Testing the Profitability of Technical Analysis in Singapore and Malaysian Stock Markets

Department of Electrical and Computer Engineering

Zoheb Jamal

HT080461R

In partial fulfillment of the

requirements for the Degree of

Master of Engineering

National University of Singapore

2010

Abstract

Technical Analysis is a graphical method of looking at the history of price of a stock to deduce the probable future trend in its return. Being primarily visual, this technique of analysis is difficult to quantify as there are numerous definitions mentioned in the literature. Choosing one over the other might lead to data-snooping bias. This thesis attempts to create a universe of technical rules, which are then tested on historical data of Straits Times Index and Kuala Lumpur Composite Index. The technical indicators tested are Filter Rules, Moving Averages, Channel Breakouts, Support and Resistance and Momentum Strategies in Price. The technical chart patterns tested are Head and Shoulders, Inverse Head and Shoulders, Broadening Tops and Bottoms, Triangle Tops and Bottoms, Rectangle Tops and Bottoms, Double Tops and Bottoms. This thesis also outlines a pattern recognition algorithm based on local polynomial regression to identify technical chart patterns that is an improvement over the kernel regression approach developed by Lo, Mamaysky and Wang [4].

Acknowledgements

I would like to thank my supervisor Dr Shuzhi Sam Ge whose invaluable advice and support made this research possible. His mentoring and encouragement motivated me to attempt a project in Financial Engineering, even though I did not have a background in Finance. I would also like to thank my co-supervisor Dr Lee Tong Heng for his guidance and support.

I am also grateful to my friends in the NUS Invest Club with whom I had many fruitful discussions. Some of the ideas applied in this thesis owe their origin to these discussions.

Contents

List of Figures

List of Tables

List of Symbols and Abbreviations

TA – Technical Analysis

FA – Fundamental Analysis

EMH – Efficient Markets Hypothesis

RW – Random Walk

FR – Filter Rules

MA – Moving Average

CB – Channel Breakout

SR – Support Resistance

MSP – Momentum Strategy in Price

HS – Head and Shoulders

IHS – Inverted Head and Shoulders

BTOP – Broadening Top

BBOT – Broadening Bottom

TTOP – Triangle Top

TBOT – Triangle Bottom

RT – Rectangular Top

RB – Rectangular Bottom

DT – Double Top

DB – Double Bottom

Chapter 1 Introduction

Technical Analysis is the forecasting of price movements using past information on prices, volume and a host of other indicators. It includes a variety of techniques such as chart analysis, pattern recognition analysis, technical indicators and computerized technical trading systems to generate buy and sell signals. Pring **[1]**, a leading technical analyst, describes Technical Analysis as

> *"The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, political and psychological forces. The art of Technical Analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed."*

The history of Technical Analysis dates back to at least the 18^{th} century when the Japanese developed a form of Technical Analysis known as candlestick charting techniques, though it remained unknown to the West until the 1970s **[2]**. It shot to prominence in the West ever since Edwards and Magee wrote their influential book "Technical Analysis of Stock Trends" in 1948, now considered the cornerstone of pattern recognition analysis **[3]**. However, it has failed to impress the academia who continue to remain skeptical about its efficacy. Among some circles, Technical Analysis is known as "voodoo finance" **[4]** and in his influential book "A Random Walk Down Wall Street", Burton G. Malkiel **[5]** concludes that "under scientific scrutiny, chart-reading must share a pedestal with alchemy."

One of the most plausible reasons for this contempt of Technical Analysis by the academic critics lies in the fact that Technical Analysis is based on visual cues (and hence described by Pring as an art) as opposed to quantitative finance, which is algebraic and numerical. As Lo, Mamaysky and Wang **[4]** point out, this leads to numerous interpretations and sometimes impenetrable jargon that can frustrate the uninitiated. Campbell, Lo and Mackinlay **[6]** provide a striking example of the linguistic barriers between technical analysts and academic finance by contrasting two statements which express the same idea that past prices contain information for predicting future returns :

Statement 1:

> *The presence of clearly identified support and resistance levels, coupled with a one-third retracement parameter when prices lie between them, suggests the presence of strong buying and selling opportunities in the near-term.*

as compared to Statement 2:

> *The magnitudes and decay pattern of the first twelve autocorrelations and the significance of the Box-Pierce Q-statistic suggest the presence of a high-frequency predictable component in stock returns.*

Another important reason Technical Analysis is rejected by academia is because of the popularity of Efficient Markets Hypothesis, which if true, makes Technical

Analysis invalid. The Efficient Markets Hypothesis (EMH) has long been a dominant paradigm in explaining the behavior of prices in speculative markets. It asserts that financial markets are "informationally efficient", or that prices on traded assets, e.g., stocks, bonds, or properties, already reflect all known information. Fama, who developed this hypothesis as an academic concept, defined it as a market in which prices always 'fully reflect' available information [7]. Since Fama's survey study was published, this definition of an efficient market has long served as the standard definition in the financial economics literature.

