinder the interpretation of results.

We analyse the sensitivity of ‘trading profits’ with respect to slippage by varying the *fixed* part of the slippage penalty between 0 and 10 pips per completed trade (buy and sell or sell and buy). We can, therefore, find rules that may be profitable when traded in a low slippage environment but not under a full slippage regime e.g. from a bank trading desk as opposed to through a broker. We denote the complete slippage model (containing both 10 pip fixed and variable parts) as the *full slippage regime* and the partial slippage model (just variable parts) as the *relaxed slippage regime*. As described above, profits are measured in accumulated pips and are adjusted for slippage.

We then identify the most profitable rules that are stable to parameter shifts (i.e. we are not looking for ‘spikes’ in profit that may well occur by chance, but rules that trade well over a wide range of conditions) and apply them to the test data (1996-97) and recorded the results under full and relaxed slippage regimes.

Finally, we compare the returns of all rules that are profitable when applied to the test data.

Results tables and graphs are presented after Section 4.

3.1 Moving Average Crossover

Moving averages (MAs) are used by technical traders to detect market trends. A simple moving average is calculated from an historical price series at any point in time by taking the arithmetic average of the last n *close* points (we refer to n as the range of the average). Variations on this theme can include weighting the constituents of the average (including exponential weighting) and using the high, low or open points on each bar instead of using close points.

3.1.1 Formal Definitions

3.1.1.1 Simple Moving Average (SMA)

The arithmetic average of the last n bars (starting from the current bar). Formally, we define the n bar simple moving average at bar m ($m \geq n$, $n > 0$), $\text{SMA}(m,n)$, as follows:

$$\text{SMA}(m,n) := \frac{1}{n} \sum_{i=0}^{n-1} c_{m-i},$$

where c_i is the closing price at bar i . Note, that $\text{SMA}(m,1) = c_m$.

3.1.1.2 Weighted Moving Average (WMA)

The weighted sum of the last n bars (starting from the current bar). Formally, we define the weighted n bar moving average at bar m ($m \geq n$, $n > 0$), $\text{WMA}(m,n)$, as follows:

$$\text{WMA}(m,n) := \sum_{i=0}^{n-1} w_i c_{m-i},$$

where c_i is the closing price at bar i and w_i is the weighting factor of the bar i bars before c_m ; $0 \leq w_i < 1 \quad \forall i$ and $\sum_{i=0}^{n-1} w_i = 1$.

The *linear weighted moving average* (LWMA) is the WMA(m,m) with $w_i = \frac{i}{\sum_{j=0}^m j}$. Note

that the LWMA can be thought of as an exponential moving average (see below) with a smoothing parameter that decreases asymptotically with each step.

3.1.1.3 Exponential Moving Average (EMA)

The exponential moving average is a weighted moving average in which weighting factors decrease asymptotically with the number of bars before. As a result, the EMA reflects the entire data series. Formally, we define the exponential moving average at bar m, EMA(m) as follows:

$$\text{EMA}(m) := \sum_{i=0}^m \alpha(1-\alpha)^i c_{m-i},$$

where c_i is the closing price at bar i and $0 \leq \alpha < 1$. Note also that

$$\sum_{i=1}^n \alpha(1-\alpha)^i \rightarrow 1 \text{ as } n \rightarrow \infty.$$

Given the above definition, we see that $\text{EMA}(m+1) = \alpha c_m + (1-\alpha)\text{EMA}(m)$ and it is this definition that is normally used for calculation. Note that the EMA value at any bar is dependent on all preceding bars in the data.

3.1.2 Trading Using Moving Averages

There are various methods of using moving averages as trade entry and exit rules. The two main methods are *price/average crossover* and *average/average crossover*.

3.1.2.1 Price/Average Crossover

Here, a *long* trade is usually entered when the market is in an upward move and the price level at close crosses the level of the moving average at that bar (an *upward crossing*). The trade is then exited when the price recrosses the moving average (a *downward crossing*) or when various cash management (stop being hit, profit objective is reached, etc.) signals are received. Similarly, a *short* trade can be entered when downward crossings occur and trade exit then occurs after an upward crossing.

3.1.2.2 Average/Average Crossover

Often, raw price is ignored and a short term (n small) moving average is used instead and compared to another, longer term moving average (with larger n or EMA used); in certain cases, this method is called *moving average convergence/divergence* (MACD). Average/average crossover is by far the more common strategy of the two and it is this strategy that we test below.

In both price/average and average/average crossover techniques, omission of exogenous exit strategies results in an *always in the market* strategy (provided both long and short trades are possible).

3.1.3 Further Comments on the Moving Average Trading Rules

The moving average trading rules aim to identify the emergence of new trends in the market. The choice of range (n) for the short term and long term moving averages is a moot point. Essentially, smaller n results in a quicker response to market moves but also to noise. Larger n results in a longer term moving average which filters out the noise but can be slow to respond to changes in market direction.

3.1.4 Empirical Results

We have tested the slippage adjusted profitability of various price/average and average/average trading rules to daily, 480min, 240min, 60min and 1min data over the sample data set (mid 1989-95 inclusive). Using a number of simple, exponential and linearly weighted moving averages evaluated at various parameters, we have considered the *always in the market* trading strategy discussed above on its own and along with various overlaid cash management strategies.

In Figure 3.1.1 and Appendix Figures A.1 – A.15 we present the slippage adjusted ‘trading profits’ resulting from the application of the crossover strategies to the sample data at the above mentioned frequencies. We consider short term simple moving averages with n ranging from 2 to 40 bars crossing longer term simple moving averages

with n ranging from 50 to 700 bars, exponential moving averages with α ranging from 0.2 to 0.8 and a linearly weighted moving average. Furthermore, we test the strategies without a cash management overlay (Strategy A), with an overlaid profit objective of “exit after profit before slippage exceeds 100 pips” (Strategy B), with a 100 pip trailing stop (Strategy C) and with both a profit objective and a trailing stop (Strategy D). Reversed strategies are suffixed ‘r’.

In Figure 3.1.1, above, we plot the slippage adjusted profits for Strategy A at various parameters at the daily frequency. Amongst the results, we find that there are few profitable strategies at any frequency. Furthermore, profitable strategies are mainly ‘spikes’ at a particular set of parameter co-ordinates and so are unstable to with respect to variation in parameter. This would imply that profits are fortuitous rather than representative of any market phenomena.

In Appendix Figures A.5 – A.9, A.11, A.13 and A.15 we present examples of the slippage adjusted ‘trading profits’ resulting from reversing the previously considered strategies. Once more, we find few profitable rules that are stable with respect to variation in parameter value.

Finally, we allow the fixed part of the slippage penalty to vary from the original 10 pips to zero. We do this to analyse the profitability of the strategies at higher frequencies that trade more and so are more sensitive to slippage. Here, we find no alternative profitable rules.

Despite most strategies being unprofitable (or if profitable then unstable with respect to variation in parameter) there are some ‘pockets’ of profitable strategies that are profitable for a relatively wide range of parameter values. In each case, we have chosen the most profitable value that exhibits stability to change in parameter values and tested it on *out of sample data* (the test data – 1996-97 inc.) and present the results in Figures 3.1.2 – 3.1.6. using the following nomenclature:

strategy/data frequency/short term MA parameter/long term MA parameter.

As well as considering profitability under full slippage (as above – time dependent slippage + 10 pips fixed), we consider a *relaxed* slippage regime consisting of the time dependent portion with no fixed part; in the following figures, relaxed slippage is denoted by the dotted line.

We note that none of the profitable strategies continued to remain so in the out of sample test period. Even when slippage was relaxed only one strategy, Strategy A/480min/MA(12)/MA(200), makes a small profit. Furthermore, we observe that post mid 1993, the strategies chosen began to lose money.

3.1.5 Conclusions About Trading Using Moving Average

As a whole, moving average strategies are not profitable in this market. Furthermore, reversing strategies does not improve profitability. This would imply that the slippage cost of implementing these strategies outweighs the potential gain - a result that supports the weak form of the efficient markets hypothesis.

Profitable strategies occur as spikes in otherwise loss-making regions and so are unstable to shifts in parameter values. This would imply that profits are fortuitous rather than representative of any market phenomena.

It is also of note that reduction of the slippage penalty does not result in the strategies that trade at higher frequencies (and so are more sensitive to slippage) becoming profitable. We can, therefore, deduce that trading in a low slippage environment - from a bank trading desk as opposed to through a broker, for example - will not result in profitable trading at higher frequencies.

Finally, we note that out of the strategies that were analysed in depth (in Figures 3.1.2-6), none of them were profitable post 1993, which ties in with anecdotal evidence from many technical traders who have noted the demise of markets moving in ‘easy trends’.

3.2 Adaptive Moving Averages

The adaptive moving average, as defined in Kauffman (1998) is an exponential moving average in which the smoothing parameter (α) is allowed to vary in inverse proportion to recent market volatility. As with ordinary moving averages, AMAs are used by technical traders to indicate the formation of trends. The AMA has evolved out of the need for an indicator that ‘widens its focus’ to the longer term when markets are noisy and hence does not give trending signals based on noise alone.

3.2.1 Formal Definition

We define the adaptive moving average (AMA) as follows:

$$\text{AMA}(k, m) := \alpha_{k,m} c_m + (1 - \alpha_{k,m}) \text{AMA}(k, m - 1),$$

$$\text{where } \alpha_{k,m} = \frac{|c_m - c_{m-k-1}|}{\sum_{i=m-k}^m |c_i - c_{i-1}|}.$$

Note that volatility is measured as the ratio of the sum of the absolute changes in price between bars (sum of absolute 1 bar momenta) over $k+1$ bars to the absolute change in price over $k+1$ bars (absolute $k+1$ bar momentum). This ratio is proportional to volatility and ranges between 1 (attained only if the market moves in a ‘straight line’ and trending) and 0. α is then taken to be the inverse of this ratio.

3.2.2 Trading Using the AMA

When trading using moving average crossovers, shorter term indicators are compared with longer term indicators with a hope of discovering the emergence of new trends. When trading using the AMA, we only consider the one indicator since, depending on markets conditions, the AMA can exhibit characteristics of shorter term or longer term moving averages. Instead, the AMA is usually traded based on its current position relative to its recent history. First local highs (lh) and lows (ll) are defined as follows:

$$\begin{aligned}
 lh_i &= \text{AMA}(k,i) && \text{if } \text{AMA}(k,i) > \text{AMA}(k,i-1) \\
 lh_i &= lh_{i-1} && \text{otherwise;} \\
 ll_i &= \text{AMA}(k,i) && \text{if } \text{AMA}(k,i) < \text{AMA}(k,i-1) \\
 ll_i &= ll_{i-1} && \text{otherwise.}
 \end{aligned}$$

Then, a short trade is placed if the value of the AMA moves a fixed amount (F , say) below the value of the local high and a long trade is placed if the value of the AMA moves a fixed amount F above the value of the local high. In the analysis below, we consider F to be a fixed 20 pips (as is usual). However, F is not always fixed in practice, but is often based on the standard deviation of close price over the last few bars (see Kauffman (1998)).

3.2.3 Further Comments on the AMA

As we have seen above, the smoothing parameter in the AMA varies with inverse proportion to market volatility. As a result, in volatile markets, less emphasis is placed on current price and vice versa for markets where trend is more apparent. By allowing such variability, the indicator has potential to be responsive to changes in trends whilst not being overly responsive to noise.

3.2.4 Empirical Results

We have tested the slippage adjusted profitability resulting from simulated trading using the AMA trading rules outlined above on daily, 480min, 240min, 60min and 1min data over the sample data set (mid 1989-95 inclusive). We have used a selection of parameter values for k (10, 25, 50, 100 and 500) based on the usage in the practitioner literature and, as with the moving average crossovers, we have considered the *always in the market* trading strategy discussed above on its own and with various overlaid cash management strategies. Again, we have considered a reversed strategy (short instead of long and vice versa) when rules have behaved particularly badly and analysed the sensitivity of ‘trading profits’ with respect to slippage by varying the *fixed* part of the slippage penalty between 0 and 10 pips per round turn.

In Tables 3.2.1 - 3.2.4 we present the slippage adjusted ‘trading profits’ resulting from the application of the AMA strategies to the sample data at the above mentioned frequencies. As previously, we test the strategies without a cash management overlay (Strategy A), with an overlaid profit objective of “exit after profit before slippage exceeds 100 pips” (Strategy B), with a 100 pip trailing stop (Strategy C) and with both a profit objective and a trailing stop (Strategy D); as before we also consider reversed strategies, which are suffixed ‘r’.

We see from the results that when the trading rule is rarely profitable when used as intended. Furthermore, the reversed rule appears to be generally loss-making for most exit strategies and parameter values. Although profits seem to be spurious, we test the best performing strategy and, as can be seen from Figure 3.2.5, the rule makes a loss when tested out of sample.

As in Section xxx, we then allow the *fixed* part of the slippage penalty to vary from the original 10 pips to zero. As can be seen from Tables 3.2.1 - 3.2.4, this makes little difference to profitability in general although there is some improved profitability at the 1min frequency as one would expect.

3.2.5 Conclusions Regarding Trading Using The Adaptive Moving Average

As a whole, adaptive moving average strategies are not profitable in this market. Reversing the rule does improve profitability but this does not hold under test conditions. Reducing the slippage penalty only marginally improves upon these results.

3.3 Price Channel Breakout

The *price channel breakout* (PCB), or *range breakout* as it is sometimes known, is defined in Colby and Meyers (1988) and is one of the simplest trading rules. A long

trade is placed when the market closes above a previous high and a short trade is placed when the market closes below a previous low.

3.3.1 Formal Definition

The n period trading range at bar m ($m > n$) is defined by the following upper ($U(m,n)$) and lower ($L(m,n)$) bounds as follows:

$$U(m,n) := \max(c_{m-1}, c_{m-2}, \dots, c_{m-n})$$

$$L(m,n) := \min(c_{m-1}, c_{m-2}, \dots, c_{m-n}),$$

where c_i is the close price of bar i .

3.3.2 Trading Using PCB

The trading rule for the PCB is very simple: buy long when $c_m > U(m,n)$, sell short when $c_m < L(m,n)$. Thus, in the absence of cash management exit strategies, the trading rule ensures that a market position is always held ('always in the market').

3.3.3 Further Comments on the PCB

The only parameter that can be varied is n which represents the size of the period over which we calculate the high and low. Thus, the larger n is the more monumental the breakout should be since the market would have been trading in this high-low range for a longer time. Thus the breakout rule aims to identify the start of new trends after periods of market stagnation.

