Can Technical Pattern Trading Be Profitably Automated?

1. The Channel

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1. The Channel

Financial markets, such as the global foreign exchange (FX) market, often exhibit trending behaviour. Within such trends, the market level oscillates with changes in market consensus. Continued oscillations of this type result in the formation of wave patterns within the underlying trend known as *channels,* which are used by technical analysts as trade entry signals. A sample space of such channels has been constructed from a set of US Dollar/British Pound Spot FX tick data from 1989-97 using pattern recognition algorithms and the profitability of trading using such patterns has been estimated. A number of attributes of the resulting collection of channels has been subjected to statistical analysis with the aim of classifying patterns that can be traded profitably using a number of simple trading rules. Results of this analysis show that there exist statistically significant links between the channels' attributes and profitability.

1 Introduction

Technical analysis is the study of historical price data with the aim of predicting future price levels. Technical analysts who trade markets on the basis of this prediction are known as *technical traders*. Despite the supposed irrationality of such activity under the commonly held assumption (by economists, at least) of efficient markets, technical trading has been found to generate statistically significant profits in a number of markets. Excess profits as a result of technical trading have been found to exist in stock markets by Brock, Lakonishock and LeBaron [3] and in foreign exchange markets by Dooley and Schaffer [5], Levich and Thomas [8], and Sweeney [19].

The majority of work published on technical analysis has been based on filters and indicators such as the moving average. This is a result of the ease with which such indicators can be expressed algebraically. More recent work considers the use of genetic algorithms to find technical trading rules (see Neely and Weller [12], [13] and Allen and Karjalainen [1]) and the problems of 'data-snooping' when evaluating rules (Timmermann et al [20]). A large amount of technical analysis, however, is applied to technical patterns – visual patterns that can be seen to occur on price-time charts[1]. Good examples of such include the interestingly named *head & shoulders*, *flags*, *pennants* and *wedges* and can be found in Schwager [17] or Pring [16]. Such patterns do not have simple algebraic representations and, despite being easy to identify with the eye, are highly complex to represent in a systematic fashion. There is, however, some work published which contains systematic analysis of technical patterns. Levy [9] tests the profitability of a number of '5-point' chart patterns but finds no evidence of forecasting ability and Neftci [11] considers the problem of hindsight when analysing trading patterns and indicators. Osler and Chang [15], and Osler [14] test the head and shoulders pattern on a number of FX and stock markets and find statistically significant profits in some markets. There has, however, been no work that considers pattern trading under the added realism afforded by the use of high frequency. Furthermore, there has been no work on the enhancement of pattern trading.

In this paper, we aim to analyse a little known technical trading pattern known as the *channel*. Like Osler and Chang, we search for occurrences of the pattern in question using an algorithm based on local maxima and minima. However, unlike most of the existing work, we used *high frequency* (minute by minute) data. This allows us to be more realistic in our replication of a technical trader since we can

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[1] Osler [14] discovers a marked rise in trading volume within US equity markets following 'head and shoulders' entry signals.

search for occurrences of the pattern on an intra-day basis as well as make use of intra-day cash management strategies – rules used by most technical traders to protect themselves against extreme loss.

The channel is not a well known technical analysis trading pattern. Our interest in the pattern results from being approached by a Florida based trading house, FutureLogic Trading, in 1997. FutureLogic (FL) trades the accounts of a number of *high net worth* individuals using technical trading strategies. They were interested in using the channel pattern as one of their trading strategies and contracted us to investigate the potential profitability of trading such configurations (FL had thought the pattern appeared to be 'profitable' but were keen to see an objective systematic analysis). Furthermore, they asked us to attempt to enhance profitability by constructing filters and trading rules that were additional to those that they were intending to use on this pattern.

As a result, we offer new work on trading rule improvement in this paper. Here, we apply a number of statistical tests and analyses to our set of collected patterns and attempt to create profit enhancing filters based on the market conditions before and during the pattern's formation.

Despite FL's claims to the contrary, we find the pattern to be loss-making. We do, however, find links between the patterns appearance and profitability but fail to gain conclusive results from attempts to use such relationships to enhance profitability.

In Section 2 of this paper we describe the spot FX data on which we base our analysis. Section 3 describes the characteristics of the channel pattern and the methodology used to analyse it. In Section 4 we present results and we summarise our work and conclude in Section 5.

2 **The Data**

This analysis was carried out on spot foreign exchange (FX) tick[2] 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 of FX brokers whereas the FutureSource data, stored from a live satellite feed via the Omega TradeStation utility, is the

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

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: ½(bid + ask) or, by definition, (bid + ½ spread) or (ask ½ 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 pips[3] 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 $\{(q_i, t_i) \mid 0 < i \leq K ; i, K \in Z^+\}$ 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 τmin frequencies; e.g. if $\tau = 1$ then frequency is minutely and denoted 1min (but 1440min is called *daily*).

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[3] A *pip* is the minimum allowable change in price – in this case $0.0001.

The aggregation to OHLC τmin frequencies results in the following dataset:

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

where

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

$$b_0 := 0$$

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

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

$$h_j = \max\{q_{io}, q_{io+1}, \ldots, q_{ic}\}$$

$$l_j = \min\{q_{io}, q_{io+1}, \ldots, q_{ic}\}$$

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.

As we will discuss in more detail in Section 3, the aim of analysis of the channel pattern was to aid a group of traders who have been trading the pattern 'by eye' using a live FutureSource data feed visualized through Omega Tradestation. With such apparatus, 'market close' points are imposed at 2200 GMT and 0100 GMT. Such a structure was mirrored when analysing the channel pattern, resulting in shortened bars at some frequencies due to such premature closes.

Finally, the data was split into two groups –*sample data* and *test data*. The sample dataset ranges from 6.89 to 12.96 inclusive and the test dataset ranges from 1.97 to 12.97 inclusive; these sets are known as the *C-sample* data and the *C-test* data respectively.

As discussed in the introduction, this analysis was a result of being approached by a US trading group, FutureLogic, who wanted descriptive results based on a large historical dataset that they could begin work on themselves. As a result, the whole dataset at the time, the *C-sample* dataset (6.89-3.96) was used in the initial analysis and the data accumulated since then, the *C-Test* dataset, has been used subsequently for testing.

3 The Channel Pattern

3.1 Description

The *channel* configuration is a market pattern traced by *open* and/or *close* points of market price data. The pattern is similar to a regular sine wave, consisting of a pair of 'peaks' and a pair of 'troughs', with a necessary condition being that the line joining peaks be parallel to the line joining troughs. We consider two different configurations: 'up'-channels and 'down'-channels.

The up-channel (an idealised version of which is depicted in Figure 3.1) consists of a peak-trough-peak-trough configuration, denoted T1-S1-T2-S2 (T standing for target, S for source, as will become apparent when trading is considered). The market price level of T2 is higher than that of T1, giving the line T1T2 a positive gradient in price-time space. By virtue of the line S1S2 being parallel to the line T1T2 in price-time space, the line S1S2 also has a positive gradient and, therefore, the market price level of S2 lies above that of S1.

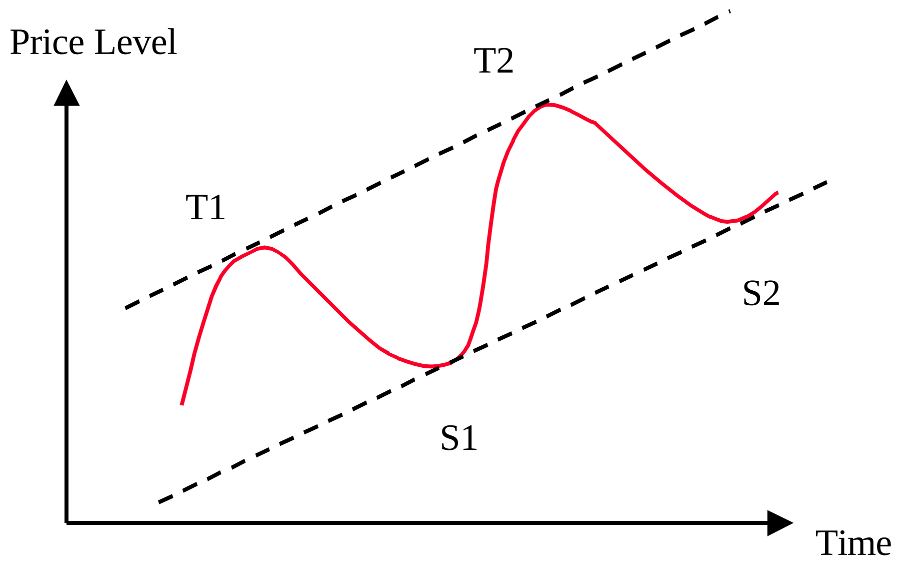

Figure 3.1: The Up-Channel Pattern

The down-channel (an idealised version of which is depicted in Figure 3.2) consists of a similar trough-peak-trough-peak configuration, denoted T1-S1-T2-S2 but the defining parallel lines have negative gradients in price-time space.

