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Article *in* European Journal of Finance · January 2002

Source: CiteSeer

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The European Journal of Finance **8**, 275–301 (2002)

Can channel pattern trading be profitably automated?

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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 1989–1997 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.

Keywords: technical analysis, technical trading, currency trading, intra-day trading systems, high frequency financial data, multivariate discriminant analysis, pattern recognition

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 – see Fama (1970)) 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, among others, Brock *et al*. (1992) and in foreign exchange markets by Dooley and Schaffer (1984), Levich and Thomas (1993), and Sweeney (1986).

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 *et al.*, 1997; Neely and Weller, 1997; and Allen and Karjalainen, 1999) and the problems of 'data-snooping' when evaluating rules (Timmermann *et al.*, 1997). A large amount of technical analysis, however, is applied to technical patterns –

The European Journal of Finance
ISSN 1351-847X print/ISSN 1466-4364 online
http://www.tandf.co.uk/journals
DOI: 10.1080/13518470110052831

visual patterns that can be seen to occur on price-time charts.[1] Good examples of such include the interestingly named *head and shoulders*, *flags*, *pennants* and *wedges* and can be found in Schwager (1996) or Pring (1985). 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 (1971) tests the profitability of a number of '5-point' chart patterns but finds no evidence of forecasting ability and Neftci (1991) considers the problem of hindsight when analysing trading patterns and indicators. Osler and Chang (1998), and Osler (1995) 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 data. Furthermore, there has been no work on the enhancement of pattern trading.

In this paper, we aim to analyse a well-known yet rarely investigated technical trading pattern known as the *channel* – a pattern traced out by the market (when price is plotted against time) that resembles a sine wave. 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 on technical trading, we used *high frequency* (minute by minute) data. This allows a more realistic replication of a technical trader since we can search for occurrences of the pattern on an intra-day basis as well as make use of intra-day cash management strategies – used by most technical traders to protect themselves against extreme loss.

The channel is not a well documented technical analysis trading pattern. Our interest in the pattern results from discussions with an industrial partner, a Florida-based trading house called FutureLogic Trading, in 1997. FutureLogic (FL) trades the accounts of a number of *high net worth* individuals using technical trading strategies. FL were interested in using the channel pattern as one of their trading strategies and sought 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). Stimulated by this discussion and by recent academic work on technical trading and market efficiency, an attempt was made to analyse this trading pattern objectively and, furthermore, to enhance profitability by constructing filters and trading rules that were additional to those already in use in the market and specifically by FL.

This paper reports on an empirical study into the *channel* based on 8 years of high frequency foreign exchange data for the British pound/US dollar currency pair. A number of statistical tests and analyses are applied to the 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, the pattern is found to be loss-making. Links are, however, found between the pattern's appearance and profitability

[1] Osler (1995) discovers a marked rise in trading volume within US equity markets following 'head and shoulders' entry signals.

but conclusive results are not gained from attempts to use such relationships to enhance profitability.

Section 2 of the paper describes the spot FX data on which the analysis is based. Section 3 describes the characteristics of the channel pattern and the methodology used to analyse it. Section 4 presents results and summarizes the work and Section 5 concludes.

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 to 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 Future Source 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: '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 by the authors for structural breakdown and irregular quotation by sweeping it with simple author-developed software. This simple set of algorithms 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. As a result, the data has been checked and found free of errors.

The data has then been aggregated to various frequencies in the standard open-high-low-close format (OHLC) whereby the *open* (O) is the price level of the first tick in a given time period for a particular frequency, *high* (H) the

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

maximum price level in that time period, *low* (L) is the minimum price level in that period and *close* (C) is the price level of the last tick to occur in that time period. For example, for minute data consolidated to hourly data between 1200 and 1300, O will be the price level of the first tick between 1201 and 1300, and C will be the price level of the last tick to occur therein; this 'OHLC bar' is then referred to as the '1300 bar'. Sometimes, data is sparse and so O may occur later than 1201 but can never occur later than 1259. If so, the '1300 bar' is non-existent. This process is carried out for various frequencies, π, denoted as πmin frequencies; e.g. if $\pi = 1$ then frequency is minutely and denoted 1min (but 1440min is called *daily*).

As will be discussed 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.

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 Fig. 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 also has a positive gradient and, therefore, the market price level of S2 lies above that of S1. Note that S1, S2, T1 and T2 are merely estimated local extrema of the price level.

The down-channel consists of a similar trough-peak-trough-peak configuration, denoted T1-S1-T2-S2 but with the defining parallel lines having negative gradients in price-time space.

Figure 2 shows a channel pattern isolated from BPUS spot FX data displayed as Japanese candlestick bars (a visualization scheme which is discussed in Schwager (1996)). Here, the white bar represents a rising market and a black bar

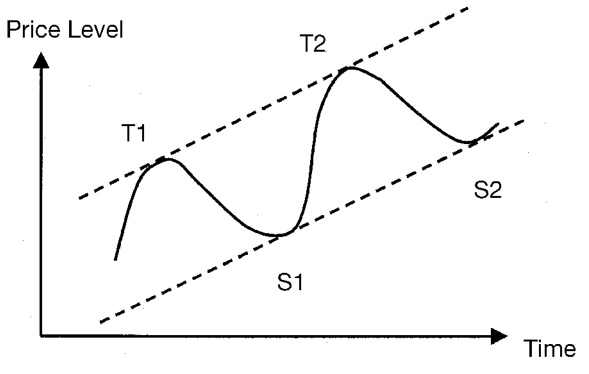

Fig. 1. The up-channel pattern

represents a falling market. The extrema of the bars themselves represent market open and close points whereas the extrema of the protruding lines represent market highs and lows in this time period.