3.3.4 Empirical Results

We have tested the slippage adjusted profitability resulting from simulated trading using the PCB trading rules outlined above on daily, 480min, 240min, 60min and 1min data over the sample data set (mid 1989-95 inclusive). We have used a wide selection of parameter values for n (5, 10, 25, 50, 250 and 500) and, as with previous rules, we have considered the *always in the market* trading strategy discussed above on its own and with

various overlaid cash management strategies. As previously, we have considered the reversed strategies and analysed sensitivity to slippage.

In Tables 3.3.1 – 3.3.5 we present the slippage adjusted ‘trading profits’ resulting from the application of the range breakout strategies to the sample data. As before, we have tested the rules with Strategies A-D and also considered reversed strategies, which are suffixed ‘r’.

The rules prove to be occasionally profitable with both reversed and ordinary strategies throughout the range of frequencies with the exception of the 1min frequency. Allowing the slippage penalty to be relaxed as before, we find profitable strategies in the reversed rule at the 1min frequency.

In Figure 3.3.5 and 3.3.6 we see the results of applying the most profitable strategies in the full and relaxed slippage cases – Strategies A at 240min and Cr at 1 min, respectively – to the test data.

3.3.5 Conclusions Regarding Trading Using The PCB

Although profitable rules based on the price channel breakout are few, it can be seen from Figures 3.3.5 and 3.3.6 that both strategies tested out of sample are profitable although one of them only when slippage is relaxed. Note also that for the best performing PCB strategy (under full slippage), as with the best performing strategy for the other indicators tested earlier, the best results can be found when there is no cash management overlay (Strategy A).

3.4 The Stochastic

The *stochastic*, as defined in Colby and Meyers (1988) and Schwager (1996), is another indicator which aims to identify the emergence of trends. It is based on the principle that, as market price rises, the market closes near the market high for the past few periods. Similarly, as the market prices decrease, closing prices are thought to be near to the local

market low. In this instance the term ‘stochastic’ is a misnomer and has few links with the mathematical term of the same name.

3.4.1 Formal Definition

The n period *stochastic*, $K(m,n)$ at bar m ($m \geq n$) is defined by the as follows:

$$K(m, n) := \frac{c_m - \text{Low}(m, n)}{\text{High}(m, n) - \text{Low}(m, n)},$$

where $\text{High}(m, n) = \max(c_{m-1}, c_{m-2}, \dots, c_{m-n})$ and $\text{Low}(m, n) = \min(c_{m-1}, c_{m-2}, \dots, c_{m-n})$, where c_i is the close price of bar i .

In the analysis of stochastics we work with the 3 period moving average of $K(m,n)$, usually referred to as $SK(m,n)$ and the 3 period moving average of SK , referred to as $SD(m,n)$. Formally

$$SK(m, n) := \sum_{j=0}^2 K(m - j, n)$$

and

$$SD(m, n) := \sum_{j=0}^2 SK(m - j, n).$$

3.4.2 Trading Using Stochastics

There are many rules for trading using stochastics, some of which are highly subjective and cannot be easily automated. We have chosen to test a commonly used rule that is neither complex nor subjective. Here we *buy long* when $SK(m,n) > SD(m,n)$ and sell short when $SK(m,n) < SD(m,n)$. Once more, in the absence of cash management exit strategies, this is an ‘always in the market’ strategy.

3.4.3 Further Comment on the Stochastic

As mentioned above, the stochastic is based on the principal that the market closes near the local high in emerging up-trends and near the local low in down-trends. However,

the stochastic, as it stands, tends to jump around erratically as old data moves out of range. This is undesirable as it can lead to false signals and so the stochastic is smoothed twice by taking successive moving averages.

3.4.4 Empirical Results

We have tested the trading rule discussed in Section 3.4.2 with a selection of exit strategies and reversed rules at a number of frequencies data over the sample data set as with previous indicators.

From Table 3.4.1 we see that the stochastic trading rule is uniformly unprofitable at all tested frequencies when traded without exit strategies and using a reversed rule yields similar results. The introduction the usual exit strategies fail to improve on these results.

Similarly, from Table 3.4.1 it can be seen that even with the introduction of the relaxed slippage regime the indicator fails to be profitable.

3.4.5 Conclusions Regarding Trading Using The Stochastic

The stochastic has proven to be unprofitable when applied to the sample data at a range of different frequencies. Furthermore, the reversal of the trading rule and the relaxation of the slippage regime failed to make any significant improvements to these results.

3.5 The Relative Strength Index

The *relative strength index* (RSI), as defined in Colby and Meyers (1988) and Schwager (1996), is an indicator that aims to reflect the ratio of market price increases to decreases. Unlike the indicators previously studied, however, it is used in a contrarian manner in as much as when recent gains heavily outweigh recent losses, a short trade is placed and vice versa. In other words, the market is expected to behave in a mean reverting manner (whereas trend following indicators bank on persistent behaviour

3.5.1 Formal Definition

The n period RSI, $RSI(m,n)$ at bar m ($m > n+1$) is defined by the as follows:

$$RSI(m, n) := \frac{RS(m, n)}{1 + RS(m, n)},$$

where

$$RS(m, n) := \frac{EG(m, n)}{EL(m, n)},$$

in which $EG(m,n)$ and $EL(m,n)$ are weighted averages of gains and losses respectively so that

$$EG(m, n) := \frac{\max(c_m - c_{m-1}, 0) + (n-1)EG(m-1, n)}{n}$$

and

$$EL(m, n) := \frac{\max(c_{m-1} - c_m, 0) + (n-1)EL(m-1, n)}{n},$$

with

$$EG(n+1, n) := \frac{1}{n} \sum_{i=2}^{n+1} \max(c_i - c_{i-1}, 0) \quad \text{and} \quad EL(n+1, n) := \frac{1}{n} \sum_{i=2}^{n+1} \max(c_{i-1} - c_i, 0)$$

where c_i is the close price of bar i .

3.5.2 Trading Using The RSI

As mentioned above, the RSI is used in a contrarian fashion with the aim of identifying markets that are ‘overbought’ and ‘oversold’. When trading using the RSI, it is usual for the market to be considered overbought when the RSI is above 70 and a short position taken. Similarly, the market is thought to be oversold when below 30 and a long position taken.

3.5.3 Further Comments on the RSI

The RSI takes values between 0 (when the market has moved exclusively downwards over the past n periods) and 100 (when the market has moved exclusively upwards). The trading thresholds of 70 and 30 are seemingly arbitrary and so the threshold of 50 has also been tested below. The increases and decreases in market moves are smoothed in the indicator making it less volatile as a result of data falling out of the lookback window. Due to the nature of the indicator, its value becomes very stable for large n and so there are few trade signals.

3.5.4 Empirical Results

We have tested the trading rule discussed in Section 3.5.2 with a selection of exit strategies and reversed rules at a number of frequencies over the sample data set (mid 1989-95 inclusive) as with previous indicators. We have considered values of n between 5 and 50 and trading thresholds of 70/30 (as commonly used in the practitioner literature). Unlike other indicators, we have not considered values of n above 50 since, for $n > 50$, this indicator is very stable and offers few trading signals.

In Tables 3.5.1- 3.5.4 we present the results of applying to the sample data the RSI with a 70/30 threshold and Strategies A to D exit overlays, respectively. It can be seen that Strategy Br (15) yielded the best trading profits and profitability is stable to shifts in parameter value.

Figure 3.5.5 shows the results of applying the RSI 70/30 with $n = 15$ at the 480min frequency with Strategy Br exit overlay (the best performing rule) to the test data. It can be seen that the rule is unprofitable when tested on unseen data.

3.5.5 Conclusions Regarding Trading Using The RSI

The RSI is generally unprofitable, especially at high frequencies. At lower frequencies, some rules are profitable in sample but only when reversed. The best of these rules, when tested makes a loss out of sample, even when slippage is relaxed.

3.6 The Commodity Channel Index

The *commodity channel index* (CCI), as defined in Colby and Meyers (1988) and Schwager (1996), is another momentum based trend following index. However, it is scaled by a measurement of the dispersion of price level and makes use of information contained in the period high and low prices as well as closing price.

3.6.1 Formal Definition

The n period CCI, $CCI(m,n)$ at bar m ($m \geq n$) is defined by the as follows:

$$CCI(m, n) := \frac{M(m, n) - \bar{M}(m, n)}{0.015\bar{D}(m, n)},$$

where

$$M(m, n) := \frac{1}{3}(h_m + l_m + c_m), \quad \bar{M}(m, n) := \frac{1}{n} \sum_{i=0}^{n-1} M(m - i, n)$$

and

$$\bar{D}(m, n) := \sqrt{\sum_{i=0}^n |M(m - i, n) - \bar{M}(m, n)|^2},$$

where h_i , l_i , and c_i , are the bar high, low and close respectively.

3.6.2 Trading Using The CCI

The most common trading strategy is to buy when the CCI rises above +1 and sell the long position when the CCI falls back below +1. Similarly, a short position is entered when the CCI falls below -1 and that position is closed when the CCI rises once more above +1.

3.6.3 Further Comments on the CCI

The CCI is a momentum indicator that is said to reflect non-random fluctuations in the market (i.e. emerging trends) when outside the ± 1 envelope. Like the adaptive moving average, the CCI uses a momentum measurement scaled using a dispersion measurement. However, the CCI considers deviation from the n period mean rather than just a

convoluted moving average measurement and so can be traded using more obvious rules. Furthermore, rather than close points, the mean of the market high, low and close is considered and hence is less prone to yielding an exaggerated value based on an erratic close point. The downside of this, however, is that the indicator will be slower to catch market moves and especially so at lower frequencies.

3.6.4 Empirical Results

We have tested the trading rule discussed in Section 3.6.2 with a selection of exit strategies and reversed rules at a number of frequencies over the sample data set (mid 1989-95 inclusive) as with previous indicators. We have considered values of n between 5 and 500 as with previous indicators. Furthermore, we try two thresholds for buying/selling: +1/-1 as discussed above and 0 (i.e. buy long when CCI crosses above 0, sell short when it crosses below).

In Figures 3.6.1a-e we present the results of applying the CCI with a 0 threshold (Strategies A-D numbered 1-4 respectively) and with a +1/-1 threshold (Strategies A-D numbered 5-8 respectively) to the sample data. We see that for many values of n , the indicator is consistently profitable at all but the higher frequencies when used with the +1/-1 threshold. At all profitable frequencies, an optimal value of n occurs around 25 and then profits tend to deteriorate as n is further increased. Under the full slippage regime it can be seen that the most profitable strategy is Strategy B with a +1/-1 threshold at 480min frequency and $n = 25$. It is also worthy of note that this strategy is particularly profitable at daily and 240min frequencies and is stable to changes in parameter.

When we allow slippage to be relaxed this strategy remains the best but the most profitable level to trade at switches to the 240min frequency.

Reversed strategies were also tested but, as one would expect from the above results, proved to be loss-making.

In Figure 3.6.2 we present the results of applying the best performing strategy (outlined above) on the test data set (1996-97). As can be seen, the strategy continued to be profitable when applied to this unseen data.

3.6.5 Conclusions Regarding Trading Using The CCI

The CCI is the second of the indicators that we have tested that remains profitable under test conditions with full slippage (the other being the PCB). Furthermore, both the CCI and PCB in this case are ‘unreversed’. It is also worthy of note that when tested out of sample, the behaviour of the CCI rule is similar to its ‘in’ sample behaviour and behaves in a consistently profitable manner throughout.

3.7 Comparison of Profitable Rules

We have shown, above, that the majority of technical market indicator based rules are loss-making when applied to price data under test conditions. Only rules based on the PCB and CCI, remain profitable when tested on unseen data and do so under full slippage and in an un-reversed state. Rules based on the RSI and AMA show some profits but the best performance is achieved by reversing the rules and this profitability lapses when the rules are tested out of sample, suggesting that the profits were spurious. Similarly, the moving average rules were generally loss-making and the best of those few that were profitable failed to make a profit out of sample with full slippage.

By analysis of the results of applying the rules to the sample data (89-95) it can be seen that the CCI is by far the most stable to shifts in parameter, exit strategy and frequency of underlying data and, as we have seen, this stability is borne out in the test (96-97) results.

Table 3.7.1, below, displays a comparison of results for the two (out of sample) profitable indicators. We have previously reported ‘cumulative profit per traded pound’ as a result of the pound being the underlying instrument of the quotation ($\text{£}1 = \$x$) and this is a good test of profitability. However, in order to report comparative results, we use percentage

return based on a \$1 million trading line where profits are allowed to accumulate and then ‘banked’ and converted to percentage returns on an annual basis. Returns are not compounded as we aim to emulate the position of a bank trader with a fixed maximum position size. It should be noted that interest revenue on the traded dollars has not been considered since the all trading occurs at intra-day frequencies and so minute-by-minute liquidity would need to be maintained. Furthermore, a bank trader would not be rewarded for interest income on traded assets since it is common for a credit line to be traded as opposed to actual funds.

We see that, under the full slippage regime, the CCI and PCB both make profits but, in both cases, profitability is reduced when the rules are considered under test conditions although the profit is still reasonable. It should be noted that these results contain an immense survivor bias and should not be taken to be of anything other than general interest. Under a relaxed slippage regime, the CCI is more profitable overall both in and out of sample.

Figures 3.7.2 and 3.7.3 show annual returns and cumulative profits and it can be seen that 1993 was by far the most profitable year for the PCB whereas the CCI made the most profits in 1992.

It was noted that the above results above contain immense selection bias since they were selected as the few rules that made a profit out-of-sample out of a population of many losing rules and accordingly, these results contain no implications for market efficiency. To overcome such bias, we now consider the out-of-sample returns from trading a portfolio of the most profitable trading (under full slippage) rule for each indicator (where profitable rules existed), namely

Moving Average Strategy A/60min/MA(20)/MA(400) at 60min frequency,
Adaptive Moving Average Strategy Ar(500) at daily frequency,
PCB Strategy A for n = 250 at 240min frequency,
RSI Strategy Br 70/30 n = 15 at 480min frequency,
CCI Strategy B +1/-1 n = 25 at 480min frequency.

Such portfolio constituents would be the rational choice for a technical trader who would select his rules on the basis of past performance.

It can be seen from Table 3.7.4 that such a portfolio makes an out of sample loss under full slippage and just a negligible gain under relaxed slippage. Such results are in accord with the efficient market hypothesis.

4 Summary and Conclusions

We have created trading rules using a number of technical market indicators and exit strategies and tested them on daily and intra-day FX data. The majority of technical trading rules are not profitable. Some rules make a profit and even remain profitable out of sample but such results have little significance due to selection bias. When a portfolio of best performing rules is chosen on the basis of past performance (the way in which a trader may choose rules) they make a loss when tested on unseen data – a result in support of the efficient market hypothesis.