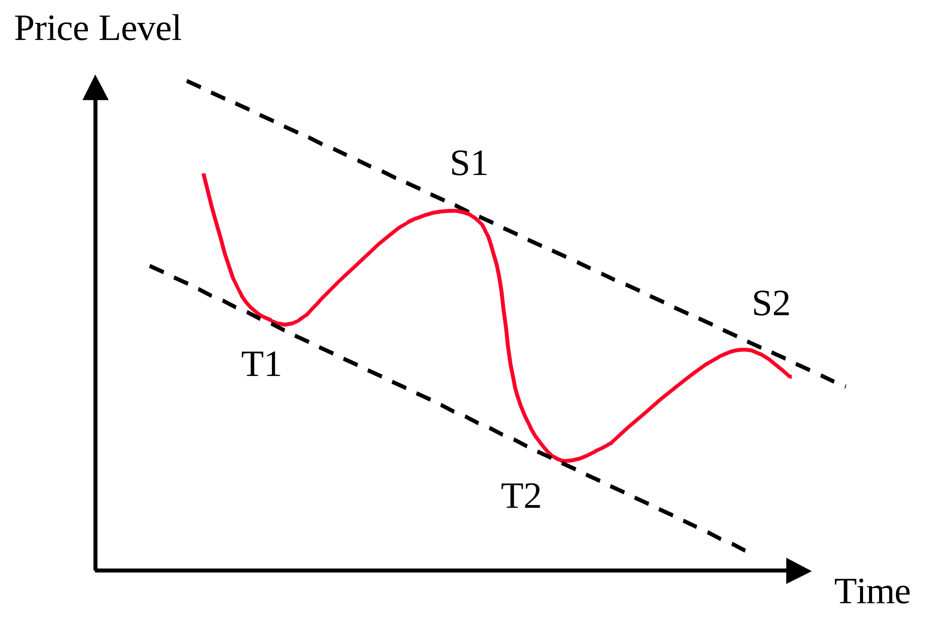

Figure 3.2: The Down-Channel Pattern

Figure 3.3 shows a channel pattern isolated from BPUS spot FX data displayed as Japanese candlestick bars (a visualisation scheme which is discussed in Schwager [17]).

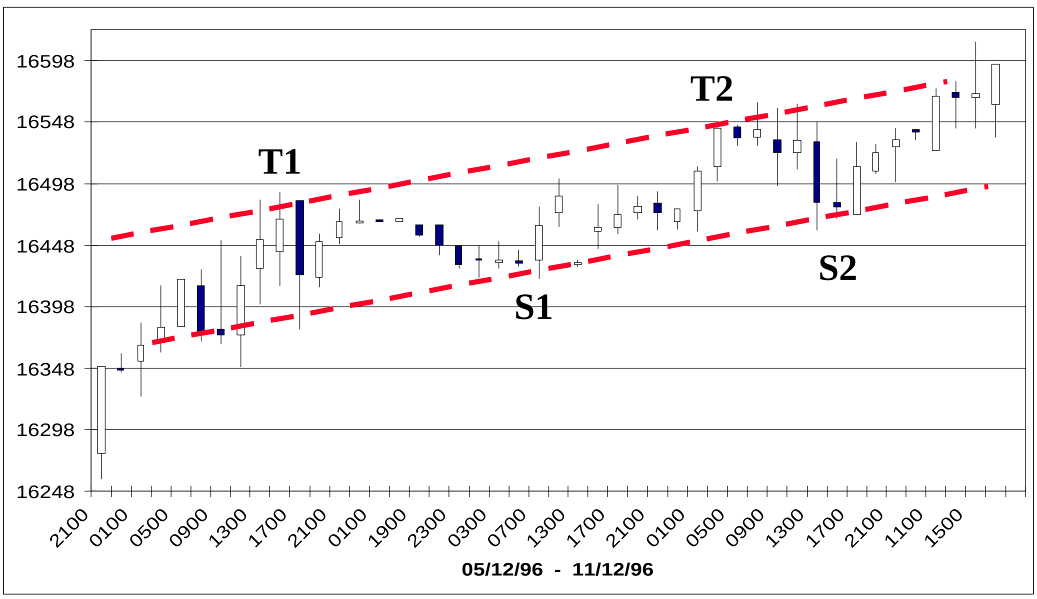

Figure 3.3: Isolated Up-Channel Pattern

3.2 Trading Channel Formations

In order to be of practical use, any trading pattern needs to have a set of trade entry and exit rules associated with it. FL had some idea of the trading rules they wished to use in conjunction with the channel pattern which were then made rigorous as part of our analysis.

The aim was to enter the trade as soon as the channel formation occurs. This is when the S2 turning occurs such that the line S1S2, known as the *source wall*, is (approximately) parallel to the line T1T2, known as the *target wall*. The trade is then entered as soon as some confirmatory entry signal, based on the market price action, is registered. If an up-channel is to be traded then a long position is established whereas if a down-channel is to be traded then a short position is established. Should a valid entry signal not be received within a set period of time or should the market price action send some negating signal, then the potential trade is abandoned.

Once the trade is entered, 'successful' trade exit occurs when the market price reaches a level defined by a band running parallel to and surrounding the target wall. Otherwise, trade exit occurs when the trade has been active for a set period of time, or when the market price reaches a level defined by *stops* – pre-established price levels set to limit loss. Trailing stops are usually used; here, the trade is exited when, given a long (short) position, the market falls (rises) from its maximum (minimum) point by a predetermined amount. Stops and trailing stops are described in detail in Schwager [17]; a recent analysis of exit strategies is carried out by James & Thomas [6].

3.3 Methodology

An algorithm has been constructed to isolate up- and down-channel patterns at a number of different data frequencies and the algorithm has been coded (in Visual Basic on a P200 PC) to allow fast automatic pattern isolation. Using the 60min data frequency as a proxy for all frequencies, a number of different trade entry and exit rules have been tested on the set of channel pattern specimens isolated on 7 years of BPUS spot FX tick data – the *C-sample* data – aggregated to 60min frequency. The combination of rules that yielded the best slippage-adjusted profits have been applied to the set of isolated channel pattern specimens on the following data frequencies: daily, 480min, 240min, 120min, 60min, 30min, 15min, 10min, 5min, 2min, 1min.

The resulting slippage-adjusted profit distributions have been analysed. Pattern attributes that give insights to each pattern's shape and the market price's action prior to and during the pattern's formation have been isolated. Various statistical analyses have been performed on the resulting pattern attributes and slippage-adjusted profits and classification rules constructed which have been tested on a test data set of one year of BPUS spot FX data from 1997 (the *C-test* data). Finally, as a result of the analysis, trading rules and filters have been constructed and tested on the sample and test data and resulting shifts in profit/loss have been analysed.

In order to gain an appreciation of the key points of the pattern and to build a test set in order to validate any automatic isolation algorithm or code, a year of BPUS spot FX data at the usual range of frequencies was searched by inspection and the channel specimens were isolated.

FL was then presented with this set and confirmed that it matched the profile that they were interested in (they had also been isolating patterns by inspection).

An algorithm was then developed to automate the isolation procedure. In the isolation algorithm, we look, essentially, for potential peaks and troughs by searching for local maxima and minima. Furthermore, we check to see that various constraints, needed for the pattern to resemble the sine wave we expect to see, are not broken. In Figure 3.4 we provide a pictorial representation of each step of the isolation algorithm which can be found in more detail in Jones [7].

To facilitate fast, automatic pattern isolation, the algorithm has been coded in Visual Basic. The software searches the chosen data set automatically and lists the co-ordinates of any up- or down-channel formation. For test purposes, the algorithm was applied to the data set on which channel patterns have been isolated by inspection and the automatically and 'hand' isolated channels were matched up. The software user interface screen is displayed in Figure 3.5.