In order to be of practical use, any trading pattern needs to have a set of trade entry and exit rules associated with it. Consultation with traders provided some details on the trading rules typically used with the channel pattern, which were then made rigorous as part of the analysis.

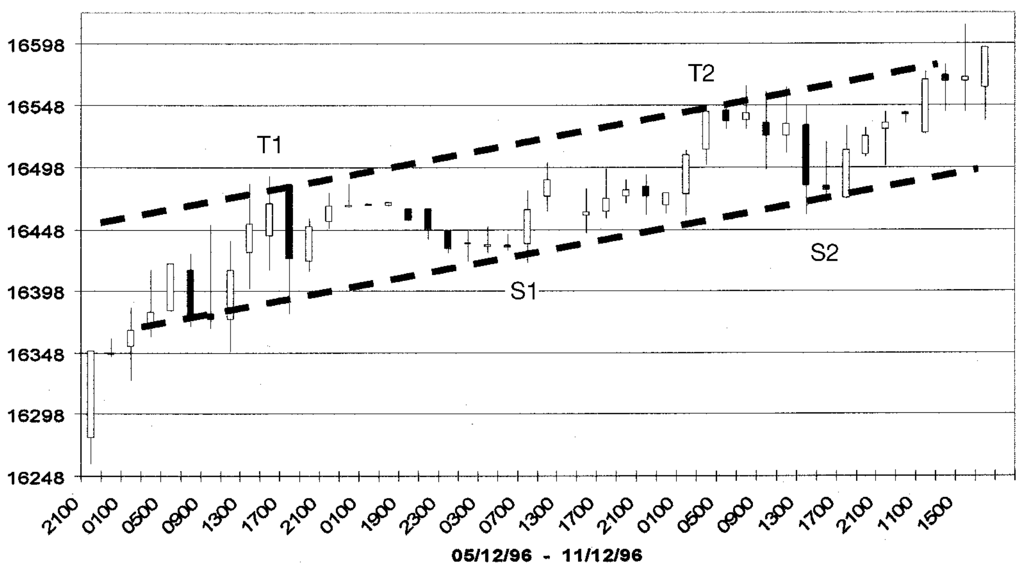

Fig. 2. Isolated up-channel pattern

3.2 Trading channel formations

The aim is to enter the trade as soon as the channel formation occurs. This is when the S2 turning occurs in such a way 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 as outlined below, is registered. These entry rules were chosen after discussion with traders as to what is reasonable when trading such a pattern, and are 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 15% of the vertical channel width from the S2 turning point.*

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, a 'successful' trade exit occurs when the market price reaches a level defined by a band running parallel to and containing 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 or movements 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 or to a predetermined price level. The amount in question varies with the individual trader's preference, with the values used here discussed further in Section 3.3 and detailed in Table 1 in Section 4. Stops and trailing stops are described in detail in Schwager (1996); a recent analysis of exit strategies is carried out by James and Thomas (1998).

3.3 Methodology

This section describes first the algorithm used for channel specimen isolation and its application to the data set. The development of the rules used to simulate the trading of such specimens is then outlined. Finally, the way in which the various attributes of each channel specimen are collated in order to search for any linkage between specific pattern types and profitability is described.

An algorithm has been constructed to isolate up- and down-channel patterns at a number of different data frequencies and coded to allow fast, automatic, objective pattern isolation.

In order to gain an appreciation of the key points of the pattern and to build a test set to validate the automatic isolation algorithm, a year of BPUS spot FX data at the usual range of frequencies was searched by inspection and the channel specimens isolated. A number of traders were then presented with this set and confirmed that it matched instances of the channel.

An algorithm was subsequently developed. The algorithm isolates local maxima and minima of price levels in the market and isolates the co-ordinates of such points when they occur in the order and time-frame that would result in the appearance of a channel pattern Furthermore, it also checks to see that various constraints, needed for the pattern to resemble the expected sine wave, are not broken. Figure 3 provides a pictorial representation of each step of the