It is worthy of note that indicator-based rules also failed to be profitable when reversed indicating that, although profits may be possible in frictionless markets, after slippage is taken into account losses are found. These results indicate that losses are not economically significant.

The majority of moving average rules failed to make a profit despite previous work (e.g. Levich and Thomas (1993)) showing such rules to be profitable. However, on closer inspection it can be seen that such rules are only loss-making post 1992/93 – a result which is supported by anecdotal evidence from traders. Furthermore, evidence of significantly different statistical behaviour before and after 1993 can be found in Jones (1999).

Given the vast amount of practitioner literature devoted to the rules tested above and the high level of credence given to them by traders, it is surprising that they prove to be loss-

making. However, a technical trader typically makes trading decisions based on combinations of a number of rules and it is this method of trading that is studied in Dempster & Jones (1999c).

Results Tables

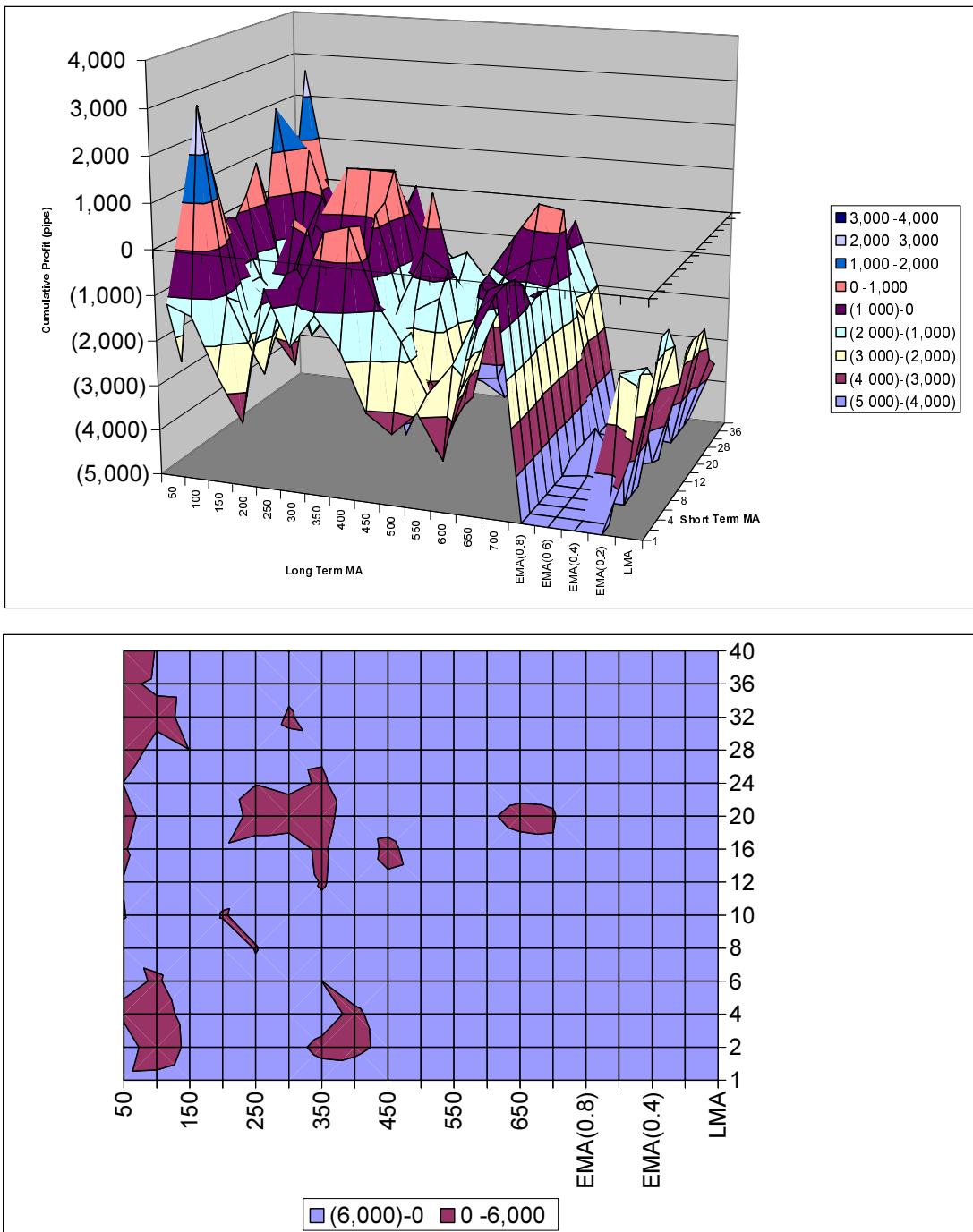


Figure 3.1.1: Cumulative Trading Profits from Moving Average Strategy A at Daily Frequency

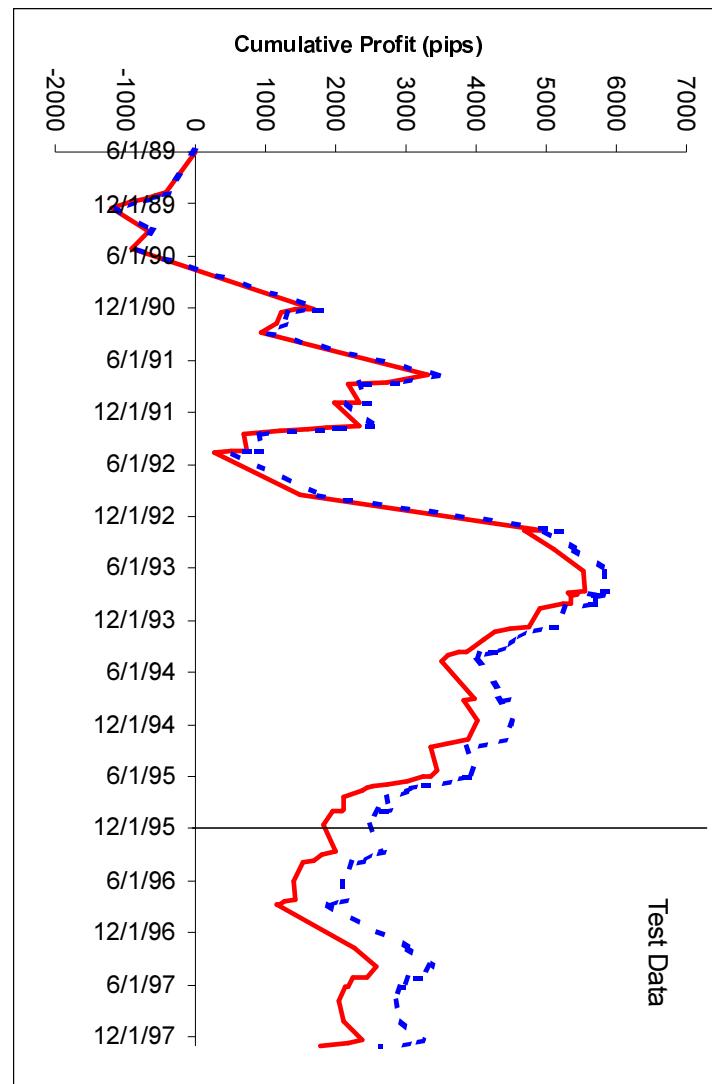


Figure 3.1.2: Test Results for Strategy A/480min/MA(12)/MA(200)

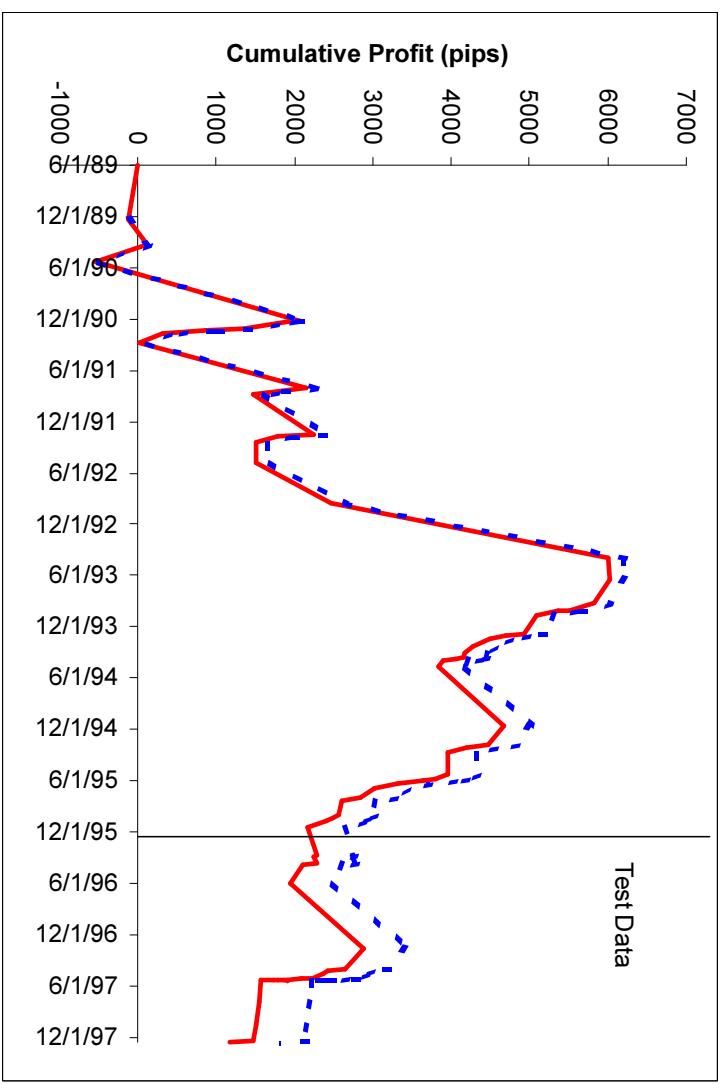


Figure 3.1.3: Test Results for Strategy A/240min/MA(20)/MA(500)

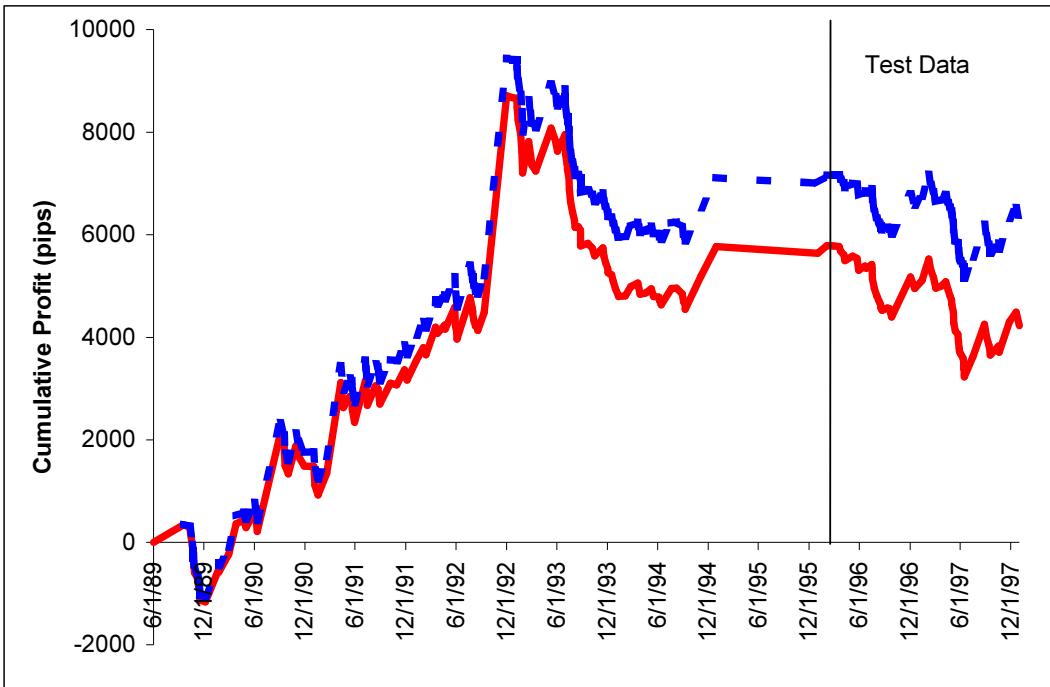


Figure 3.1.4: Test Results for Strategy A/60min/MA(20)/MA(400)

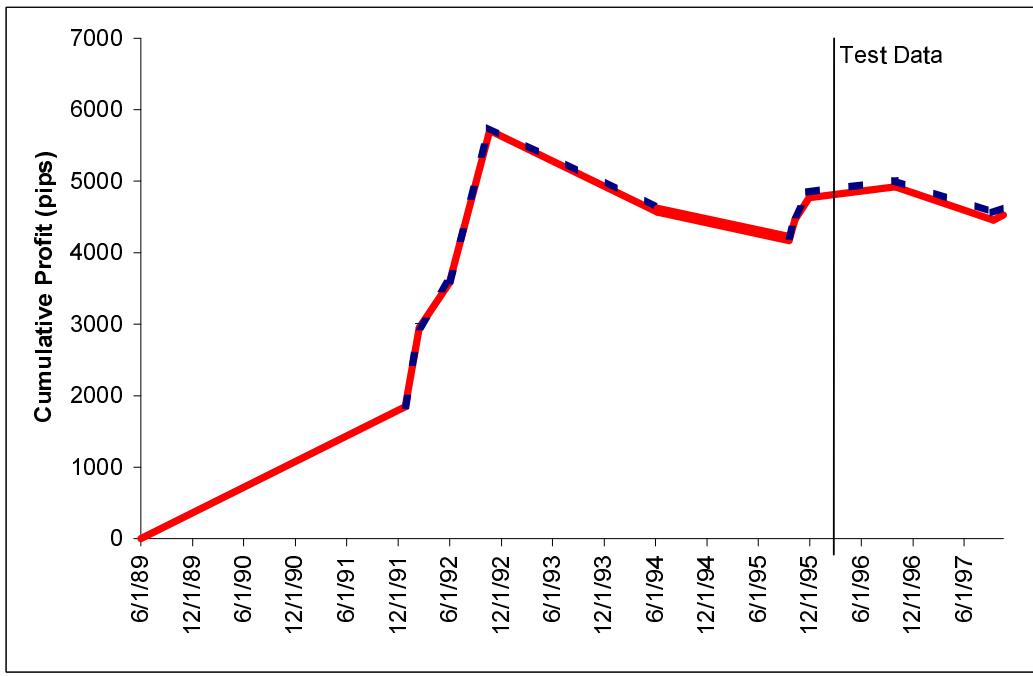


Figure 3.1.5: Test Results for Strategy Ar/daily/MA(40)/MA(500)