A number of trading rules and combinations of rules were tested on the set of channels isolated in the 60min frequency *C-sample* data and the 'best' rule/collection of rules was identified. The testing procedure was constructed to imitate actual trading in as much as it made no use of hindsight.

The channel patterns were used as a technical trader would use them – as entry signals. As soon as the channel configuration was confirmed, i.e. as soon as the market had completed forming the S2 turning point, the rule/set of rules was activated and then trade entry was simulated if and when the trading rules emitted a trade entry signal. Similarly, trade exit was simulated when the appropriate exit rule was activated.

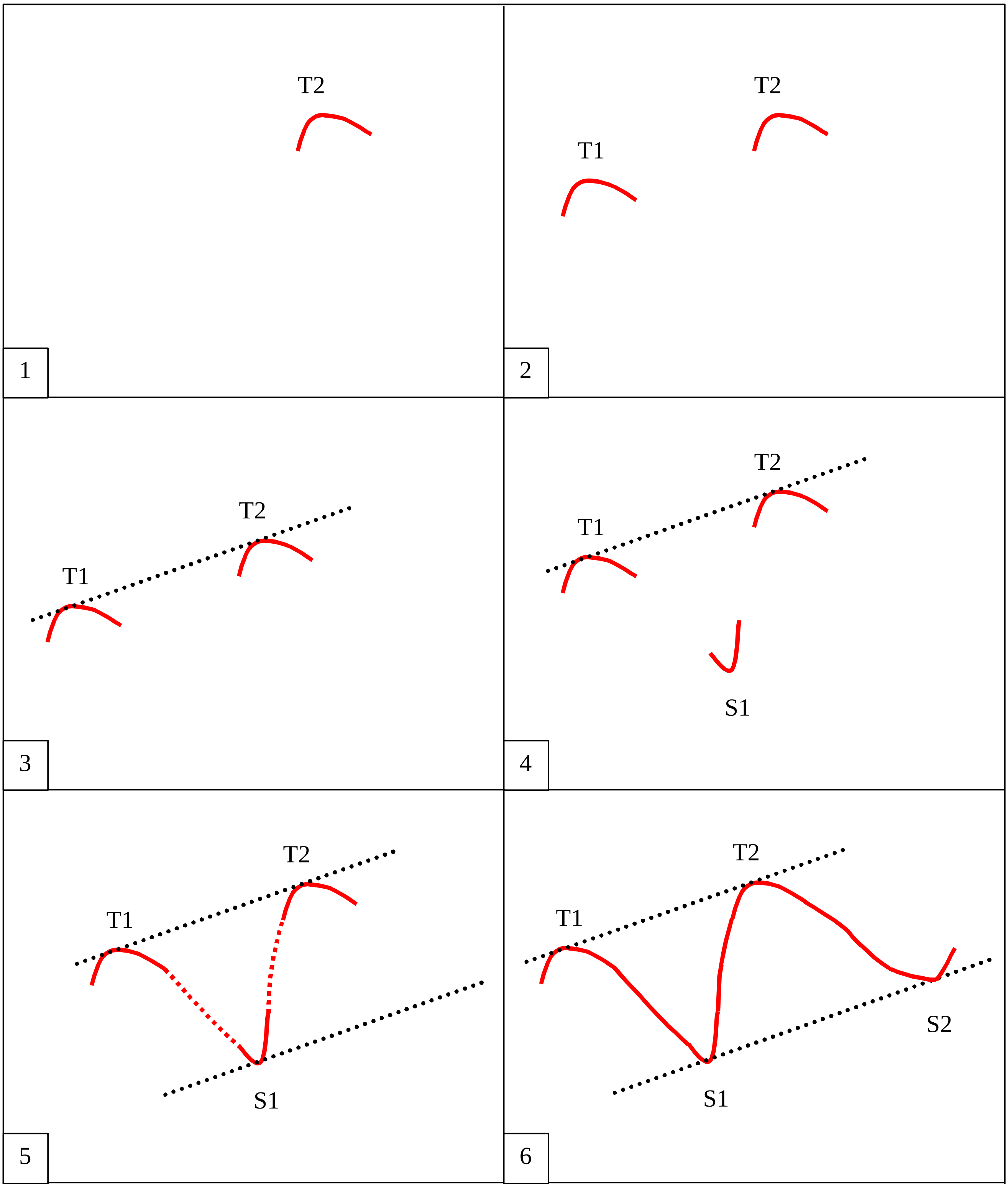

Figure 3.4: Pictorial Representation of Up-Channel Isolation Algorithm

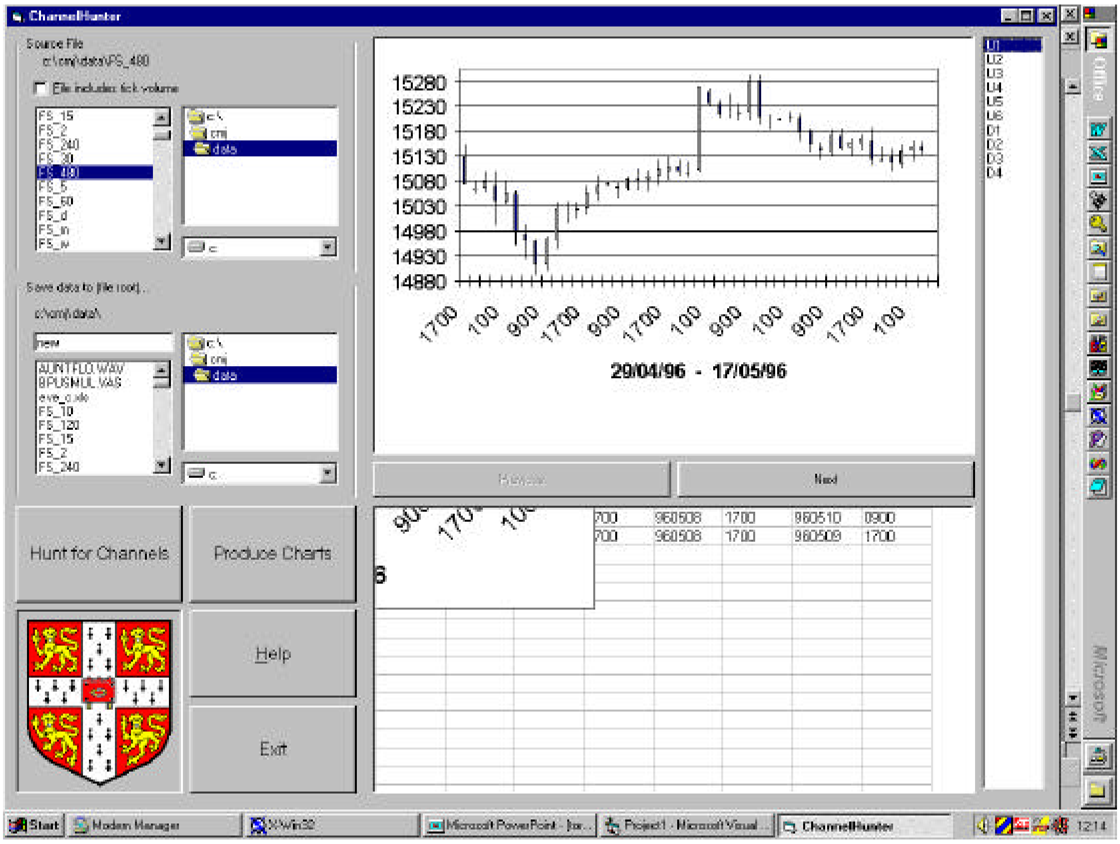

Figure 3.5: User Interface of Channel Isolation Software

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, over all ‘entered’ trades (since sometimes, due to market behaviour, the entry rule did not emit an entry signal). Slippage (including transaction costs) was taken to be a flat 20 pips per round turn (*buy and sell* or *sell and buy*). For example, if we bought British Pounds at $1.6100 and sold at $1.6150 then our pips profit per pound traded before slippage and transaction costs would be $(1.6150 – 1.6100) = $0.0050 = 50 pips and, with adjustment for slippage and costs would be (50 – 20) pips = 30 pips per traded pound.

As soon as the channel pattern is formed, entry and exit rules read the 1min frequency data at the corresponding time. Once more, this is aimed at replicating the actions of the technical trader who, once he has gained his entry signal from the technical pattern, will look at the higher frequency for entry and exit signals and not ‘sit on his hands’ while another hourly bar is fully formed.