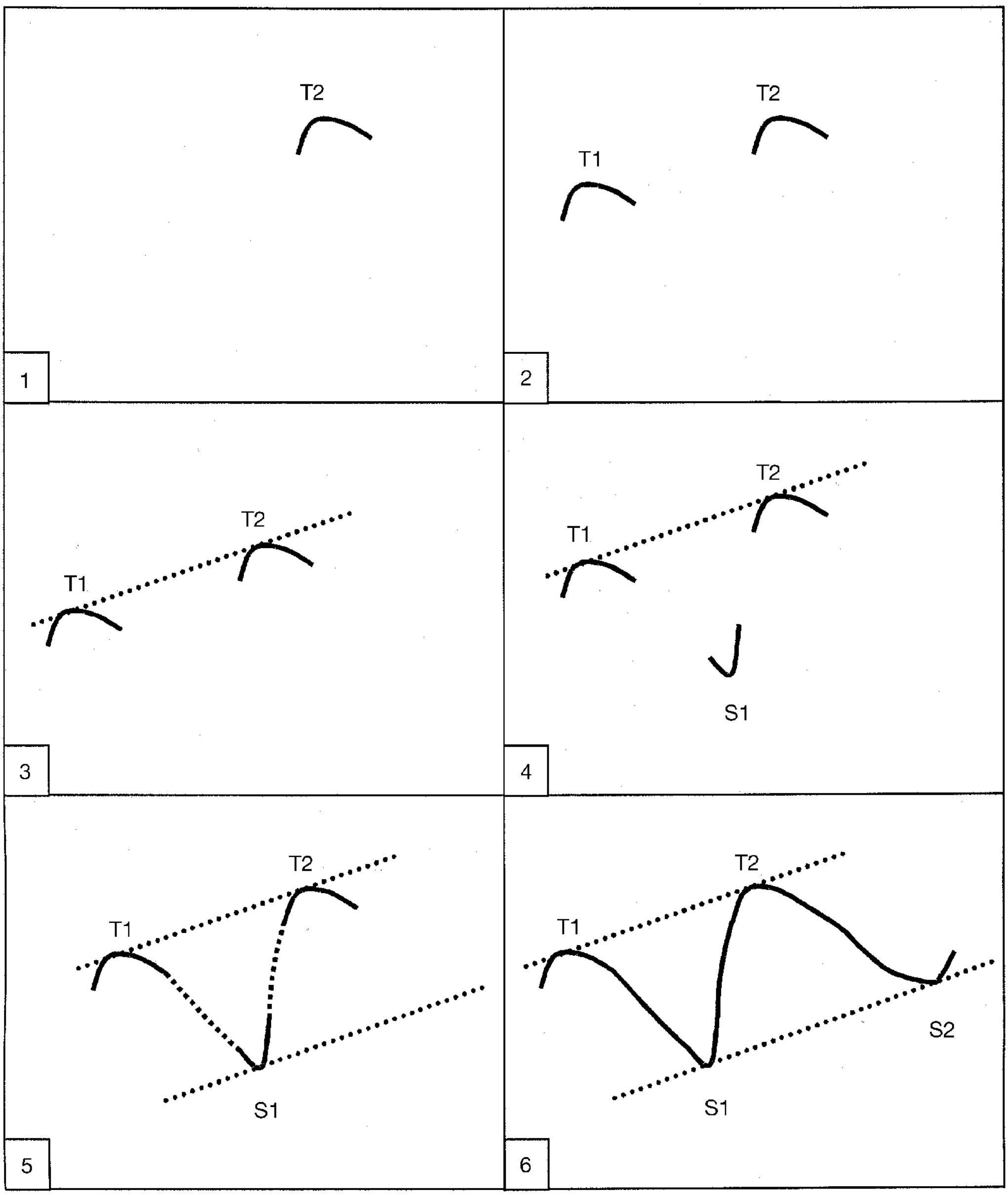

Fig. 3. Pictorial representation of up-channel isolation procedure.

isolation algorithm and a more rigorous definition of this algorithm can be found in the Appendix.

For test purposes, the algorithm was applied to the data set on which channel patterns had been isolated by inspection and the automatically and ‘hand’ isolated channels were matched up. Following the successful test of the algorithm, the data was combed and patterns isolated at the frequencies typically used in technical analysis: namely, daily, 480min, 240min, 120min, 60min, 30min, 15min, 10min, 5min, 2min, 1min.

The channel patterns were then used as a technical trader would use them – as entry signals. The test-trading procedure was constructed to imitate actual trading in as much as it made no use of hindsight. As soon as the channel configuration was confirmed, i.e. as soon as the market had completed forming the S2 turning point, the set of trading rules outlined below 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, as detailed below, signalled so.

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

> *Enter the 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 the trade is entered then exit when either the target wall is hit, the market moves 15% of channel width from the source wall outside the channel or a trailing stop is hit.*

There was also a rule that stipulated trade exit after a fixed number of bars but the suggested number was so large that the rule was rendered obsolete.

From the above, the following generalized rules were constructed:

> *Enter the trade if market moves x% of channel width away from S2 in the direction of the channel.*

> *Exit the trade if market moves y% of channel width in a direction counter to that of the channel or if the market moves through the target wall or the market moves 15% of channel width from the source wall outside the channel.*

These rules were 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 use of one particular frequency as a proxy was based on the need to pick a reasonable and sensible set of rules without introducing a bias from over-optimization and data-snooping, as may have been found if the rules were derived from analysis across all frequencies. The 60min data was chosen in this instance as it is commonly used by technical traders and represented a reasonable mid-way point between higher and lower frequencies.

The parameters of the rules were next allowed to vary as outlined in Table 1 and the new rules outlined below were added and, in each case, the performance was tested and the ‘best’ rule/collection of rules was identified.

The new rules were developed by paying much attention to the behaviour of the exit rules, and were:

A1: Abandon the trade if before the trade is initiated the market moves through a threshold placed 15% of channel width away from the source wall outside the channel.

A2: Enter the trade if market moves a2% of channel width away from the source wall (not necessarily S2) in the direction of the channel.

A3: Exit the trade if market moves y% of channel width or a3 pips in a direction counter to that of the channel or if the market moves through the target wall or the market moves 15% of channel width from the source wall outside the channel.

The parameters used are detailed in Table 1 and the performance of the various rules is discussed in Section 4.

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.

It should be noted that, 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.

The best set of rules, described below, 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 the 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 or by 15% of channel width from S2.