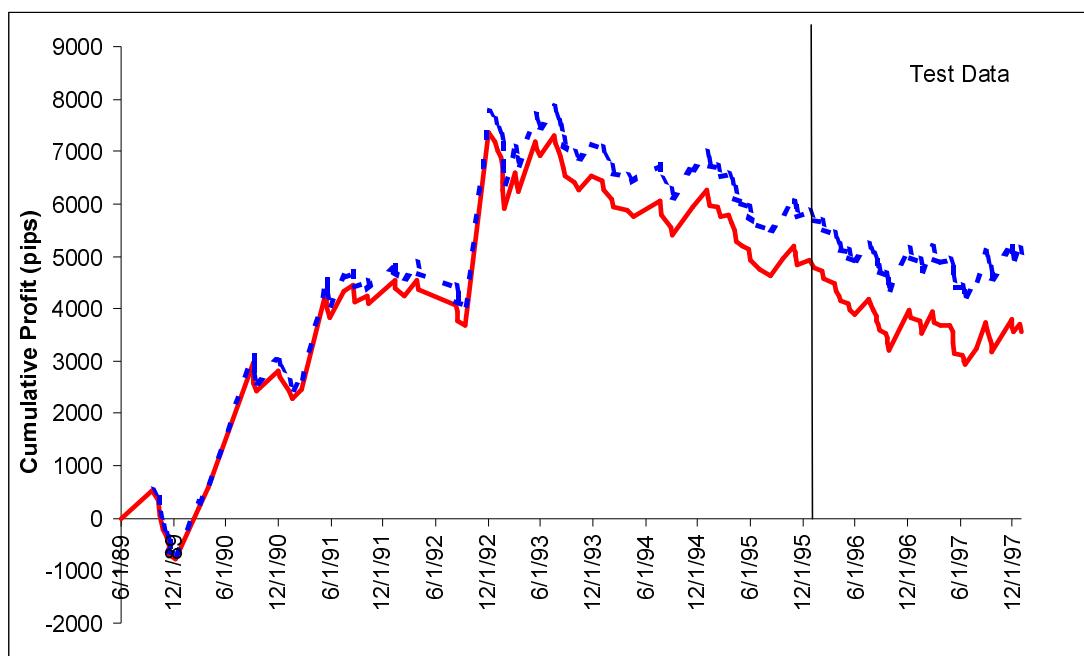


Figure 3.1.6: Test Results for Strategy Dr/daily/MA(32)/EMA(0.4)

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	10	-6609	-3831	-3999	-1221
Daily	25	-2769	-4191	-1029	-2451
Daily	50	-7100	1620	-5730	2990
Daily	100	-108	-3572	812	-2652
Daily	500	-5183	3983	-4883	4283
480min	10	-3633	-14823	1697	-9493
480min	25	-9602	-4494	-5582	-474
480min	50	-8184	-2800	-5034	350
480min	100	-3240	-4356	-1080	-2196
480min	500	2656	-6064	3646	-5074
240min	10	-10947	-18919	-2447	-10419
240min	25	-8990	-11838	-3080	-5928
240min	50	-13637	-3471	-8837	1329
240min	100	-6613	-6269	-2993	-2649
240min	500	-3853	-2563	-2053	-763
60min	10	-48057	-27287	-26857	-6087
60min	25	-20384	-28186	-6694	-14496
60min	50	-13987	-24741	-3147	-13901
60min	100	-18730	-13056	-9840	-4166
60min	500	-11156	-7402	-5996	-2242
1min	10	-224098	-85634	-134788	3676
1min	25	-158661	-79335	-89851	-10525
1min	50	-131296	-65564	-74396	-8664
1min	100	-100580	-61916	-53760	-15096
1min	500	-56984	-43900	-28064	-14980

Table 3.2.1: Cumulative Trading Profits from Adaptive Moving Average Strategies A and Ar under *Full* and *Relaxed* Slippage Regimes

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	10	-11308	-8372	-6388	-3452
Daily	25	-6768	-8712	-2898	-4842
Daily	50	-10357	-2523	-7137	697
Daily	100	-3307	-7053	-717	-4463
Daily	500	-6513	2113	-5413	3213
480min	10	-10506	-22058	-1146	-12698
480min	25	-16103	-10285	-8553	-2735
480min	50	-13682	-8510	-7312	-2140
480min	100	-8240	-9440	-3170	-4370
480min	500	-1112	-9872	2058	-6702
240min	10	-19876	-27706	-6236	-14066
240min	25	-16668	-20012	-6168	-9512
240min	50	-20674	-10154	-11884	-1364
240min	100	-13231	-13053	-5721	-5543
240min	500	-9265	-7467	-4485	-2687
60min	10	-59744	-39106	-31794	-11156
60min	25	-31899	-40275	-11429	-19805
60min	50	-25731	-36035	-8301	-18605
60min	100	-28579	-23559	-13879	-8859
60min	500	-20418	-16054	-10138	-5774
1min	10	-235382	-100230	-138612	-3460
1min	25	-172446	-95398	-95036	-17988
1min	50	-146216	-82048	-80246	-16078
1min	100	-115527	-79725	-59257	-23455
1min	500	-72018	-62468	-33398	-23848

Table 3.2.2: Cumulative Trading Profits from Adaptive Moving Average Strategies B and Br under *Full* and *Relaxed* Slippage Regimes

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	10	-7129	-5631	-3939	-2441
Daily	25	-5777	-5023	-3077	-2323
Daily	50	-7273	-2407	-4853	13
Daily	100	-3798	-5042	-1588	-2832
Daily	500	-8775	2295	-7155	3915
480min	10	-4734	-15226	1036	-9456
480min	25	-8226	-7866	-3596	-3236
480min	50	-9661	-4471	-5581	-391
480min	100	-4710	-6534	-1480	-3304
480min	500	97	-8553	2557	-6093
240min	10	-10985	-19867	-2175	-11057
240min	25	-10472	-12424	-3932	-5884
240min	50	-11764	-7602	-6284	-2122
240min	100	-6979	-8943	-2459	-4423
240min	500	-3972	-6080	-1082	-3190
60min	10	-48210	-27536	-26880	-6206
60min	25	-20695	-28729	-6745	-14779
60min	50	-16385	-23695	-5115	-12425
60min	100	-18715	-14335	-9405	-5025
60min	500	-10567	-10075	-4767	-4275
1min	10	-227073	-84373	-137273	3427
1min	25	-163122	-77034	-93712	-7624
1min	50	-135550	-63298	-78100	-5848
1min	100	-106606	-58170	-59156	-10720
1min	500	-64931	-38641	-35271	-8981

Table 3.2.3: Cumulative Trading Profits from Adaptive Moving Average Strategies C and Cr under *Full* and *Relaxed* Slippage Regimes

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	10	-12087	-10473	-6447	-4833
Daily	25	-10804	-9596	-5704	-4496
Daily	50	-11413	-6467	-6943	-1997
Daily	100	-8158	-9402	-3768	-5012
Daily	500	-11289	-831	-8259	2199
480min	10	-11519	-22401	-1759	-12641
480min	25	-14566	-13806	-6406	-5646
480min	50	-14920	-10552	-7580	-3212
480min	100	-9966	-12042	-3636	-5712
480min	500	-4714	-13478	546	-8218
240min	10	-19873	-28675	-5923	-14725
240min	25	-18419	-20303	-7299	-9183
240min	50	-19105	-14351	-9535	-4781
240min	100	-14193	-15895	-5563	-7265
240min	500	-9750	-11738	-3570	-5558
60min	10	-11519	-22401	-1759	-12641
60min	25	-14566	-13806	-6406	-5646
60min	50	-14920	-10552	-7580	-3212
60min	100	-9966	-12042	-3636	-5712
60min	500	-4714	-13478	546	-8218
1min	10	-238318	-99074	-141038	-1794
1min	25	-176874	-92988	-98904	-15018
1min	50	-150354	-79784	-83864	-13294
1min	100	-121079	-76089	-64279	-19289
1min	500	-79413	-56925	-40283	-17795

Table 3.2.4: Cumulative Trading Profits from Adaptive Moving Average Strategies D and Dr under *Full* and *Relaxed* Slippage Regimes

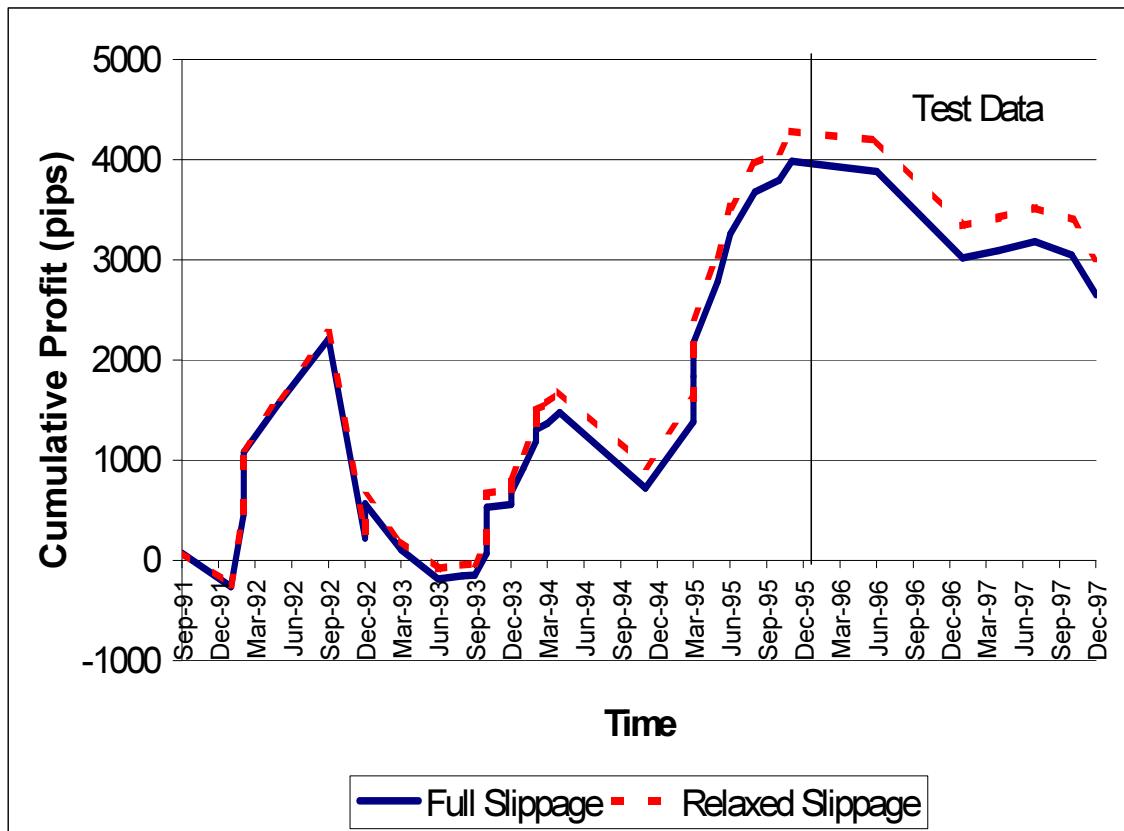


Figure 3.2.5: Out of sample Testing of Adaptive Moving Average Strategy Ar(500) at Daily Frequency under *Full* and *Relaxed* Slippage Regimes

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-5085	-4275	-2745	-1935
Daily	10	-1913	-2487	-813	-1387
Daily	25	-566	-1354	-86	-874
Daily	50	3758	-4558	3958	-4358
Daily	250	-2906	2706	-2856	2756
Daily	500	-4274	4194	-4254	4214
480min	5	-9828	-13036	-3268	-6476
480min	10	-5112	-6644	-1752	-3284
480min	25	346	-4774	1606	-3514
480min	50	2974	-5214	3614	-4574
480min	250	844	-1240	954	-1130
480min	500	1697	-1877	1747	-1827
240min	5	-16153	-27023	-3553	-14423
240min	10	-9537	-13243	-2977	-6683
240min	25	-3243	-5433	-743	-2933
240min	50	-894	-3192	306	-1992
240min	250	5478	-6186	5678	-5986
240min	500	646	-1030	756	-920
60min	5	-100772	-79120	-50622	-28970
60min	10	-47607	-42965	-21987	-17345
60min	25	-15734	-18976	-5824	-9066
60min	50	-5520	-12124	-520	-7124
60min	250	3223	-6305	4123	-5405
60min	500	1464	-3168	1944	-2688
1min	5	-4301524	-2336658	-2427754	-462888
1min	10	-2274335	-1120439	-1315435	-161539
1min	25	-985586	-416336	-589156	-19906
1min	50	-505861	-199241	-306711	-91
1min	250	-112385	-34983	-70425	6977
1min	500	-45277	-25047	-24877	-4647

Table 3.3.1: Cumulative Profits from Range Breakout Strategies A and Ar

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-9532	-9188	-4852	-4508
Daily	10	-5518	-6402	-2538	-3422
Daily	25	-3506	-4294	-1556	-2344
Daily	50	1682	-7082	3032	-5732
Daily	250	-3866	1746	-3336	2276
Daily	500	-4075	3475	-3925	3625
480min	5	-17128	-20336	-6378	-9586
480min	10	-11123	-12885	-4253	-6015
480min	25	-4042	-9402	-202	-5562
480min	50	-410	-8806	2230	-6166
480min	250	-592	-3120	478	-2050
480min	500	717	-3317	1477	-2557
240min	5	-25619	-36489	-7529	-18399
240min	10	-17659	-21365	-6379	-10085
240min	25	-9032	-11608	-3072	-5648
240min	50	-5372	-7996	-1492	-4116
240min	250	3263	-9107	4943	-7427
240min	500	-866	-3026	254	-1906
60min	5	-112736	-91084	-55736	-34084
60min	10	-59993	-55351	-27273	-22631
60min	25	-26852	-30094	-10582	-13824
60min	50	-14660	-21264	-4420	-11024
60min	250	-1624	-11378	2106	-7648
60min	500	-2276	-6908	334	-4298
1min	5	-4306934	-2342068	-2430054	-465188
1min	10	-2282581	-1128685	-1318921	-165025
1min	25	-998778	-429528	-594688	-25438
1min	50	-522149	-215529	-313589	-6969
1min	250	-129925	-52523	-77805	-403
1min	500	-61781	-41551	-31851	-11621