FL was consulted on the initial selection of entry and exit rules and their ‘intuitive’ rules were made rigorous and formulated as the following:

> *Enter trade once the S2 point has been formed and the market has moved in the direction of the channel (up or down) by 15% of the vertical channel width from the S2 turning point;*
>
> *If no signal is reached after a fixed number of bars then abandon trade;*
>
> *If the trade is entered then exit when either target wall is hit, the source wall is hit in an adverse market move, a trailing stop is hit or a fixed number of bars have passed since S2 was formed.*

These rules were then coded as an extension to the channel isolation software and tested on the 60min frequency *C-sample* data whenever the channel pattern occurred; the performance – tested in terms of average profit – was noted. The parameters of these rules were then changed and various new rules were added and, in each case, the performance was tested.

The new rules were developed by paying much attention to the behaviour of the exit rules. The various rules are listed and their performance discussed in Section 4.

The best set of rules was identified and applied to the following data frequencies: daily, 480min, 240min, 120min, 60min, 30min, 15min, 10min, 5min, 2min, 1min and, in each instance, the rules’ performance was measured.

The best set of rules was as follows:

> *Enter trade once the S2 point has been formed and the market has moved in the direction of the channel (up or down) by 25% of the channel width from the source wall;*
>
> *If no signal is reached after a fixed number of bars then abandon the trade;*
>
> *If the market moves by outside a band placed at 15% of the channel width away from the source wall in an opposite direction of the channel then abandon the trade;*

If the trade is entered then exit when either target wall is hit, the 15% error band below (above for down-channels) the source wall is hit in an adverse market move, a trailing stop is hit or a fixed number of bars have passed since S2 was formed.

In order to analyse any linkage between pattern shape and profit, various characteristics of the patterns, that give insights into each pattern's shape and the market price's action prior to and during the pattern's formation, have been measured for each pattern. The characteristics, or attributes, considered are listed below:

CA1	*bar velocity*	ratio of T1T2 price move to T1T2 barcount
CA2	*vertical channel width*	vertical distance between source and target walls
CA3	*perp. channel width*	perpendicular (to wall) distance between source and target walls
CA4	*velocity*	ratio of T1T2 price move to time elapsed between T1 and T2
CA5	*S1 symmetry*	ratio of T1S1 barcount to T1T2 barcount
CA6	*S2 symmetry*	ratio of T2S2 barcount to T1S1 barcount
CA7	*leg-in*	5-bar momentum at T1 (price level at T1 – close value 5 bars before)
CA8	*T1T2 barcount*	Bars elapsed between T1 and T2.

These attributes can all be measured at or before the pattern's formation and so any predictive power with respect to trading profitability can be exploited in a 'live' trading situation.

Various statistical analyses have been carried out and, as a result, classification rules to classify profitable situations with respect to above attributes have been constructed.

3.4 The Channel Pattern – Summary

Above, we outline work that has been carried out on a technical trading pattern known as the channel pattern – a little known technical trading pattern that we have analysed as a collaborative project with a US trading house. Using BPUS spot FX tick data aggregated to various frequencies, we have developed an algorithm to isolate specimens of such a pattern. Trading rules, that use the pattern as an entry signal, have been constructed and their performance tested. Pattern attributes have been analysed for any linkage with trading profit and rules to classify profit-making patterns by attribute have been constructed. The results of this work can be found in the next section.

4 Results

First we present the results of tests to choose the best set of trading rules. Further, the slippage adjusted profitability of such trading rules applied to BPUS spot FX data is examined for each pattern. Next, the link between various attributes of each pattern and trading profit is explored - initially by analysing the statistical significance of the difference between mean attribute values of patterns grouped with respect to profitability and then by constructing classification rules with the aim of classifying profitable patterns by consideration of attributes alone. Such classification rules are then tested on a separate set of BPUS data.

Results are presented in table form following this text.

4.1 Profitability Analysis

In Table 1, we present the results of testing a number of different sets of trading rules at the 60min data frequency in conjunction with the channel technical trading pattern, along with a description of each rule. Any occurrence of the pattern was taken to be a primary trade entry signal and a position was taken on the signal of the entry rules that we have tested. Trade exit was on the signal of the tested entry rules.

As discussed in Section 3.3, performance of each set of rules is measured by average profit per trade. Profit is measured in ‘pips per traded British Pound’ and adjusted for slippage. Trading situations that are abandoned before entry are ignored.

Note from Table 1 that the slippage-adjusted profits are consistently negative and losses are greater than the slippage deduction of twenty pips. Therefore, before slippage is even considered, this trading strategy is loss-making.

The improvement from worst to best trading rule is less than 5 pips for up-channels and less than 10 pips for down channels.

For up- and down-channels, the best set of rules was Set 12 and this rule-set was applied to data at various data frequencies. The results, presented in Tables 2a and b, show that in all but one instance – the daily frequency for down-channels, losses are made. Furthermore, when losses are made they are greater than the slippage deduction in all but one case – 240min up-channel - and so profit before slippage is also generally negative.

For both up-and down channels we find that slippage-adjusted profit distributions have negative means (as the above results imply) but, with the exception of the 1min frequency, have positive skewness. In the case of 1min frequency, skewness is negative and, furthermore, kurtosis is significantly higher than for other frequencies.

Tables of descriptive statistics and histograms for slippage-adjusted profits can be found in Jones [7] and an example of a profit histogram can be found in Figure 4.1, below.

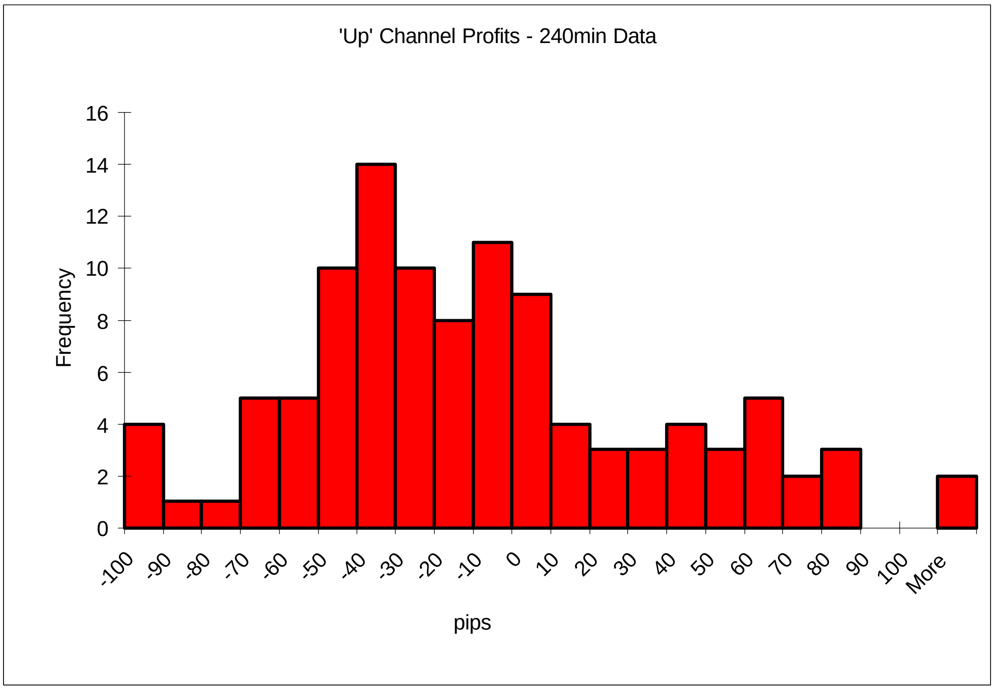

Figure 4.1: Profit Histogram for 'Up' Channels at 240min Frequency

4.2 Analysis of Pattern Attributes

Having found no radical difference between performance results at many frequencies, we restrict our analysis to the following frequencies: daily, 480min, 240min, 60min and 1min. These particular frequencies appear to be the most popular amongst traders.

Table 3 shows the results of a *Wilkes lambda* test (see Sharma [18]) on the eight different attributes of the channel patterns isolated in the *C-sample* data (1989-96). The samples have been split into 4 groups on the basis of slippage adjusted profits:-

large profit (>60 pips),

small profit (60 pips ≥ p > 0 pips),

small loss (0 ≥ l ≥ -60 pips),

large loss (<-60 pips).

The threshold value of 60bp has been chosen to fall in with the needs of the sponsor.

The first section of the table (top of page) displays the results of the test (in terms of statistical significance) when sets of attributes are partitioned into 4 groups as above.