If the market moves by outside a band placed at 15% of the channel width away from the source wall in an opposite direction to 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 or a trailing stop (of 100% of channel width or 50 pips) is hit.

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 T1and 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.

Wilks' lambda tests and multivariate discriminant analyses were then performed, as is described further in Section 4. The motivation for the use of this work was to test for the effectiveness of the channel attributes as discriminators of profitability and, using these attributes, develop and test classification functions capable of classifying future observations with respect to profitability. Such classification rules, which classify profitable situations with respect to above attributes, have been constructed and tested on the *C-test* data. Resulting trading rules and filters have then been constructed and tested on the *C-sample* and *C-test* data and the resulting shifts in profit/loss have been analysed.

4. RESULTS

First the results of tests to choose the best set of trading rules are presented. Then 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. These classification rules are finally tested on a separate set of BPUS data.

4.1 Profitability analysis

Table 1 presents 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

Table 1. Profitability of various trading rules at 60min frequency

	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		

signal of the entry rules tested. Trade exit was on the exit 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 not included in the calculations since they would not affect a trader's profits.

Note from Fig. 4 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 Figs 5a and 5b, 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.

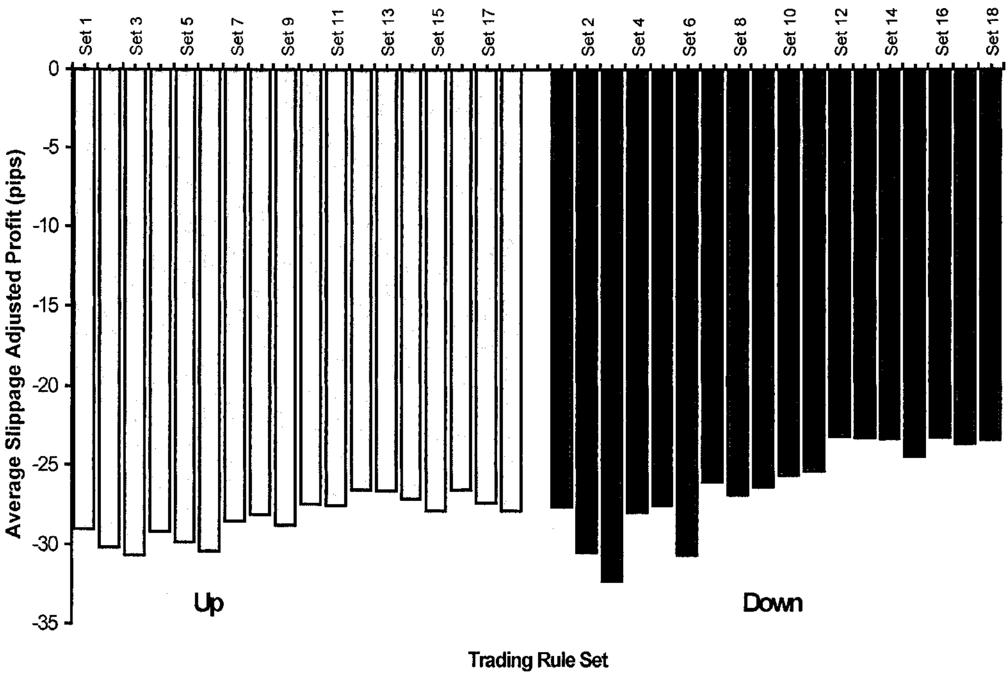

Fig. 4. Performance of rules applied to 60min data frequency

For both up- and down channels it is found 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

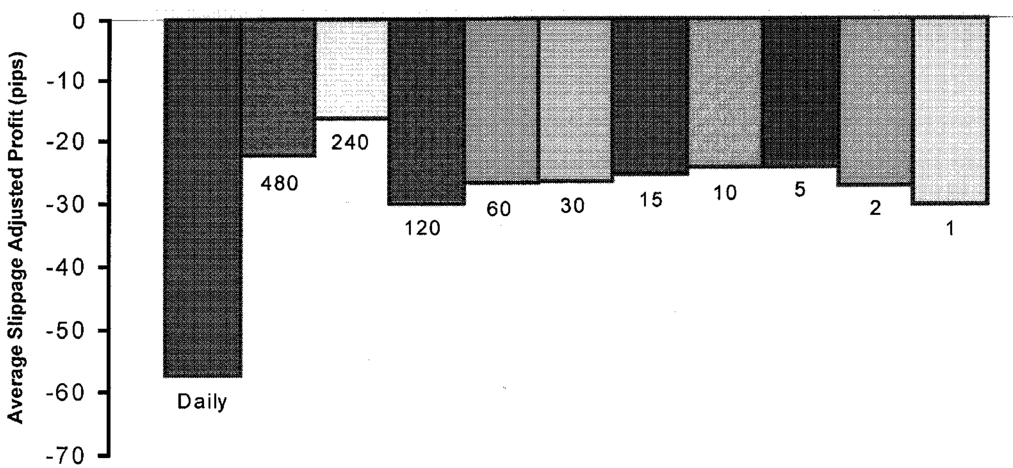

Fig. 5a. Average slippage adjusted profit of best set of trading rules (up)