Table 3.3.2: Cumulative Profits from Range Breakout Strategies B and Br

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-6182	-5458	-3272	-2548
Daily	10	-4040	-3400	-2180	-1540
Daily	25	-2273	-2487	-1083	-1297
Daily	50	-556	-2724	264	-1904
Daily	250	-508	-772	-188	-452
Daily	500	-589	149	-479	259
480min	5	-9300	-14860	-2360	-7920
480min	10	-3991	-10801	269	-6541
480min	25	764	-9092	3164	-6692
480min	50	1335	-7367	3075	-5627
480min	250	1377	-3681	2037	-3021
480min	500	1621	-3181	2071	-2731
240min	5	-18674	-25786	-5704	-12816
240min	10	-9370	-15954	-2070	-8654
240min	25	-4913	-9057	-893	-5037
240min	50	-2442	-6870	248	-4180
240min	250	-894	-3390	326	-2170
240min	500	-472	-2324	328	-1524
60min	5	-101127	-79257	-50837	-28967
60min	10	-47689	-44165	-21699	-18175
60min	25	-16328	-22226	-5288	-11186
60min	50	-8621	-15557	-1721	-8657
60min	250	-3152	-6714	-312	-3874
60min	500	-2759	-4483	-679	-2403
1min	5	-4302841	-2336049	-2428881	-462089
1min	10	-2275679	-1119969	-1316539	-160829
1min	25	-988096	-415098	-591316	-18318
1min	50	-508773	-198121	-309123	1529
1min	250	-119170	-33776	-75630	9764
1min	500	-57912	-22010	-34832	1070

Table 3.3.3: Cumulative Profits from Range Breakout Strategies C and Cr

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-10502	-9778	-5432	-4708
Daily	10	-7120	-6480	-3720	-3080
Daily	25	-4393	-4607	-2143	-2357
Daily	50	-2196	-4364	-556	-2724
Daily	250	-1228	-1492	-548	-812
Daily	500	-809	-71	-589	149
480min	5	-16356	-21916	-5366	-10926
480min	10	-9563	-16373	-2113	-8923
480min	25	-2812	-12668	1628	-8228
480min	50	-1285	-9987	1955	-6747
480min	250	173	-4885	1543	-3515
480min	500	745	-4057	1715	-3087
240min	5	-28012	-35124	-9622	-16734
240min	10	-17028	-23612	-5268	-11852
240min	25	-10031	-14175	-3061	-7205
240min	50	-6012	-10440	-1272	-5700
240min	250	-2696	-5192	-446	-2942
240min	500	-1684	-3536	-194	-2046
60min	5	-113113	-91243	-55963	-34093
60min	10	-59895	-56371	-26905	-23381
60min	25	-26776	-32674	-9756	-15654
60min	50	-16657	-23593	-5157	-12093
60min	250	-6644	-10206	-1814	-5376
60min	500	-5325	-7049	-1785	-3509
1min	5	-4308235	-2341443	-2431175	-464383
1min	10	-2283909	-1128199	-1320019	-164309
1min	25	-1001210	-428212	-596810	-23812
1min	50	-524913	-214261	-315933	-5281
1min	250	-136190	-50796	-82780	2614
1min	500	-73034	-37132	-41204	-5302

Table 3.3.4: Cumulative Profits from Range Breakout Strategies D and Dr

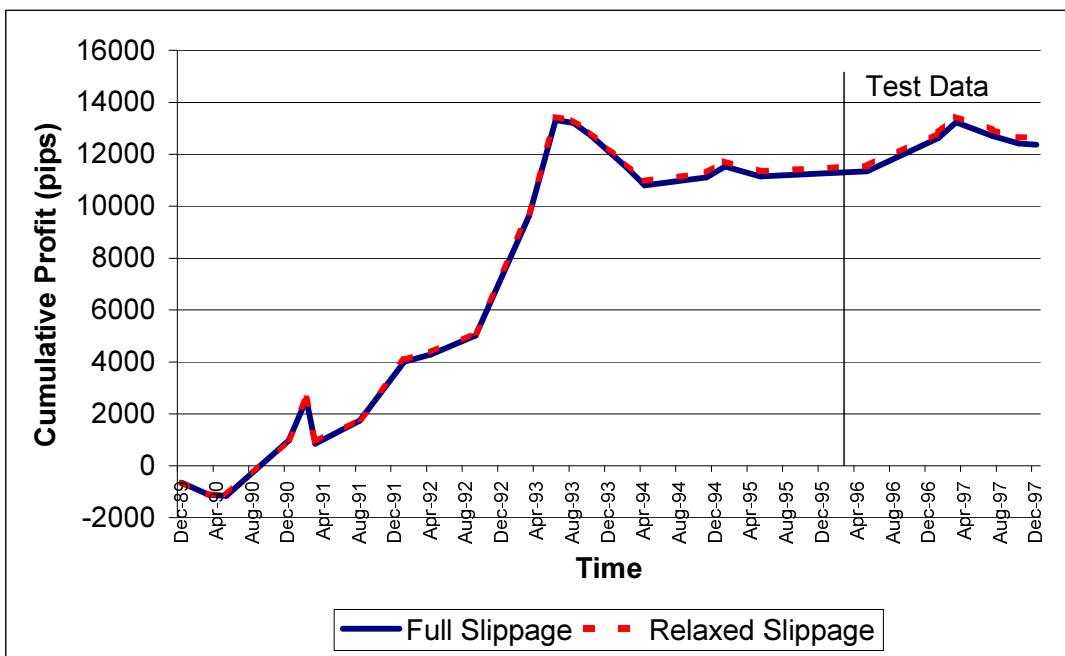


Figure 3.3.5: Test Results of PCB Strategy A for $n = 250$ at 240min Frequency

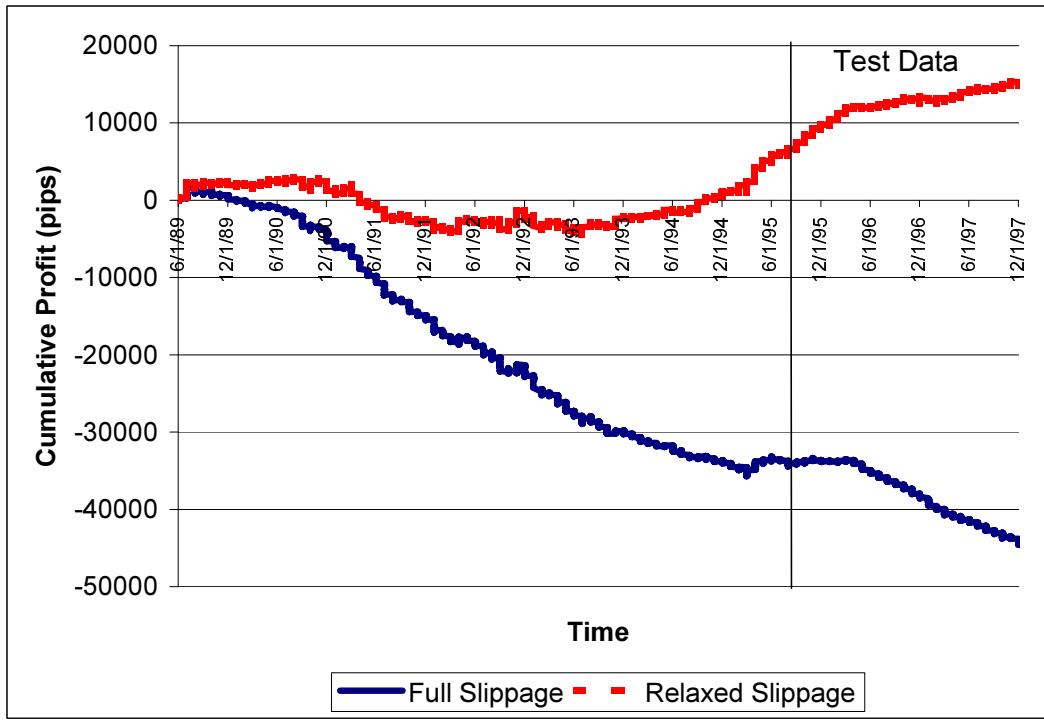


Figure 3.3.6: Test Results of PCB Strategy Cr for $n = 250$ at 1min Frequency

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-5118	1678	-4258	2538
Daily	10	-3085	1885	-2785	2185
Daily	15	-5841	5481	-5751	5571
Daily	20	-4109	3909	-4059	3959
Daily	25	-867	707	-827	747
Daily	50	0	0	0	0
480min	5	-4187	-5345	-1587	-2745
480min	10	-7181	4565	-6461	5285
480min	15	-8860	6608	-8530	6938
480min	20	-3729	2821	-3489	3061
480min	25	-5926	5594	-5836	5684
480min	50	2481	-2589	2511	-2559
240min	5	-8638	-9108	-3668	-4138
240min	10	-5655	377	-4155	1877
240min	15	-7531	5059	-6831	5759
240min	20	-5678	4266	-5278	4666
240min	25	-3321	2311	-3041	2591
240min	50	371	-473	401	-443
60min	5	-31027	-30741	-13387	-13101
60min	10	-14838	-4236	-9338	1264
60min	15	-5487	-4061	-2697	-1271
60min	20	-2341	-3355	-671	-1685
60min	25	-8340	5192	-7440	6092
60min	50	4162	-4896	4362	-4696
1min	5	-622854	-1256628	-91434	-725208
1min	10	-119790	-263668	-10450	-154328
1min	15	-46254	-95072	-5834	-54652
1min	20	-26912	-39052	-8002	-20142
1min	25	-12413	-22739	-2283	-12609
1min	50	-5356	584	-3986	1954

Table 3.5.1: Cumulative Profits from RSI 70/30 Trading Strategies A and Ar

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-5159	879	-4089	1949
Daily	10	-5210	3410	-4760	3860
Daily	15	-729	-311	-469	-51
Daily	20	1229	-2029	1429	-1829
Daily	25	1221	-1581	1311	-1491
Daily	50	384	-464	404	-444
480min	5	-6409	-3963	-3579	-1133
480min	10	-8812	5384	-7862	6334
480min	15	-8572	6792	-8092	7272
480min	20	-4995	3667	-4635	4027
480min	25	-2844	1992	-2604	2232
480min	50	516	-660	556	-620
240min	5	-8969	-9645	-3749	-4425
240min	10	-6519	-23	-4649	1847
240min	15	-7948	4570	-6988	5530
240min	20	-8009	6003	-7439	6573
240min	25	-4641	3243	-4251	3633
240min	50	851	-1101	921	-1031
60min	5	-31374	-30844	-13604	-13074
60min	10	-15389	-4751	-9589	1049
60min	15	-9265	-1385	-6175	1705
60min	20	-5400	-1798	-3300	302
60min	25	-8695	4385	-7455	5625
60min	50	1132	-2210	1432	-1910
1min	5	-622132	-1258230	-90472	-726570
1min	10	-118997	-265737	-9307	-156047
1min	15	-45478	-97860	-4498	-56880
1min	20	-26184	-42392	-6524	-22732
1min	25	-14326	-24428	-3166	-13268
1min	50	-5270	-1560	-3310	400

Table 3.5.2: Cumulative Profits from RSI 70/30 Trading Strategies B and Br

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-4716	-3044	-2776	-1104
Daily	10	-3969	249	-3039	1179
Daily	15	-2992	1112	-2522	1582
Daily	20	-3001	1721	-2681	2041
Daily	25	-2921	2241	-2751	2411
Daily	50	-66	-14	-46	6
480min	5	-7099	-11081	-2109	-6091
480min	10	-6970	-1478	-4650	842
480min	15	-7591	2635	-6241	3985
480min	20	-3261	-3	-2371	887
480min	25	-1443	-225	-983	235
480min	50	-228	40	-178	90
240min	5	-12659	-16389	-4499	-8229
240min	10	-7106	-7264	-3016	-3174
240min	15	-8637	287	-6267	2657
240min	20	-4946	-194	-3486	1266
240min	25	-3501	229	-2571	1159
240min	50	-430	34	-320	144
60min	5	-33729	-40311	-12609	-19191
60min	10	-20452	-15026	-10242	-4816
60min	15	-17949	-4779	-11369	1801
60min	20	-11755	-3657	-7305	793
60min	25	-10592	888	-7812	3668
60min	50	-1133	-447	-693	-7
1min	5	-627295	-1256407	-94685	-723797
1min	10	-124482	-266328	-13072	-154918
1min	15	-57362	-97290	-13132	-53060
1min	20	-39800	-46290	-15150	-21640
1min	25	-29689	-25261	-13899	-9471
1min	50	-5356	584	-3986	1954

Table 3.5.3: Cumulative Profits from RSI 70/30 Trading Strategies C and Cr

Frequency	n	Cumulative Trading Profit			
		Full Slippage	Full Slippage Reversed Rule	Relaxed Slippage	Relaxed Slippage Reversed Rule
Daily	5	-1604	-6196	346	-4246
Daily	10	-3715	-45	-2775	895
Daily	15	-592	-1328	-112	-848
Daily	20	-302	-978	18	-658
Daily	25	-1737	1057	-1567	1227
Daily	50	52	-132	72	-112
480min	5	-11330	-6838	-6340	-1848
480min	10	-7380	-1064	-5060	1256
480min	15	-5357	393	-4007	1743
480min	20	-2292	-1004	-1402	-114
480min	25	-981	-703	-521	-243
480min	50	-374	186	-324	236
240min	5	-11330	-6838	-6340	-1848
240min	10	-7380	-1064	-5060	1256
240min	15	-5357	393	-4007	1743
240min	20	-2292	-1004	-1402	-114
240min	25	-981	-703	-521	-243
240min	50	-374	186	-324	236
60min	5	-34110	-40338	-12870	-19098
60min	10	-21593	-14085	-11323	-3815
60min	15	-16863	-5993	-10273	597
60min	20	-9077	-6401	-4617	-1941
60min	25	-9846	134	-7066	2914
60min	50	-127	-1483	323	-1033
1min	5	-626197	-1258287	-93377	-725467
1min	10	-122858	-269338	-11068	-157548
1min	15	-55190	-101322	-10440	-56572
1min	20	-37406	-50372	-12266	-25232
1min	25	-26414	-29886	-10234	-13706
1min	50	-5341	-5971	-2091	-2721