The second section of the table (middle) displays the results of the test (in terms of significance) when sets of attributes are partitioned into 2 groups: *large loss* and *other*.

The third section of the table (bottom) displays the results of the test (in terms of significance) when sets of attributes are partitioned into 2 groups: *large profit* and *other*.

Various attributes differ significantly between groups at different data frequencies. Attributes CA1 – CA4 give particularly promising and consistent significance levels for up-channels.

Next, a number of discriminant analyses (described in Sharma [18]) were carried out using the channel attributes as independent variables with profit, grouped as above, as the dependent variable. Various inclusion rules were tried including those based on the Wilkes lambda test significance values presented above. A *stepwise* discriminant analysis was also tried. Eventually, it became evident that the most powerful analysis (in terms of classification) would be achieved by including all attributes.

The resulting canonical discriminant functions show reasonable levels of significance but the associated *squared canonical correlation* (cc^2) values are often very low (usually <<1). The exceptions to this are the cc^2 values at daily level in the 'up' and 'down' multiple discriminant analysis (mda). These values can be found in Jones [7].

Tables 4a and 4b present classification matrices (actual grouping along the vertical, proposed group along the horizontal) resulting from a 4-group multiple discriminant (4mda) analysis of the sample data with groupings as above.

The lower part of the table contains the results of classification of an out-of-sample data set - the *C-test data* (1997) - using the classification functions derived from the 4mda of the sample data.

'% correct' is the percentage of group members that have been correctly classified as such.

'% better than chance' is the excess of '% correct' over the expected result should classification be left to chance, expressed as a percentage; e.g. in the 4mda, chance would be 25% and so should, under the 4mda classification regime, 50% be correctly classified then this would be 100% greater than chance.

'% correctly identified as p/l' lists the percentage of profits (large and small) correctly identified as profits (large or small), and the percentage of losses (large and small) correctly identified as losses (large or small).

The overall number of correctly classified entities, expressed as a percentage, can be found in the extreme left hand column.

There are no large profits in the patterns isolated in the daily data and so here, a 3 group analysis has been carried out.

For 'up' and 'down' channels, in both test and sample data, classification results are consistently better than if left to chance at 480min and 1min levels.

The upper parts of the Tables 5a and 5b present classification matrices (actual grouping along the vertical, proposed group along the horizontal) resulting from a 2-group discriminant (-2da) analysis of the sample data with groupings as *large loss* or *other* as before.

The lower part of the table contains the results of classification the *C-test data* (1996-7) using the classification functions derived from the -2da of the sample data.

All classification in the sample data is better than if left to chance whereas results are mixed in the test data. For both ‘up’ and ‘down’ channels there are good test data results at 480min and 1min level; also, ‘down’ channels have good results at the 60min level. There is not enough data to analyse at *daily* frequency. It is hard to properly interpret results in the test data due to the scarcity of ‘large profit’ and ‘large loss’ channels.

Tables 6a and b report results from a 2-group discriminant analysis (+2da) with groupings as *large profit* or *other,* as previously defined. Reporting is in the same style as for the –2da.

There are no large profits in the patterns isolated in the daily data and so here, no analysis has been carried out. Results here are mixed and interpretation is further impaired by the scarcity of ‘large profit’ channels.

Tables 7a and 7b present the results of classification using the rules from both +2da and –2da (+/-2da).

The classification rules used are as follows:

if classified as -2 by the -2da rules and *other* by the +2da rules then classify as –2;

if classified as -2 by the -2da rules and +2 by the +2da rules then classify as *other*;

if classified *other* by the -2da rules and +2 by the +2da rules then classify as +2;

if classified *other* by the -2da rules and *other* by the +2da rules then classify as *other*.

‘% better than chance’ is the excess of ‘% correct’ over the expected result should classification be left to chance, expressed as a percentage; e.g. in the above analysis, chance would be 100/3% and so should, under the above classification regime, 66.67% be correctly classified then this would be 100% greater than chance.

As one would expect from previous tables, the scarcity of large profits and losses makes the results difficult to interpret. However, for ‘up’ channels, results are reasonably good at 480min and 240min levels.

A large number of different rules for trading the channel pattern have been tested and proven to be generally unprofitable, both before and after slippage considerations.

A number of pattern attributes have been analysed for linkage with profitability. Some attributes – namely velocity (calculated w.r.t. time and bars) and channel width (vertical and perpendicular) – prove to be significantly different between profit-making and loss-making configurations. However, when the attributes are used to construct classification rules and are tested on out-of-sample data, results are mixed.

Despite the initial findings of FutureLogic Trading, when rigorously tested this trading pattern appears to be generally unprofitable. Furthermore, attempts to enhance profitability using the techniques described above show little success.

Despite the lack of success in utilizing the relationships that we have uncovered between profitability and pattern shape, the fact that such relationships exist imply a degree of predictability that is not accounted for in the Efficient Markets Hypothesis. Furthermore, knowledge of such relationships between profit and pattern shape may be of use in enhancing trading strategies for this, or other, technical trading pattern formations.

5 Summary, Further Work and Concluding Remarks

The above work constitutes an effort to conduct a thorough analysis of a technical trading pattern: the channel pattern. By developing proprietary pattern recognition software it has been possible to accumulate large samples of isolated specimens of the pattern – a job that would be unfeasible were it to be attempted using hand and eye alone. Given these samples, it has been possible to test a number of different trading rules associated with the pattern and assess its profitability. The pattern did not prove to be consistently profitable, despite being thought of as such by our colleagues at FutureLogic.

Various attributes that hold information about the pattern's shape and formation were isolated with each specimen and a statistical analysis was conducted which aimed to discover any link between such attributes and the pattern's profitability. As a result such links were discovered to exist at a statistically significant level. However, these dependencies could not effectively be exploited to develop trading filters that improved significantly upon profitability.

This work is merely an indication of what is needed in this area. Few studies mix the analysis of trading rules with the use of high frequency data and so there is much work to be done in many related areas. For a start, there exists a litany of trading patterns and it may be the case that others are immediately profitable[4]. In future, it would be of great use to subject the methods of inter-market technical analysis (as discussed in Murphy [10]) to rigorous analysis in an attempt to discover the link between trading profitability and the movement of other related markets, e.g. bonds, interest rate futures, stock index futures, etc. Finally, another untapped area that shows promise is the analysis of news and macro-economic indicators on trading profitability[5].

In this paper, every effort has been made to replicate the actions of the trader, from the use of tick data to the application of realistic trading rules with accurate slippage models. To some, these results will be welcomed as proof of the irrational trading behaviour of technical analysis based noise traders. Such a conclusion is incorrect. The most that can be concluded is that trading such patterns in a *solely systematic* manner is unprofitable. The most successful technical traders use such patterns merely as indication of a particular circumstance and, having digested the results of analysing the pattern and many other indicators, will then consider whether or not to place a trade.

It is hoped that this paper will be of use to both academics and practitioners. From an academic point of view, this is the first published study of pattern trading under the realistic conditions afforded by the use of high frequency data and hence contributes to this area of study. Furthermore, we are the first to study the potential for enhancing pattern trading using multivariate statistical methods. Such techniques, we hope, may be of use to those practitioners who work in this area.

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[4] In a companion paper [4] we report on a similar analysis of the popular head & shoulders pattern which met with somewhat more success.

[5] A study of the impact of such macro-level indicators on high frequency data has been published by Almeida et al [2].