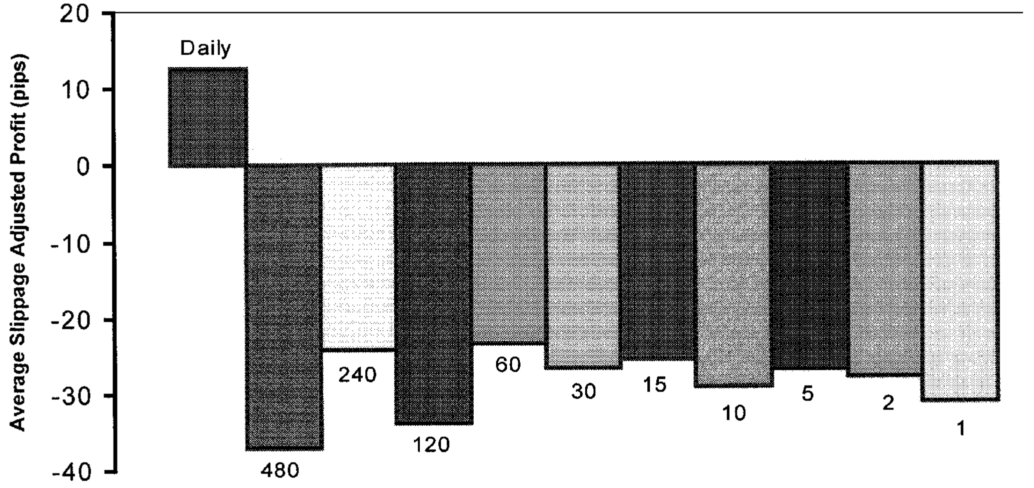

Fig. 5b. Average slippage adjusted profit of best set of trading rules (down)

higher than for other frequencies. Tables of descriptive statistics and histograms for slippage-adjusted profits can be found in Jones (1999) and an example of a profit histogram can be found in Fig. 5c.

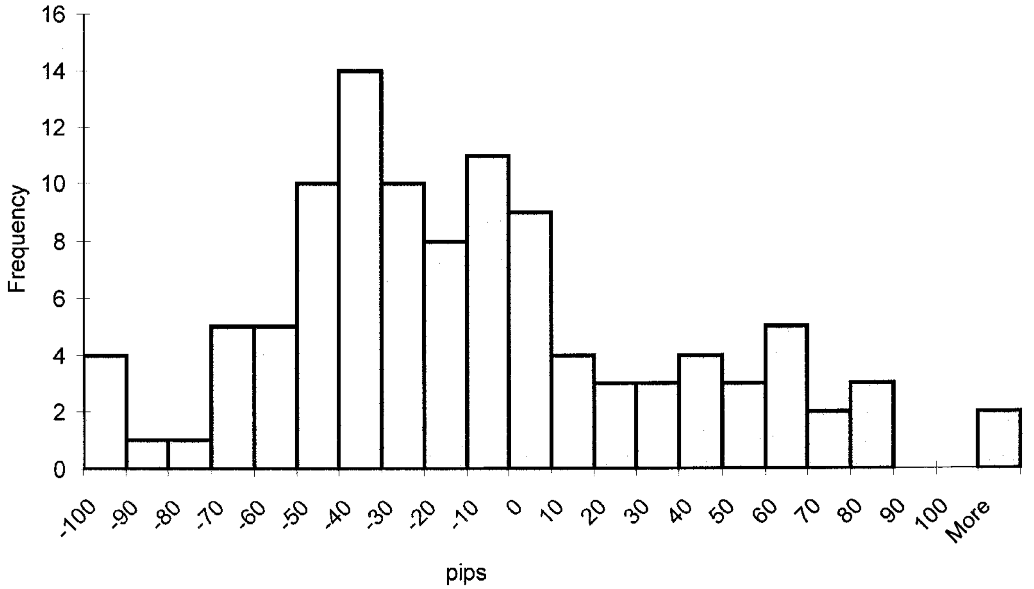

Fig. 5c. Profit histogram for up-channels at 240min frequency

4.2 Analysis of pattern attributes

Having found no radical difference between performance results at many frequencies, the analysis is restricted to the following frequencies: daily, 480min, 240min, 60min and 1min. These particular frequencies appear to be the most popular among those technical traders consulted.

A *Wilks' lambda* test (Sharma, 1996) was performed on the eight different attributes of the channel patterns isolated in the *C-sample* data (1989–96). The aim of this analysis is to test for the effectiveness of the channel attributes as discriminating variables for profitability, i.e. do the attributes significantly differentiate between profitable and loss making channels.

Ideally it is required to isolate the most profitable pattern formations and so the samples have been split into four groups on the basis of slippage adjusted profits (the threshold value of 60bp having been chosen following consultation with traders as to what would be reasonable):

Group +2	large profit (>60 pips)
Group +1	small profit (60 pips $\geq p >$ 0 pips)
Group –1	small loss (0 $\geq l \geq$ –60 pips)
Group –2	large loss ($<–60$ pips)

The Wilks' lambda test simply tests for significant difference between the group means of each channel attribute calculated for each of the above groups.

Table 2 shows the results of this test for both up- and down-channels. For each, the upper section of the table displays the results of the test in terms of statistical significance when sets of attributes are partitioned into four groups as above, the middle section displays the results of the test when sets of attributes are partitioned into two groups: *large loss* and *other* and the lower section of the table displays the level of significance when sets of attributes are partitioned into two groups: *large profit* and *other*.