Table 3.5.4: Cumulative Profits from RSI 70/30 Trading Strategies D and Dr

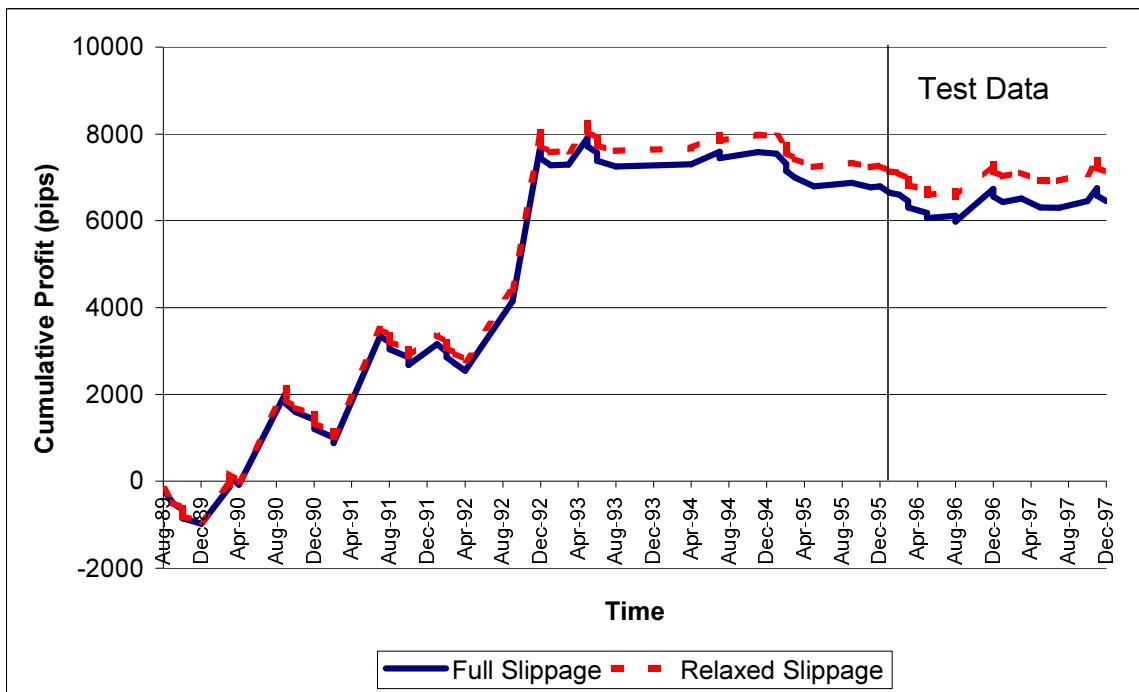


Figure 3.5.5: Test Results of Strategy Br for RSI 70/30 n = 15 at 480min Frequency