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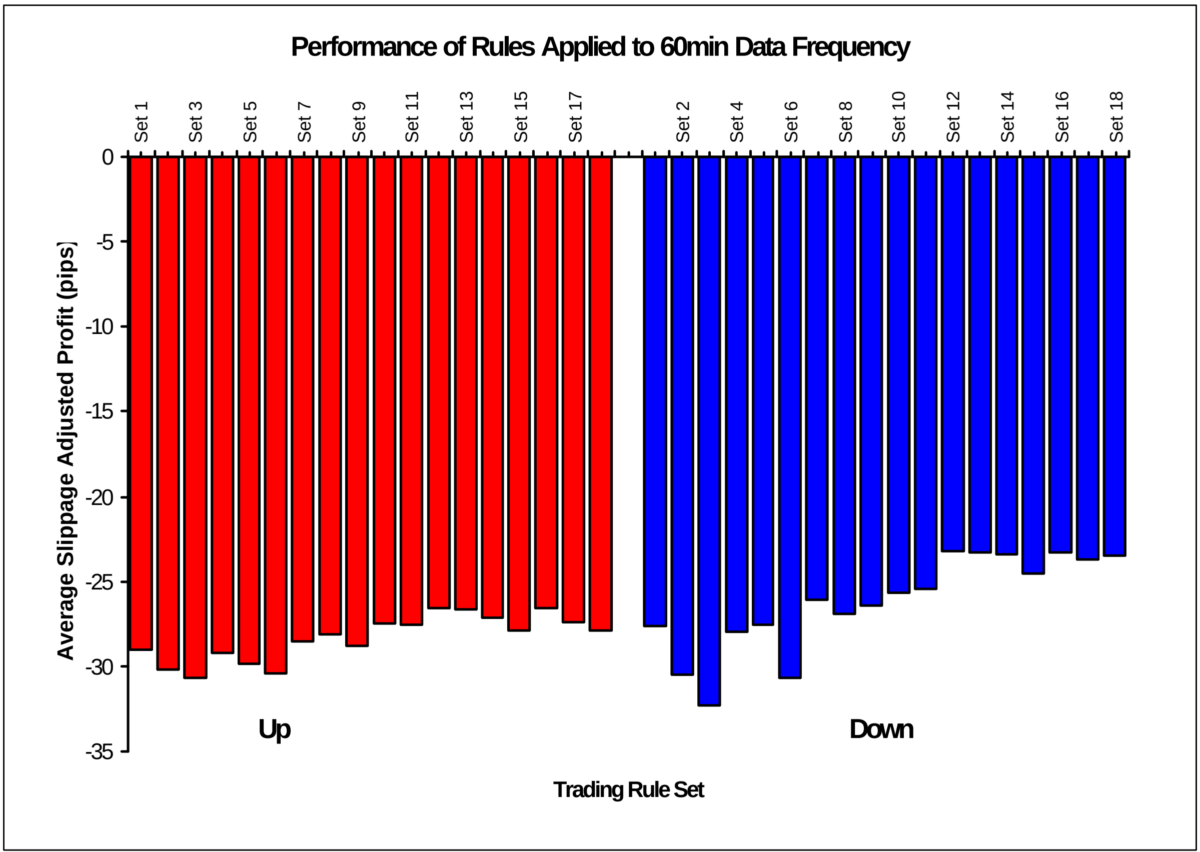
Results Tables



Various Trade Entry & Exit Rules Tested for Channel Trading			
Run 1	entry = 0.15	exit = 1.00	
Run 2	entry = 0.25	exit = 1.00	
Run 3	entry = 0.35	exit = 1.00	
Run 4	entry = 0.15	exit = 0.75	
Run 5	entry = 0.15	exit = 0.50	
Run 6	entry = 0.25	exit = 0.75	
Run 7	entry = 0.15	exit = 1.00	A1
Run 8	entry = 0.25	exit = 1.00	A1
Run 9	entry = 0.15	exit = 0.75	A1
Run 10	entry = 0.15	exit = 1.00	A1 & A2(0.25)
Run 11	entry = 0.15	exit = 1.00	A1 & A2(0.25) & A3(100)
Run 12	entry = 0.15	exit = 1.00	A1 & A2(0.25) & A3(50)
Run 13	entry = 0.15	exit = 1.00	A1 & A2(0.25) & A3(30)
Run 14	entry = 0.15	exit = 1.00	A1 & A2(0.25) & A3(70)
Run 15	entry = 0.15	exit = 1.00	A1 & A2(0.35) & A3(50)
Run 16	entry = 0.15	exit = 1.00	A1 & A2(0.15) & A3(50)
Run 17	entry = 0.15	exit = 0.75	A1 & A2(0.15) & A3(50)
Run 18	entry = 0.15	exit = 0.50	A1 & A2(0.15) & A3(50)
Entry Parameter	Entry threshold at x% of channel width from S2		
Exit Parameter	Exit at (y% of channel width) retracement or in exit zone		
A1	If market moves out of entry zone before trade is entered then do not enter		
A2	Entry threshold at a1% from source wall		
A3	Exit at min((y% of channel width), a2) retracement or in exit zone		

Table 1: Profitability of Various Trading Rules at 60min Frequency

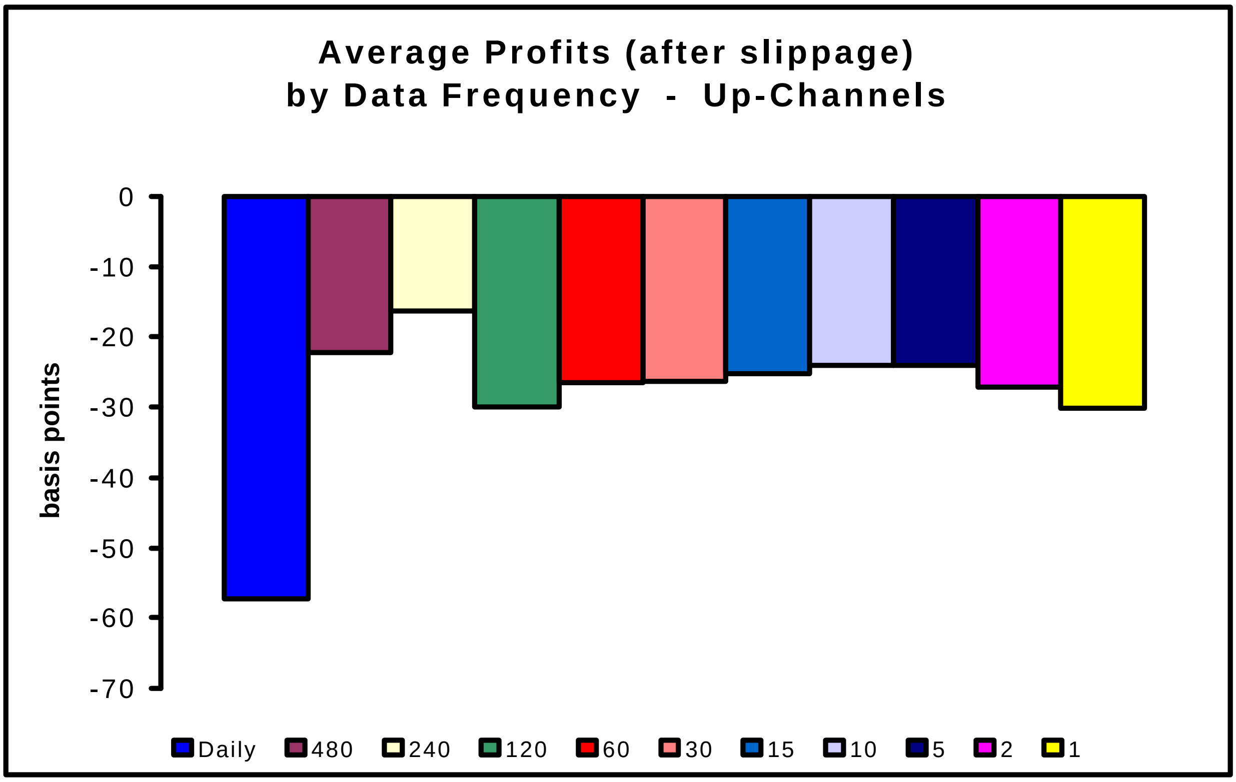


Table 2a: Average Slippage Adjusted Profit of Best Set of Trading Rules (Up)