The significance, and hence effectiveness as discriminating variables, of the attributes differs from test to test and frequency to frequency. However, attributes CA1–CA4 (bar velocity, perpendicular and vertical channel width and velocity outright) have reasonably consistent high significance levels when tested on up-channels. As a result, it can be concluded that these attributes are potentially useful in predicting the profitability of up-channel trading.

Next, a number of discriminant analyses (described in Sharma, 1996) were carried out using the channel attributes as independent variables with profit, grouped as above, as the dependent variable.

The aim of the discriminant analyses were to develop functions that could be used to effectively classify profitable and loss-making channel formations using the channel attributes alone, and hence develop enhanced trading rules. A discriminant analysis seeks to develop an equation (the inputs of which are the channel attributes in this case) that computes an index that will parsimoniously represent the difference between groups (profitability groups in this case). This can be thought of as defining new axes in attribute space in such a way that

Table 2. Wilks' lambda test results – significance (> 99% bolded)

Up Channels

	Wilks' lambda significance for 4-group multiple discriminant analysis							
	CA1 bar velocity	CA2 vertical channel width	CA3 perp. channel width	CA4 velocity	CA5 S1 symmetry	CA6 S2 symmetry	CA7 leg-in	CA8 T1T2 barcount
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%
	Wilks' 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%
	Wilks' lambda significance for 2-group multiple discriminant analysis (large profit 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

	Wilks' 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%
	Wilks' 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%**	53.5%	96.15%
	Wilks' lambda significance for 2-group multiple discriminant analysis (large profit 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%

optimizes the clustering within profitability groups and emphasizes the differences between groups. In actuality, the ratio of *between group sum of squares* to *within group sum of squares* is maximized. The analysis results in the formation of classification functions, which can be used to perform out-of-sample discrimination and hence, in this case, enhanced trading rules.

Various inclusion rules for attributes were tried including those based on the Wilks' lambda test significance values presented above with the premise that if an attribute was found to be an ineffective discriminant then it should not be included in the analysis. A *stepwise* discriminant analysis was also attempted, where an algorithm that automatically executes the analysis using various combinations of attributes was utilized. Eventually, it became evident that the most powerful analysis (in terms of classification) would be achieved by including all attributes.

The levels of success of the analysis outlined above, with various profitability groupings, are reported below.

Tables 3a and 3b present classification matrices (actual grouping along the vertical, proposed group along the horizontal) resulting from a four-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 three-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 4a and 4b present classification matrices (actual grouping along the vertical, proposed group along the horizontal) resulting from a two-group discriminant (-2da) analysis of the sample data with the groupings *large loss* or *other* as before. The lower part of the table contains the results of classification of 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.

Table 3a. 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	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 3b. MDA classification results for down-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	4	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 4a. –2DA classification results for up-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 4b. –2DA classification results for down-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 5a. +2DA classification results for up-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	76.190%	52.38%
72.73%	+2	1	0	1	0.00%	–100.00%
60	Oth	61	6	67	91.04%	81.09%
91.04%	+2	0	0	0	xxx	xxx
1	Oth	100	5	105	95.24%	90.48%
95.24%	+2	0	0	105	xxx	xxx

Table 5b. +2DA classification results for down-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	xxx	xxx	xxx
xxx	+2	xx	xx	xxx	xxx	xxx
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

Tables 5a and b report results from a two-group discriminant analysis (+2da) with the groupings *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 again are mixed and interpretation is further impaired by the scarcity of 'large profit' channels.

Tables 6a and 6b 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 again the excess of '% correct' over the expected result should classification be left to chance, expressed as a percentage; e.g. for the

Table 6a. +/–2DA classification results for up-channels

		–2	Other	+2	Group totals	% correct	% better than chance
Sample data							
480	–2	5	2	0	7	71.43%	114.29%
61.11%	Other	6	15	4	25	60.00%	80.00%
	+2	0	2	2	4	50.00%	50.00%
240	–2	7	6	3	16	43.75%	31.25%
66.36%	Other	12	60	12	84	71.43%	114.29%
	+2	1	2	4	7	57.14%	71.43%
60	–2	12	31	1	44	27.27%	–18.18%
78.79%	Other	28	325	19	372	87.37%	162.10%
	+2	2	10	1	13	7.69%	–76.92%
1	–2	70	86	1	157	44.59%	33.76%
84.95%	Other	139	1612	65	1816	88.77%	166.30%
	+2	0	7	0	7	0.00%	–100.00%
Test data							
480	–2	1	0	0	1	100.00%	200.00%
87.50%	Other	0	6	1	7	85.71%	157.14%
	+2	0	0	0	0	xxx	xxx
240	–2	1	2	1	4	25.00%	–25.00%
63.64%	Other	2	12	3	17	70.59%	111.76%
	+2	0	0	1	1	100.00%	200.00%
60	–2	1	4	0	5	20.00%	–40.00%
80.60%	Other	7	53	2	62	85.48%	156.45%
	+2	0	0	0	0	xxx	xxx
1	–2	0	0	0	0	xxx	xxx
96.15%	Other	0	100	4	104	96.15%	188.46%
	+2	0	0	0	0	xxx	xxx