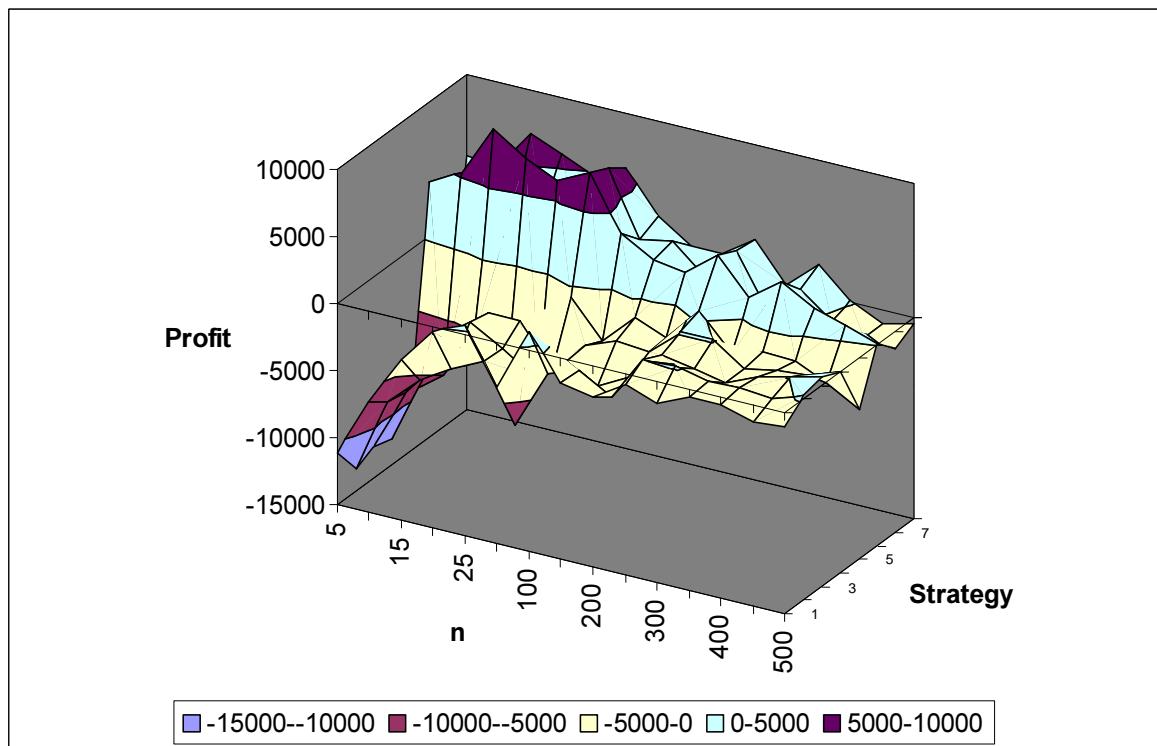


Figure 3.6.1a: Cumulative Profits from CCI at Daily Frequency

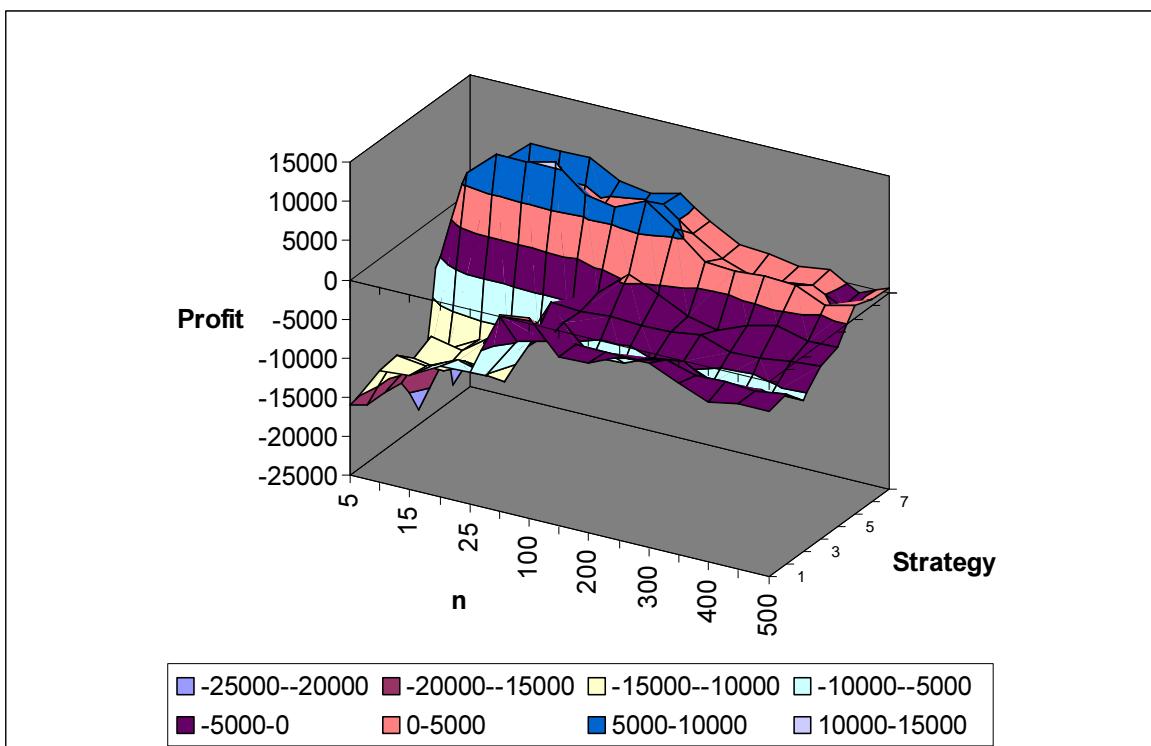


Figure 3.6.1b: Cumulative Profits from CCI at 480min Frequency

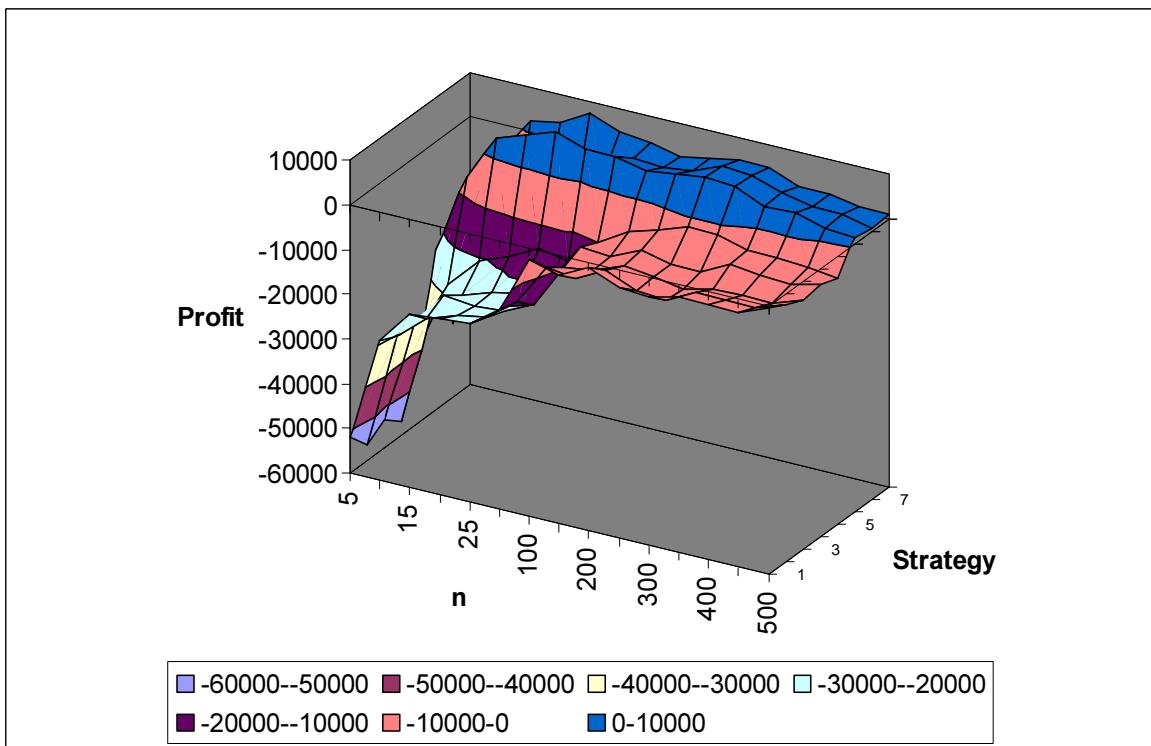


Figure 3.6.1c: Cumulative Profits from CCI at 240min Frequency

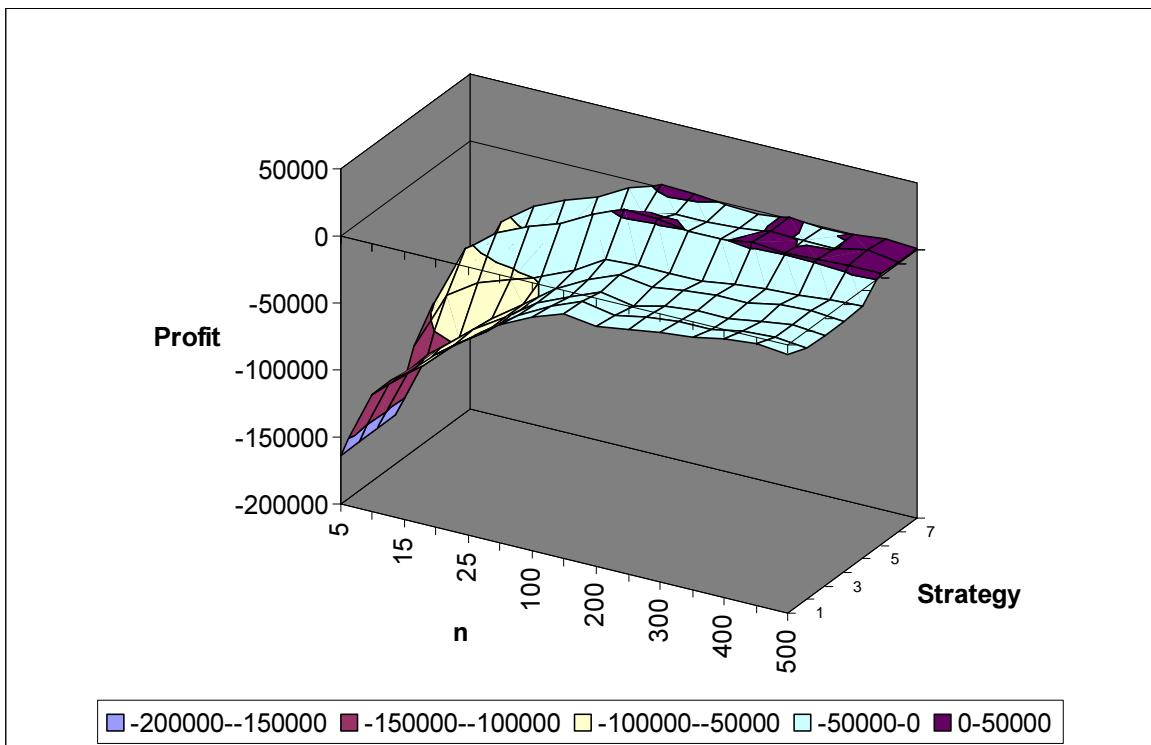


Figure 3.6.1d: Cumulative Profits from CCI at 60min Frequency

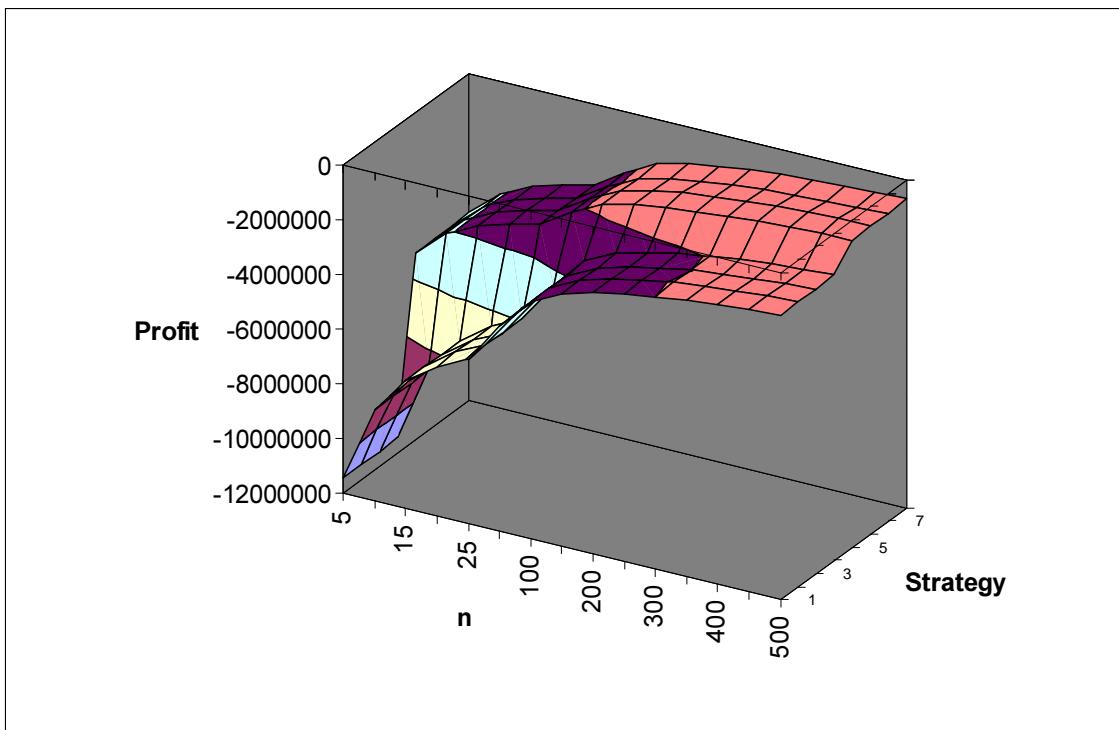


Figure 3.6.1e: Cumulative Profits from CCI at 1min Frequency

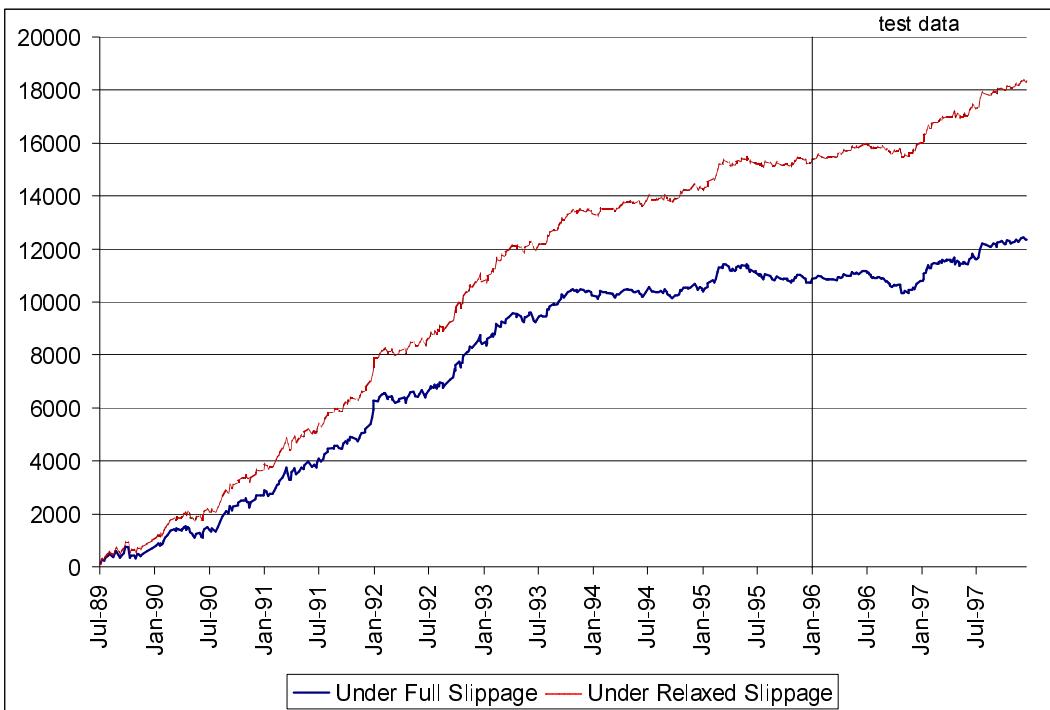


Figure 3.6.2: Test Results of Strategy B for CCI +1/-1 n = 25 at 480min Frequency

Full Slippage	CCI	PCB
Total Return (%)	73.57%	71.75%
Average Annual Return (89-95)	9.79%	9.79%
Average Annual Return (96-97)	4.98%	4.05%
Average Annual Return (ex 92-93)	6.40%	1.82%
Average Annual Return (89-97)	8.65%	8.44%

Relaxed Slippage	CCI	PCB
Total Return (%)	110.18%	73.34%
Average Annual Return (89-95)	14.01%	9.98%
Average Annual Return (96-97)	9.54%	4.24%
Average Annual Return (ex 92-93)	10.62%	1.99%
Average Annual Return (89-97)	12.96%	8.63%

Table 3.7.1: Comparative Results of Profitable Rules

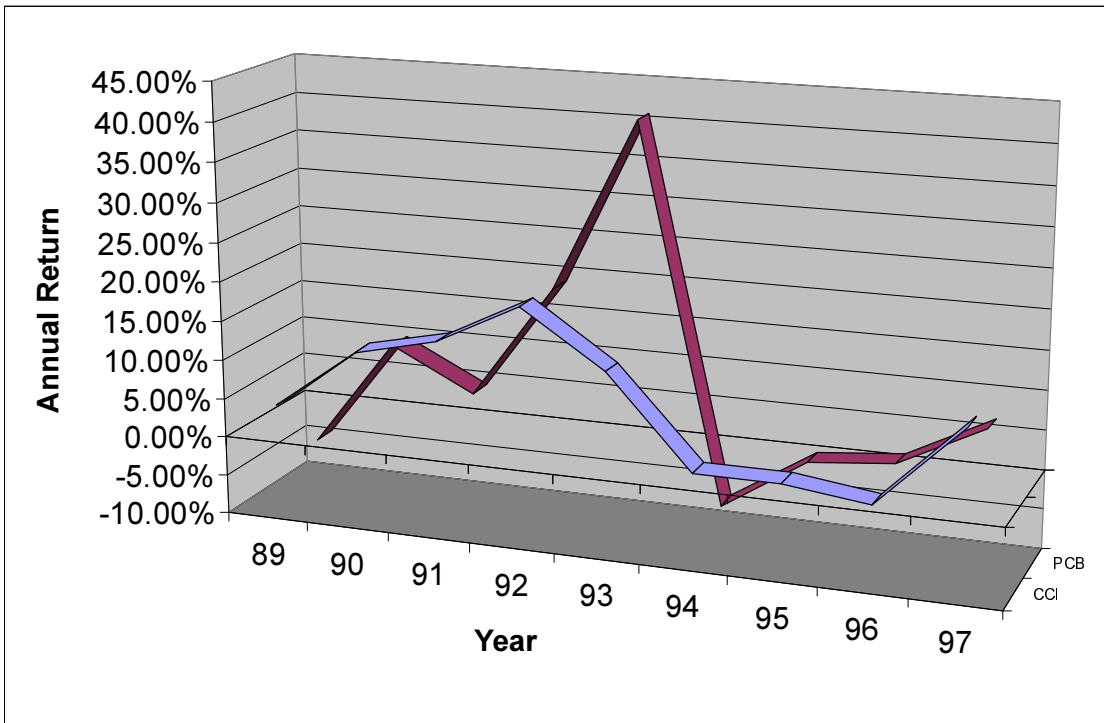


Figure 3.7.2: Annual Returns by Year and Indicator (Full Slippage)

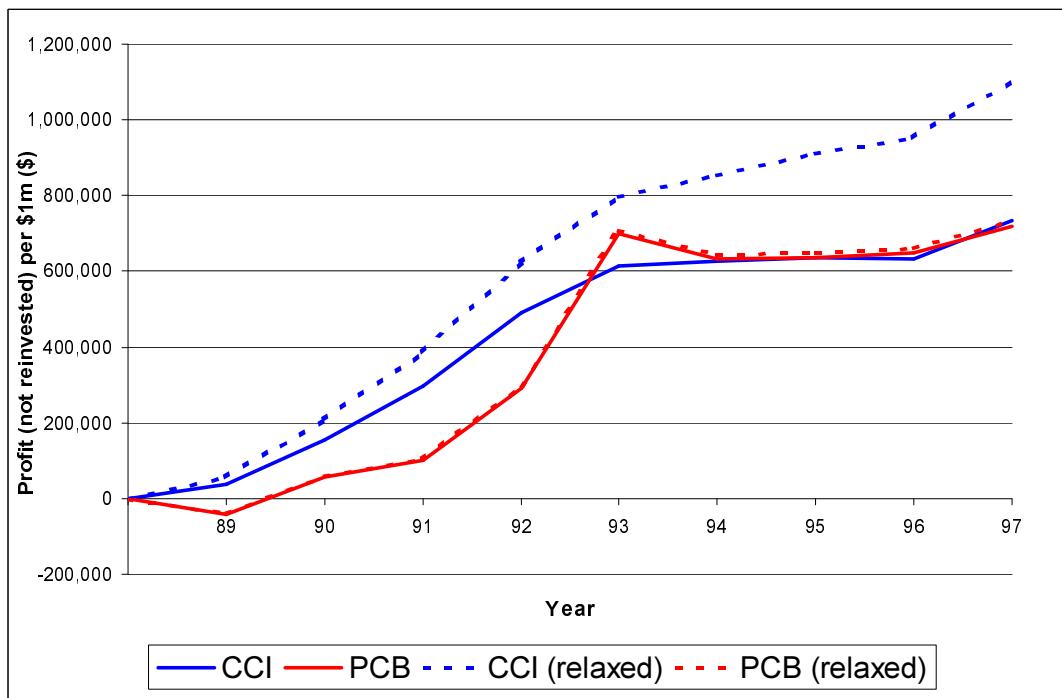


Figure 3.7.3: Cumulative Profit by Year and Indicator (Full Slippage)

'Best Rules'	Full	Relaxed
Total Return (%)	38.43%	51.60%
Average Annual Return (89-95)	6.13%	7.33%
Average Annual Return (96-97)	-2.26%	0.16%
Average Annual Return (ex 92-93)	1.96%	3.40%
Average Annual Return (89-97)	4.27%	5.73%

Table 3.7.4: Comparative Results of ‘Best’ Rules

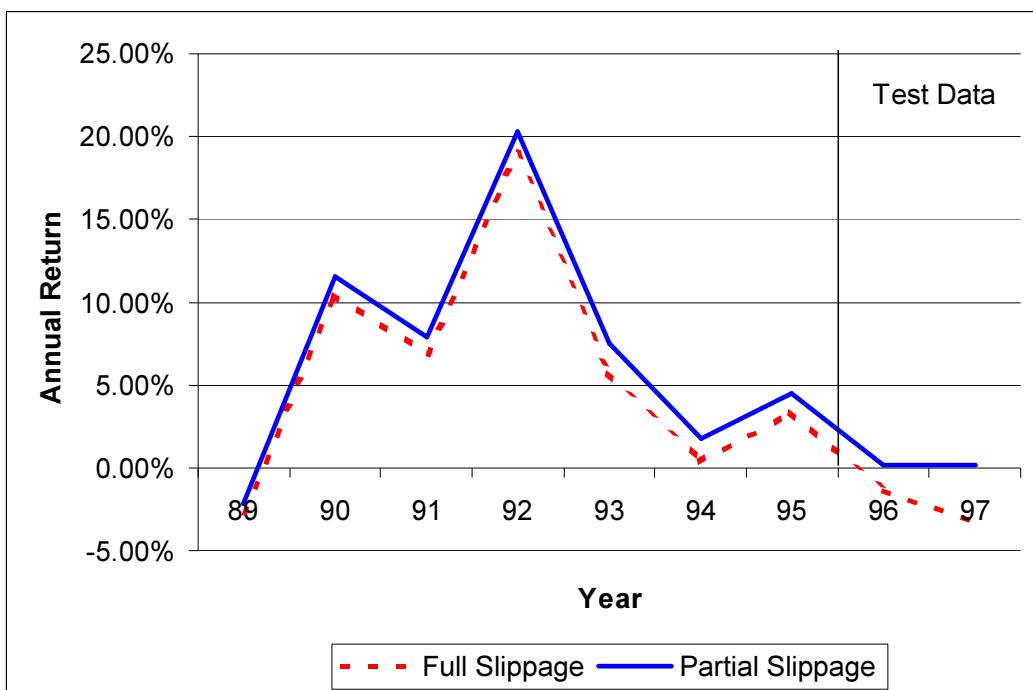
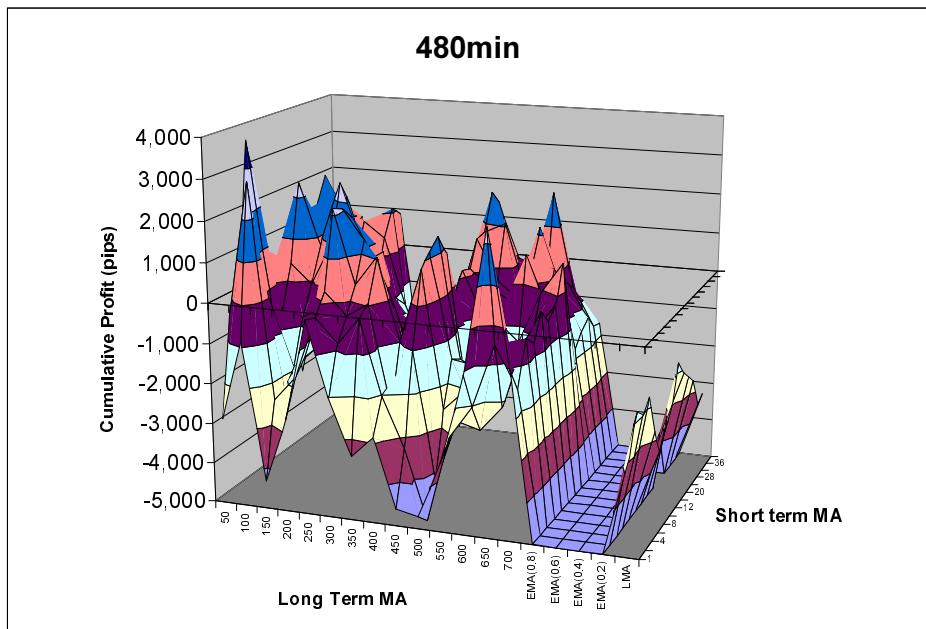
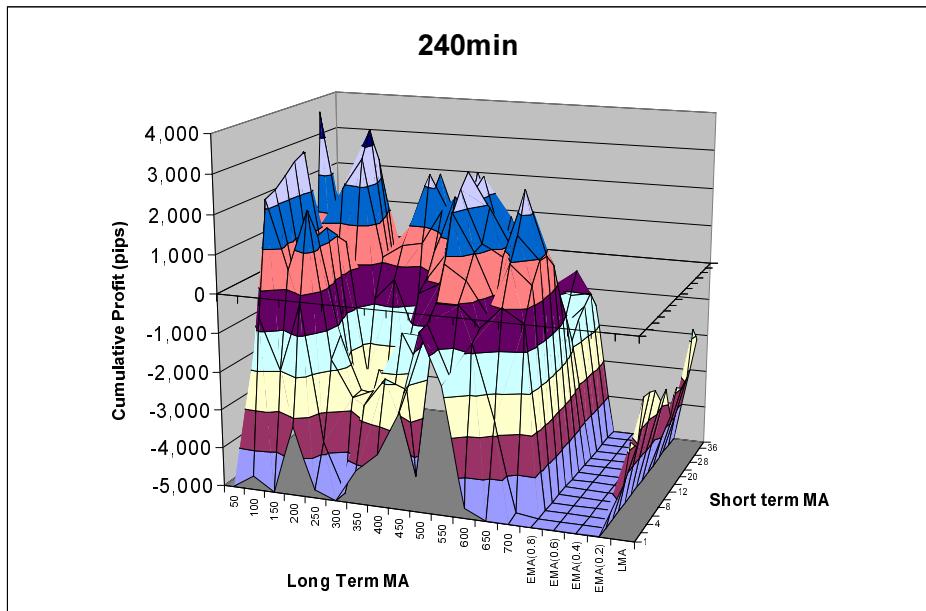