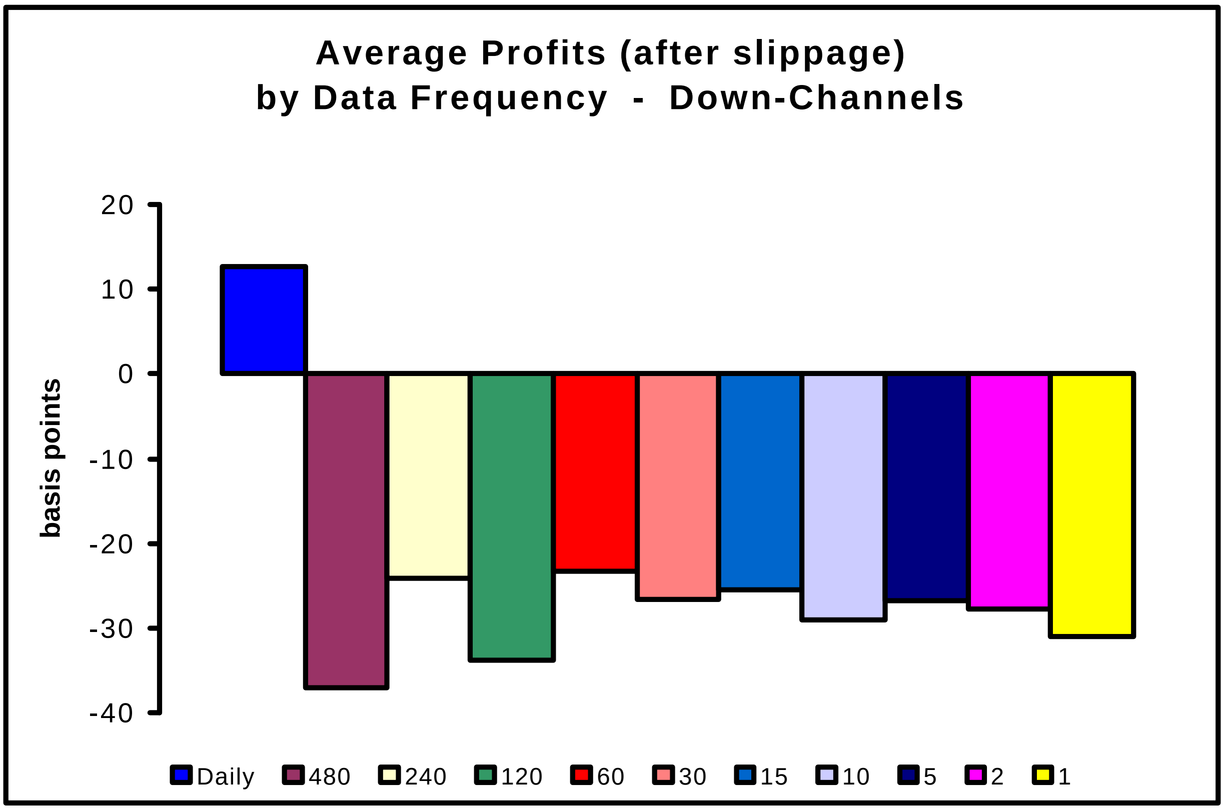


Table 2b: Average Slippage Adjusted Profit of Best Set of Trading Rules (Down)

UP Channels

	Wilke's Lambda Significance for 4 Group Multiple Discriminant Analysis							
	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Daily	83.53%	12.16%	80.64%	89.70%	17.57%	67.41%	39.24%	22.90%
480	93.01%	58.10%	36.39%	83.06%	88.19%	58.99%	14.11%	8.54%
240	86.85%	99.93%	97.87%	97.61%	74.80%	51.39%	27.47%	68.58%
60	99.98%	100.00%	99.73%	99.96%	66.35%	48.48%	12.65%	95.17%
1	100.00%	100.00%	100.00%	100.00%	83.24%	99.04%	92.76%	97.56%

	Wilke's Lambda Significance for 2 Group Multiple Discriminant Analysis (Large Loss or Other)							
	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Daily	76.88%	35.37%	58.79%	70.77%	35.49%	77.07%	37.64%	55.16%
480	94.06%	81.37%	53.68%	94.36%	47.31%	31.08%	46.62%	12.81%
240	81.33%	99.99%	99.62%	39.98%	25.60%	16.78%	7.55%	58.64%
60	99.99%	100.00%	82.17%	99.98%	38.47%	59.87%	5.00%	87.09%
1	100.00%	100.00%	100.00%	97.44%	94.09%	99.90%	13.97%	98.86%

	Wilke's Lambda Significance for 2 Group Multiple Discriminant Analysis (Large Loss or Other)							
	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
480	80.21%	57.83%	31.15%	20.04%	92.54%	91.37%	23.24%	53.44%
240	92.85%	40.78%	85.47%	99.68%	27.74%	15.36%	17.88%	85.90%
60	70.96%	99.94%	34.58%	54.76%	85.47%	19.21%	12.39%	93.21%
1	100.00%	98.60%	59.81%	100.00%	64.02%	54.04%	56.49%	83.48%

DOWN Channels

	Wilke's Lambda Significance for 4 Group Multiple Discriminant Analysis							
	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Daily	60.97%	49.13%	56.94%	60.59%	22.54%	62.69%	83.00%	8.35%
480	58.81%	40.76%	10.13%	59.91%	35.08%	32.92%	58.45%	31.79%
240	10.77%	21.93%	32.71%	30.15%	5.76%	81.84%	85.35%	21.82%
60	99.88%	100.00%	43.99%	99.62%	49.29%	26.44%	45.83%	67.56%
1	100.00%	100.00%	100.00%	100.00%	67.38%	99.14%	74.67%	86.79%

	Wilke's Lambda Significance for 2 Group Multiple Discriminant Analysis (Large Loss or Other)							
	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
480	84.69%	61.94%	32.22%	85.58%	63.00%	51.02%	71.42%	44.79%
240	7.06%	62.28%	61.62%	30.51%	16.63%	14.25%	17.59%	36.04%
60	99.50%	100.00%	14.46%	98.88%	84.02%	20.51%	79.37%	78.45%
1	100.00%	100.00%	100.00%	100.00%	92.30%	99.89%	53.55%	96.15%

	Wilke's Lambda Significance for 2 Group Multiple Discriminant Analysis (Large Loss or Other)							
	CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
Daily	60.97%	49.13%	56.94%	60.59%	22.54%	62.69%	83.00%	8.35%
480	11.31%	4.91%	23.67%	34.49%	6.46%	76.26%	70.32%	64.70%
240	12.98%	34.04%	51.28%	35.06%	2.10%	97.15%	69.07%	16.11%
60	98.99%	97.04%	40.97%	98.22%	47.81%	34.02%	34.62%	83.76%
1	92.68%	58.27%	0.43%	98.33%	33.14%	61.34%	93.75%	75.85%

Table 3: Wilkes Lambda Test Results - Significance

		-2	-1	+1	+2	Group Totals	% correct	% better than chance	% correctly identified as p/l
Sample Data									
Daily	-2	4	0	1	xxx	5	80.00%	140.00%	80.00%
% Correctly	-1	0	2	0	xxx	2	100.00%	200.00%	100.00%
Classified:	+1	0	0	1	xxx	1	100.00%	200.00%	100.00%
87.50%	+2	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
480	-2	3	0	3	1	7	42.86%	71.43%	42.86%
% Correctly	-1	1	14	3	3	21	66.67%	166.67%	71.43%
Classified:	+1	0	0	4	0	4	100.00%	300.00%	100.00%
66.67%	+2	0	0	1	3	4	75.00%	200.00%	100.00%
240	-2	8	1	4	3	16	50.00%	100.00%	56.25%
% Correctly	-1	10	29	14	9	62	46.77%	87.10%	62.90%
Classified:	+1	1	7	9	5	22	40.91%	63.64%	63.64%
46.73%	+2	1	2	0	4	7	57.14%	128.57%	57.14%
60	-2	13	11	8	11	43	30.23%	20.93%	55.81%
% Correctly	-1	31	150	73	34	288	52.08%	108.33%	62.85%
Classified:	+1	4	35	35	10	84	41.67%	66.67%	53.57%
47.43%	+2	3	2	3	5	13	38.46%	53.85%	61.54%
1	-2	73	48	25	11	157	46.50%	85.99%	77.07%
% Correctly	-1	116	1041	414	45	1616	64.42%	157.67%	71.60%
Classified:	+1	19	95	69	16	199	34.67%	38.69%	42.71%
59.93%	+2	0	1	3	3	7	42.86%	71.43%	85.71%
Test Data									
Daily	-2	0	0	0	0	0	xxx	xxx	xxx
% Correctly	-1	0	0	0	0	0	xxx	xxx	xxx
Classified:	+1	1	0	0	0	1	0.00%	-100.00%	0.00%
0.00%	+2	0	0	0	0	0	xxx	xxx	xxx
480	-2	1	0	0	0	1	100.00%	300.00%	100.00%
% Correctly	-1	1	4	2	0	7	57.14%	128.57%	71.43%
Classified:	+1	0	1	1	0	2	50.00%	100.00%	50.00%
60.00%	+2	0	0	0	0	0	xxx	xxx	xxx
240	-2	1	1	2	0	4	25.00%	0.00%	50.00%
% Correctly	-1	2	4	1	3	10	40.00%	60.00%	60.00%
Classified:	+1	0	5	1	1	7	14.29%	-42.86%	28.57%
27.27%	+2	0	1	0	0	1	0.00%	-100.00%	0.00%
60	-2	0	3	1	1	5	0.00%	-100.00%	60.00%
% Correctly	-1	5	29	10	2	46	63.04%	152.17%	73.91%
Classified:	+1	0	6	8	2	16	50.00%	100.00%	62.50%
55.22%	+2	0	0	0	0	0	xxx	xxx	xxx
1	-2	0	0	0	0	0	xxx	xxx	xxx
% Correctly	-1	0	62	29	2	93	66.67%	166.67%	66.67%
Classified:	+1	0	8	3	0	11	27.27%	9.09%	27.27%
62.50%	+2	0	0	0	0	0	xxx	xxx	xxx