Table 6b. +/–2DA classification results for down-channels

		–2	Other	+2	Group totals	% correct	% better than chance
Sample data							
480	–2	9	2	1	12	75.00%	125.00%
76.67%	Other	4	12	0	16	75.00%	125.00%
	+2	0	0	2	2	100.00%	200.00%
240	–2	5	12	1	18	27.78%	–16.67%
47.22%	Other	14	28	4	46	60.87%	82.61%
	+2	1	6	1	8	12.50%	62.50%
60	–2	13	25	4	42	30.95%	–7.14%
63.00%	Other	55	236	53	344	68.60%	105.81%
	+2	3	8	3	14	21.43%	–35.71%
1	–2	53	82	12	147	36.05%	8.16%
76.53%	Other	96	1222	199	1517	80.55%	141.66%
	+2	1	2	3	6	50.00%	50.00%
Test data							
480	–2	1	0	1	2	50.00%	50.00%
50.00%	Other	3	6	2	11	54.55%	63.64%
	+2	0	1	0	1	0.00%	–100.00%
240	–2	1	1	2	4	25.00%	–25.00%
50.00%	Other	5	9	0	14	64.29%	92.86%
	+2	0	2	0	2	0.00%	–100.00%
60	–2	0	0	0	0	xxx	xxx
65.45%	Other	5	36	14	55	65.45%	96.36%
	+2	0	0	0	0	xxx	xxx
1	–2	0	0	0	0	xxx	xxx
81.05%	Other	0	77	18	95	81.05%	143.16%
	+2	0	0	0	0	xxx	xxx

above rules, 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 the traders consulted, 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 pattern recognition software it has been possible to accumulate large samples of isolated specimens of the pattern – a task 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 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 intermarket technical analysis (as discussed in Murphy, 1991) 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 macroeconomic 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 for the BPUS currency pair.

[4] In a companion paper (Dempster and Jones, 1999) we report on a similar analysis of the popular head and shoulders pattern which met with somewhat more success than has been attained here.

[5] A study of the impact of such macro-level indicators on high frequency data has been published by Almeida *et al.* (1997).

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.

APPENDIX – THE CHANNEL ISOLATION ALGORITHM

Parameters

r	strictly positive integer	used in isolating local maximum T2
s	strictly positive integer	used in isolating local maximum T2
p	strictly positive integer	used in isolating local maximum T1
q	strictly positive integer	used in isolating local maximum T1
z	strictly positive integer	used in defining T1 search space
v_{min}	real number	minimum acceptable channel velocity
w_{min}	real number	minimum acceptable channel width
s_{max}	strictly positive integer	used in defining S2 search space

Variables

i	positive integer
j	positive integer
n	strictly positive integer
k	strictly positive integer

Definitions

line AB	The line connecting points A and B taking value $AB(t_i)$ at bar b_i
$b_i(o_i,h_i,l_i,c_i,t_i,L)$	Bar number i (where T2 is at b_0, T1 is at b_k) consisting of open, high, low, close, time of close and data frequency respectively
$top(b_i)$	$max(o_i,c_i)$
$bottom(b_i)$	$min(o_i,c_i)$
velocity	average price move per minute
bar velocity	average price move per bar
$[(Tl_n, S1_n) \mid T2]$	The set of N potential T1s and S1s for a given T2 where N is a positive integer
line $S1_nX$	The line passing through $S1_n$ that runs parallel to $T1_nT2$
line $[S1_1X,\ldots,S1_NX]$	The set, S, of lines $S1_nX$ ranked in descending order of bar velocity (average price movement per bar)
barcount	the number of bars from one bar (or point in time) to another e.g. the b_ib_j barcount is $j - i$

The Algorithm

A1.0 **Find a suitable T2**

A1.1 Read data moving forward in time, bar by bar. Consider a point to be a potential T2 if the top (as defined in *Definitions*, above) of the bar in question is higher than the tops of the previous r bars and at least as high as the top of the next s bars. When a potential T2 is found, it is said to occur at b_0 (specifically top(b_0)) with previous bars being b_{-1}, b_{-2},. . ., etc., and subsequent bars being b_1, b_2,. . .

A1.2 *Comment*

We should choose r to be the minimum desired T1T2 barcount. Given that a channel can move from T2 to form S2 and then breakout past the target wall in two bars and still be tradeable, we should take s to be 1. Note that T2 has to be only at least as high as the subsequent s bars. This is in order to include channels where T2 is formed over a number of bars (in such a case the first bar is chosen as T2). If we were to have a similarly relaxed constraint on the previous r bars then in such a case the market would be immediately breaking the target wall (given that we are looking at channels with a positive velocity).

A2.0 **Locate T1**

A2.1 A bar will be a prospective T1 if the following properties hold:

A2.11 The bar, b_{-k} say, lies in the region $[t_{-z}, t_{-r}]$ where $z>r>0$;

A2.12 The top of its real body is higher than the tops of the next *q* bars (b_{-k+1}, . .,b_{-k+q});

A2.13 The top of its real body is at least as high as tops of the previous *p* bars (b_{-k-1},. . .,b_{-k-p});

A2.14 The tops of the real bodies of all the bars (b_{-k-1},. . .,b_0) (in $[t_{-k}, t_o]$) do not lie above the target wall line T1T2; i.e. top(b_i) $\leq$ line T1T2(t_i) for $(-k+1) \leq i \leq 0$;

A2.15 The target wall has a velocity greater than some minimum velocity v_{min}.