Figure 3.7.5: Annual Returns of ‘Best’ Rules

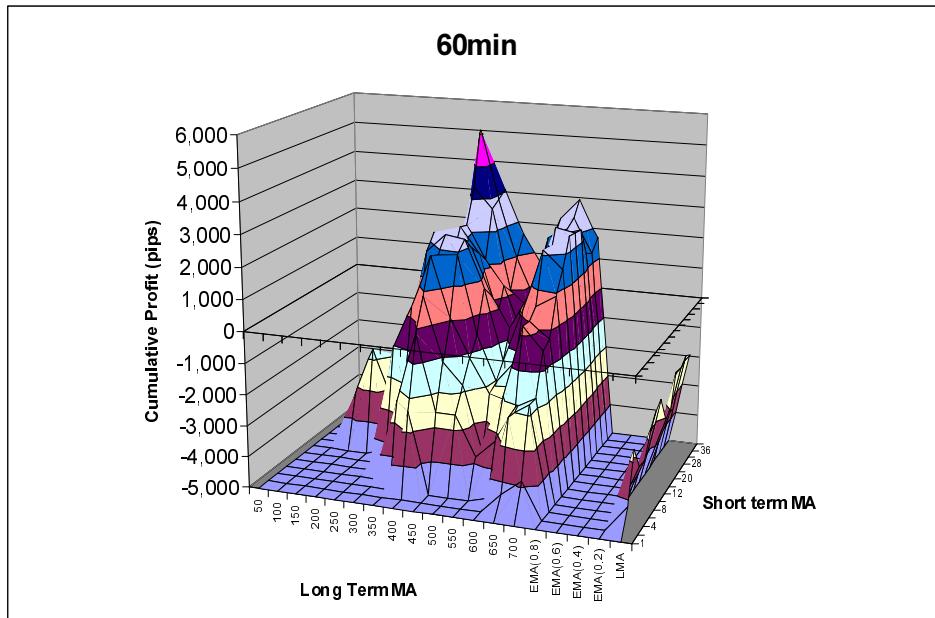
Appendix



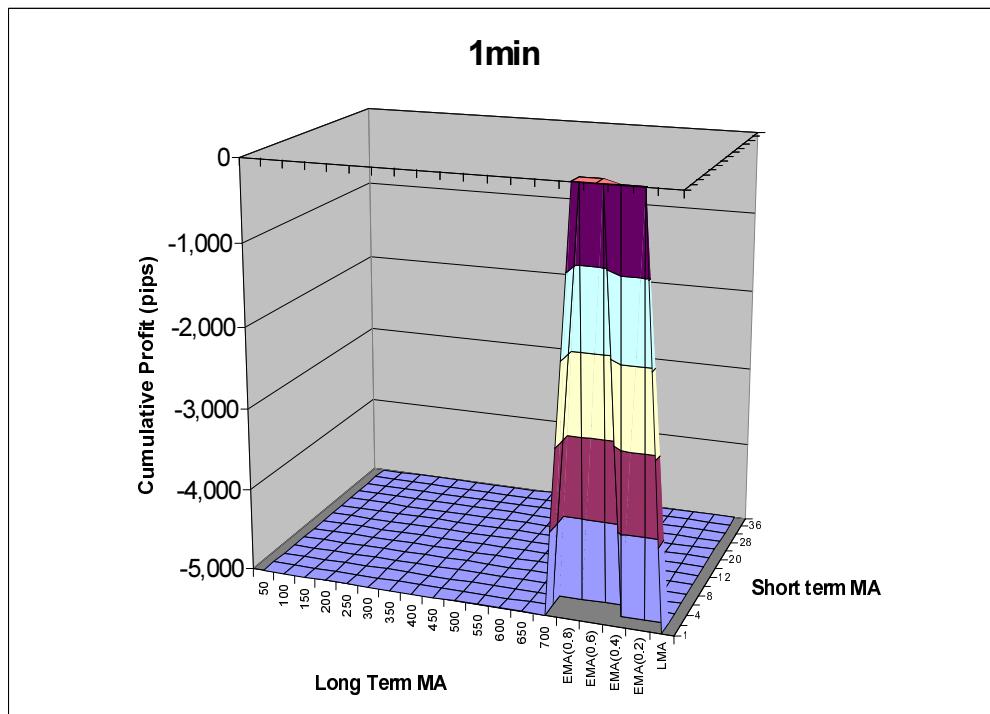
Appendix Figure A.1: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy A at 480min Frequency



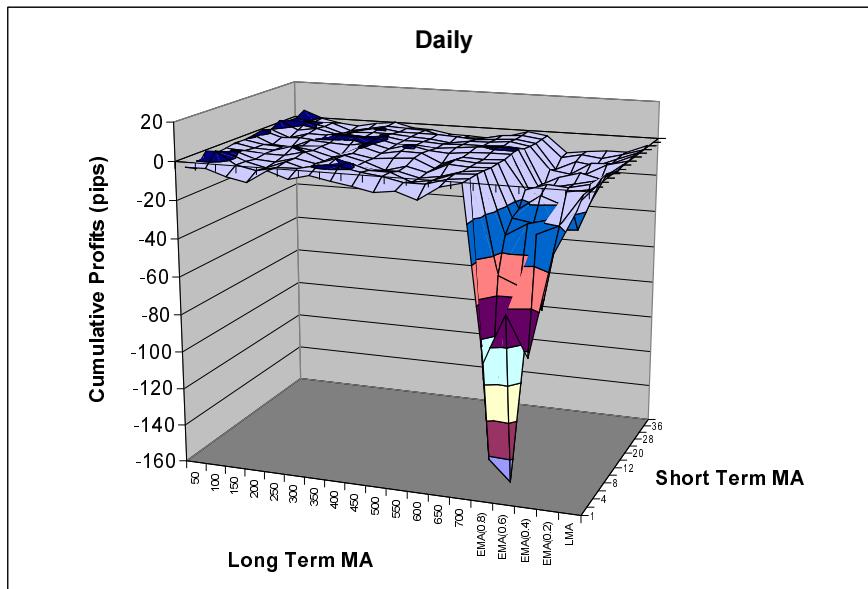
Appendix Figure A.2: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy A at 240min Frequency



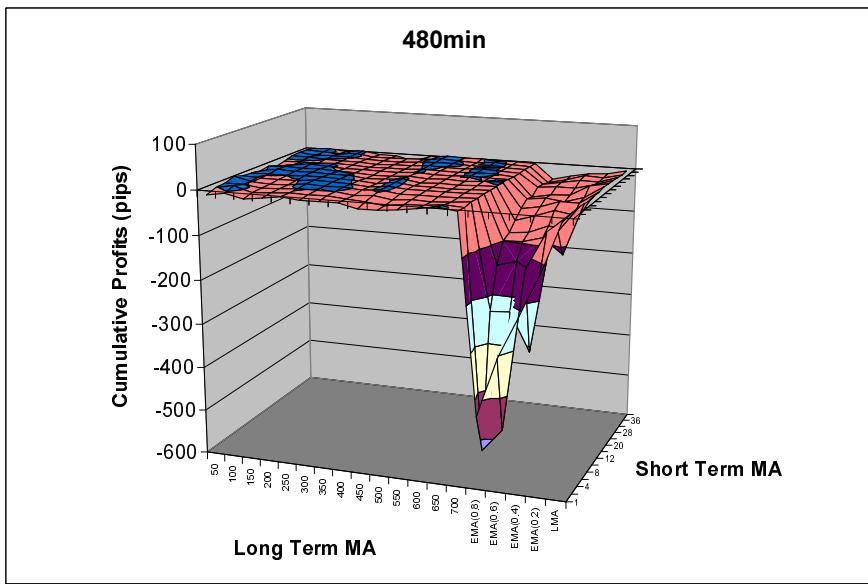
Appendix Figure A.3: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy A at 60min Frequency



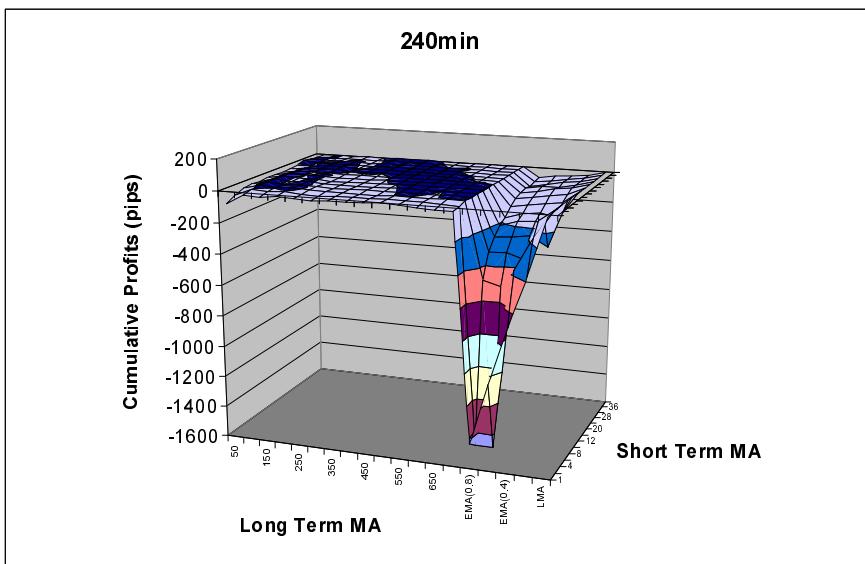
Appendix Figure A.4: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy A at 1min Frequency



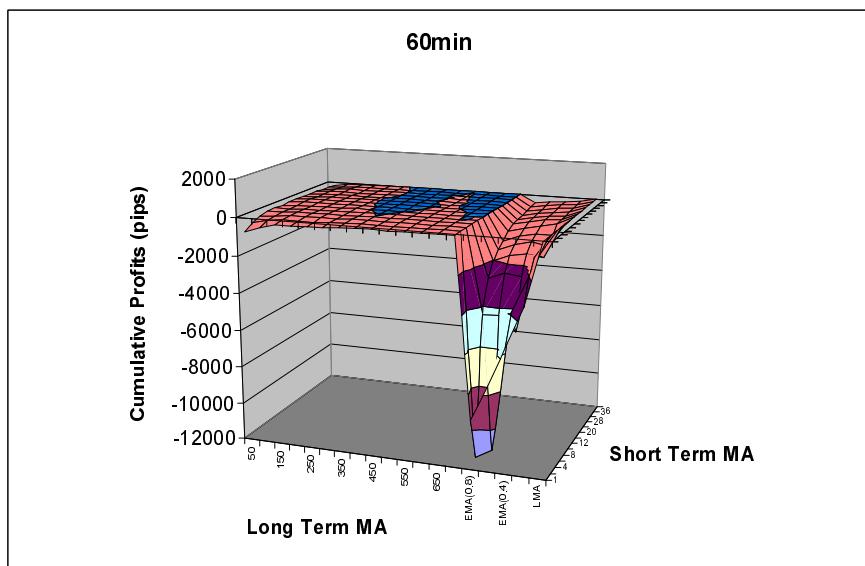
Appendix Figure A.5: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy Ar at Daily Frequency



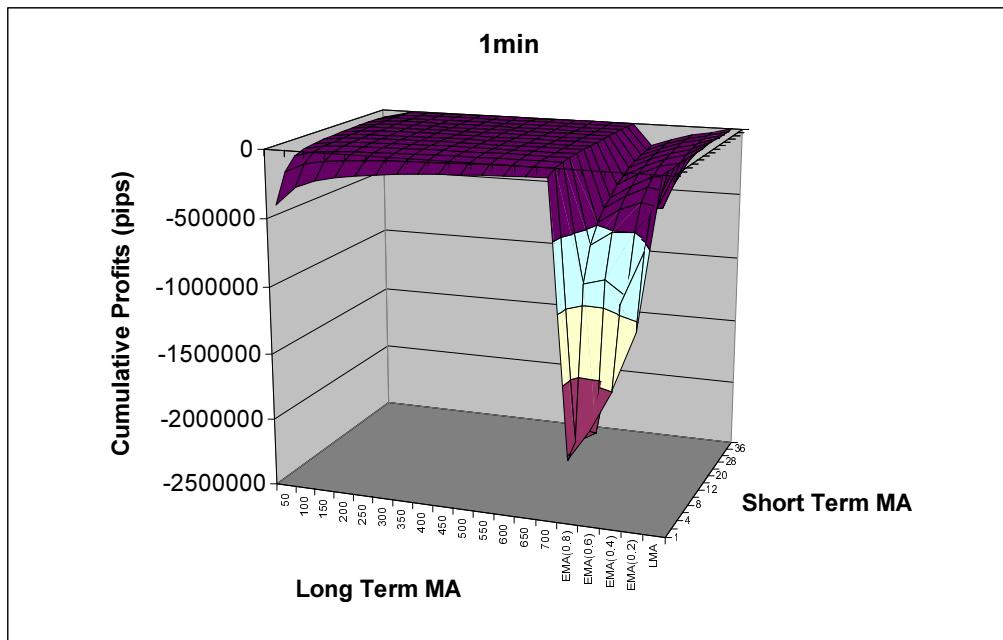
Appendix Figure A.6: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy Ar at 480min Frequency



Appendix Figure A.7: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy Ar at 240min Frequency



Appendix Figure A.8: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy Ar at 60min Frequency



Appendix Figure A.9: Slippage Adjusted Trading Profits of Moving Average Crossover Rules with Exit Strategy Ar at 1min Frequency

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