Table 4a: MDA Classification Results for Up-Channels

		-2	-1	+1	+2	Group Totals	% correct	% better than chance	% correctly identified as p/l
Sample Data									
Daily	-2	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
% Correctly	-1	xxx	7	xxx	0	7	100.00%	100.00%	100.00%
Classified:	+1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
80.00%	+2	xxx	1	xxx	2	3	33.33%	-33.33%	33.33%
480	-2	8	2	1	1	12	66.67%	166.67%	83.33%
% Correctly	-1	3	11	1	0	15	73.33%	193.33%	93.33%
Classified:	+1	0	0	1	0	1	100.00%	300.00%	100.00%
73.33%	+2	0	0	0	2	2	100.00%	300.00%	100.00%
240	-2	5	3	6	4	18	27.78%	11.11%	44.44%
% Correctly	-1	7	16	9	2	34	47.06%	88.24%	67.65%
Classified:	+1	3	3	5	1	12	41.67%	66.67%	50.00%
38.89%	+2	1	4	1	2	8	25.00%	0.00%	37.50%
60	-2	16	9	8	9	42	38.10%	52.38%	59.52%
% Correctly	-1	39	114	62	39	254	44.88%	79.53%	60.24%
Classified:	+1	13	36	29	12	90	32.22%	28.89%	45.56%
41.25%	+2	3	3	2	6	14	42.86%	71.43%	57.14%
1	-2	71	43	12	21	147	48.30%	93.20%	77.55%
% Correctly	-1	101	811	307	163	1382	58.68%	134.73%	65.99%
Classified:	+1	10	70	29	27	136	21.32%	-14.71%	41.18%
54.76%	+2	1	0	1	4	6	66.67%	166.67%	83.33%
Test Data									
Daily	-2	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
% Correctly	-1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
Classified:	+1	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
xxx	+2	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
480	-2	1	0	0	1	2	50.00%	100.00%	50.00%
% Correctly	-1	0	7	0	2	9	77.78%	211.11%	77.78%
Classified:	+1	0	1	1	0	2	50.00%	100.00%	50.00%
64.29%	+2	0	1	0	0	1	0.00%	-100.00%	0.00%
240	-2	1	0	1	2	4	25.00%	0.00%	25.00%
% Correctly	-1	4	5	4	2	15	33.33%	33.33%	60.00%
Classified:	+1	0	1	0	0	1	0.00%	-100.00%	0.00%
30.00%	+2	0	0	0	0	0	xxx	xxx	xxx
60	-2	0	0	0	0	0	xxx	xxx	xxx
% Correctly	-1	3	22	10	10	45	48.89%	95.56%	55.56%
Classified:	+1	0	0	7	3	10	70.00%	180.00%	100.00%
52.73%	+2	0	0	0	0	0	xxx	xxx	xxx
1	-2	0	0	0	0	0	xxx	xxx	xxx
% Correctly	-1	0	45	30	11	86	52.33%	109.30%	52.33%
Classified:	+1	0	6	2	1	9	22.22%	-11.11%	33.33%
49.47%	+2	0	0	0	0	0	xxx	xxx	xxx

Table 4b: MDA Classification Results for Down-Channels

		-2	Other	Group Totals	% correct	% better than chance
Sample Data						
Daily	-2	4	1	5	80.00%	60.00%
87.50%	Oth	0	3	3	100.00%	100.00%
480	-2	6	1	7	85.71%	71.43%
75.00%	Oth	8	21	29	72.41%	44.83%
240	-2	9	7	16	56.25%	12.50%
76.64%	Oth	18	73	91	80.22%	60.44%
60	-2	28	15	43	65.12%	30.23%
78.04%	Oth	79	306	385	79.48%	58.96%
1	-2	84	73	157	53.50%	7.01%
88.48%	Oth	155	1668	1823	91.50%	83.00%
Test Data						
Daily	-2	0	0	0	xxx	xxx
0.00%	Oth	1	0	1	0.00%	-100.00%
480	-2	1	0	1	100.00%	100.00%
80.00%	Oth	2	7	9	77.78%	55.56%
240	-2	1	3	4	25.00%	-50.00%
77.27%	Oth	2	16	18	88.89%	77.78%
60	-2	2	3	5	40.00%	-20.00%
80.60%	Oth	10	52	62	83.87%	67.74%
1	-2	0	0	0	xxx	xxx
100.00%	Oth	0	104	104	100.00%	100.00%

Table 5a: -2DA Classification Results for Up-Channels

		-2	Other	Group Totals	% correct	% better than chance
Sample Data						
480	-2	9	3	12	75.00%	50.00%
76.67%	Oth	4	14	18	77.78%	55.56%
240	-2	9	9	18	50.00%	0.00%
62.50%	Oth	18	36	54	66.67%	33.33%
60	-2	24	18	42	57.14%	14.29%
72.75%	Oth	91	267	358	74.58%	49.16%
1	-2	82	65	147	55.78%	11.56%
87.19%	Oth	149	1374	1523	90.22%	80.43%
Test Data						
480	-2	1	1	2	50.00%	0.00%
71.43%	Oth	3	9	12	75.00%	50.00%
240	-2	1	3	4	25.00%	-50.00%
50.00%	Oth	7	9	16	56.25%	12.50%
60	-2	0	0	0	xxx	xxx
89.09%	Oth	6	49	55	89.09%	78.18%
1	-2	0	0	0	xxx	xxx
97.89%	Oth	2	93	95	97.89%	95.79%

Table 5b: -2DA Classification Results for Down-Channels

		Other	+2	Group Totals	% correct	% better than chance
Sample Data						
480	Oth	26	6	32	81.25%	62.50%
80.56%	+2	1	3	4	75.00%	50.00%
240	Oth	78	22	100	78.00%	56.00%
76.64%	+2	3	4	7	57.14%	14.29%
60	Oth	334	81	415	80.48%	60.96%
79.44%	+2	7	6	13	46.15%	-7.69%
1	Oth	1880	93	1973	95.29%	90.57%
95.10%	+2	4	3	7	42.86%	-14.29%
Test Data						
480	Oth	1	9	10	90.00%	80.00%
90.00%	+2	0	0	0	xxx	xxx
240	Oth	16	5	21	76.19%	52.38%
72.73%	+2	1	0	1	0.00%	-100.00%
60	Oth	61	6	67	91.04%	82.09%
91.04%	+2	0	0	0	xxx	xxx
1	Oth	100	5	105	95.24%	90.48%
95.24%	+2	0	0	0	xxx	xxx

Table 6a: +2DA Classification Results for Up-Channels

		Other	+2	Group Totals	% correct	% better than chance
Sample Data						
Daily	Oth	7	0	7	100.00%	100.00%
90.00%	+2	1	2	3	66.67%	33.33%
480	Oth	27	1	28	96.43%	92.86%
96.67%	+2	0	2	2	100.00%	100.00%
240	Oth	53	11	64	82.81%	65.63%
76.39%	+2	6	2	8	25.00%	-50.00%
60	Oth	290	96	386	75.13%	50.26%
74.50%	+2	6	8	14	57.14%	14.29%
1	Oth	1373	291	1664	82.51%	65.02%
82.46%	+2	2	4	6	66.67%	33.33%
Test Data						
Daily	Oth	xx	xx	xx	xx	xx
xxx	+2	xx	xx	xx	xx	xx
480	Oth	10	3	13	76.92%	53.85%
71.43%	+2	1	0	1	0.00%	-100.00%
240	Oth	16	4	20	80.00%	60.00%
80.00%	+2	0	0	0	xxx	xxx
60	Oth	40	15	55	72.73%	45.45%
72.73%	+2	0	0	0	xxx	xxx
1	Oth	75	20	95	78.95%	57.89%
78.95%	+2	0	0	0	xxx	xxx

Table 6b: +2DA Classification Results for Down-Channels