A2.2 *Comment*

We should take z to be the maximum desired T1T2 barcount. We can take q to be 1 to ensure that there is time for S1 to be formed. To take q to be higher may constrain channel velocity unduly. Also, the strict inequality here enforces a coherent channel shape. We should choose p to be large enough that only distinct turning points are chosen and small enough that the condition is not unduly restrictive. By using a weak inequality in A2.13, we allow for 'double' formations, taking T1 to be the last of the peaks. Condition A2.14 ensures that the channel is not 'broken'. We are not looking at flat or near-flat channels and so a minimum velocity condition, A2.15, is introduced. <u>NB There may be more than one potential T1</u>.

A3.0 **Locate S1**

A3.1 For each T1, take S1 to be the bottom (as defined in *Definitions,* above) of the bar in the period T1T2 (i.e. $[t_{-k}, t_0]$) with the lowest real body bottom.

A3.2 A (T1,S1,T2) setup is only valid if the channel width, *w*, is greater than a given minimum channel width, w_{min}.

A3.3 *Comments*

The channel width is the vertical distance from S1 to the target wall line. There may be several valid (T1,S1,T2) setups if a number of T1s exist.

A4.0 **Locate S2**

A4.1 Define [($T1_n$,$S1_n$) to be the set of N potential T1s and corresponding S1s given a particular T2. Define line $S1_nX$ to be the line projected from $S1_n$ that runs parallel with line $T1_nT2$ and define $S1_nX(t_i)$ to be the value of the line at b_i; define S := line [$S1_1X$,. . .,$S1_NX$] to be the set of such lines ranked in descending order of *bar velocity* (average price movement per bar).

A4.2 A potential S2 must occur in a region line $S1_nX$ +/− 15%*w* for some $n \leq N$.

A4.3 Starting at i=0, j=1, adopt the following procedure:

A4.3.1 If $c_i <$ (line $S1_jX(t_i)$ − 15%*w*) and j < N then restart procedure A4.3 with i = 0 and j incremented to j+1; if j = N then no valid channels exist for this T2;

A4.3.2 If (line $S1_jX(t_i)$ − 15%*w*) $\leq c_i \leq$ (line $S1_jX(t_i)$ + 15%*w*) then proceed as follows:

A4.3.2a If o_{i+1} > (line $S1_jX(t_{i+1})$ − 15%*w*) and $o_{i+1} < c_{i+1}$ then there is a valid S2 at $\min(c_i,o_{i+1})$, $S2_j$ say, and the valid channel setup is $(T1_j,S1_j,T2,S2_j)$;
A4.3.2b If o_{i+1} > (line $S1_jX(t_{i+1})$ − 15%*w*) and $o_{i+1} < c_{i+1}$ and i $< s_{max}$ then restart procedure A4.3 with i incremented to i+i; if i = s_{max} then no valid channels exist for this T2;
A4.3.2c If o_{i+1} < (line $S_jX(t_{i+1})$ − 15%*w*) then restart procedure A4.3 with i=0 and j incremented to j+1; if j = N then no valid channels exist for this T2;
A4.3.3 If line $T1_jT2(t_i) > c_i > (S_jX(t_{1+i})$ +15%*w*) then proceed as follows:
A4.3.3a If o_{i+1} > line $T1_jT2(t_{i+1})$ and j < N then restart procedure A4.3 with i=0 and j incremented to j+1; if j = N then no valid channels exist for this T2;
A4.3.3b If line $T1T2(t_{i+1}) > o_{i+1}$ > (line $S1_jX(t_{i+1})$ + 15%*w*) then restart procedure A4.3 with i incremented to i+1; if i=s_{max} then no valid channels exist for this T2;
A4.3.3c If o_{i+1} < (line $S1_jX(t_{i+1})$ − 15%*w*) then restart procedure A4.3 with i=0 and j incremented to j+1; if j = N then no valid channels exist for this T2;
A4.3.3d If (line $S1_jX(t_{i+1})$ − 15%*w*) < o_{i+1} < (line $S1_jX(t_{i+1})$ + 15%*w*) and $o_{i+1} < c_{i+1}$ then there is a valid S2 at $\min(c_i,o_{i+1})$, $S2_j$ say, and the valid channel setup is $(T1_j,S_j1,T2,S2_j)$;
A4.3.3e If (line $S1_jX(t_{i+1})$ − 15%*w*) < o_{i+1} < (line $S1_jX(t_{i+1})$ + 15%*w*) and $o_{i+1} > c_{i+1}$ and i < s_{max} then restart procedure A4.3 with i incremented to i+1; if i=s_{max} then no valid channels exist for this T2.
A4.3.4 If line $T1_jT2(t_1) < c_i$ then no valid channels exist for this T2.
A4.4 *Comment*
Here we search through each potential source wall for potential turning points until a valid S2 is found; the criteria for such a point existing is that, within a set number of bars from T2, the following occurs: the market closes within +/−15% of a particular source wall and then (immediately) opens, above 'source wall − 15%' or the market closes within the channel but above 'source wall + 15%' and then (immediately) opens within +/−15% of that source wall.

Ultimately, we consider only one channel for each T2 and we choose that channel to be the one with the following property: The (T1,S1,T2) setup is such that the resulting source wall is the first of its kind to have the market turn within +/− 15% of it.
Note that we order source walls from highest to lowest bar velocity. (This is equivalent to ordering source walls in terms of T1T2 barcount as a result of the 'channel must not break the target wall' constraint.)

A5.0 **Isolate Channel**
If a valid channel setup has been identified then the coordinates of $T1_i$, $S1_i$, $T2$ and $S2_i$ are recorded along with the other relevant information. The algorithm is then restarted on the remaining data.

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