A great deal of research has been done to test the Efficient Markets Hypothesis ever since, and much of the initial results turned out to be in its favour. For example, in their important study, Fama and Blume [8] investigated whether the degree of dependence between successive price changes of individual securities can make expected profits from following a mechanical trading rule known as Alexander's filter technique greater than those of a buy-and-hold strategy. They concluded that the market was indeed efficient, and that, even from an investor's viewpoint, the random-walk model was an adequate description of the asset price behavior.

However, recently there have been studies that have found evidence contradicting the hypothesis. Researchers have come up with additional models like the noisy rational expectations model (for e.g. Treynor and Ferguson [9], Brown and Jennings [10], Grundy and McNichols [11]), behavioral (or feedback models) (Shleifer and Summers [12]), disequilibrium models (Beja and Goldman [13]), herding models (Froot, Scharfstein and Stein [14]), agent-based models (Schmidt [15]) and chaos theory (Clyde and Osler [16]) to explain the popularity of Technical Analysis. For example, Brown and Jennings [10] demonstrated that under a noisy rational expectations model in which current prices do not fully reveal private information (signals) due to the presence of noise, historical prices (i.e. Technical Analysis) together with current prices help traders make more precise inferences about past and present signals than do current prices alone [17].

1.1 Support for Technical Analysis

Technical Analysis has experienced surging support both among practitioners and the academic world [18]. For example, surveys indicate that futures fund managers rely heavily on computer-guided technical trading systems (Irwin and Brorsen [19], Brorsen and Irwin [20], Billingsley and Chance [21]), and about 30% to 40% of foreign exchange traders around the world believe that Technical Analysis is the major factor determining exchange rates in the short-run up to six months (e.g., Menkhoff [22], Cheung, Chinn and Marsh [23], Cheung and Chinn [24]). Here, I will mention a few survey studies and empirical studies that provide more or less direct support for Technical Analysis.

1.1.1 Survey Studies

Survey studies attempt to directly investigate market participants' behavior and experiences, and document their views on how a market works. These features cannot be easily observed in typical data sets.

In 1961, Smidt [25] surveyed trading activities of amateur traders in the US commodity futures markets. In this survey, about 53% of respondents claimed that they used charts either exclusively or moderately in order to identify trends. The chartists, whose jobs hardly had relation to commodity information, tended to trade more commodities in comparison to the other traders (non-chartists).

The Group of Thirty [26] surveyed the views of market participants on the functioning of the foreign exchange market in 1985. The respondents were composed of 40 large banks and 15 securities houses in 12 countries. The survey results indicated that 97% of bank respondents and 87% of the securities houses believed that the use of Technical Analysis had a significant impact on the market. The Group of Thirty reported that “Technical trading systems, involving computer models and charts, have become the vogue, so that the market reacts more sharply to short term trends and less attention is given to basic factors.”

Taylor and Allen [27] conducted a survey on the use of Technical Analysis among chief foreign exchange dealers in the London market in 1988. The results indicated that 64% of respondents reported using moving averages and/or other trend-following systems and 40% reported using other trading systems such as momentum indicators or oscillators. In addition, approximately 90% of respondents reported that they were using some Technical Analysis when forming their exchange rate expectations at the shortest horizons (intraday to one week), with 60% viewing Technical Analysis to be at least as important as fundamental analysis.

Lui and Mole [28] surveyed the use of Technical and Fundamental Analysis by foreign exchange dealers in Hong Kong in 1995. The dealers believed that Technical Analysis was more useful than Fundamental Analysis in forecasting both trends and turning points. Similar to previous survey results, Technical Analysis appeared to be important to dealers at the shorter time horizons up to 6 months. Respondents considered moving averages and/or other trend-following systems to be the most useful. The typical length of historical period used by the dealers was 12 months and the most popular data frequency was daily data.

Cheung and Wong [29] investigated practitioners in the interbank foreign exchange markets in Hong Kong, Tokyo, and Singapore in 1995. Their survey results indicated that about 40% of the dealers believed that technical trading is the major factor determining exchange rates in the medium run (within 6 months), and even in the long run about 17% believed Technical Analysis is the most important determining factor.

Wong et al [30] concluded in their study on Singapore stock market that by applying technical indicators, member firms of the Stock Exchange of Singapore (SES) may enjoy substantial profits. It is thus not surprising that most member firms had their own trading teams that relied heavily on Technical Analysis.

In all, survey studies indicate that Technical Analysis has been widely used by practitioners in futures markets and foreign exchange markets, and regarded as an important factor in determining price movements at shorter time horizons.

1.1.2 Empirical Studies

Numerous empirical studies have tested the profitability of Technical Analysis and many of them included implications about market efficiency.

Pruitt and White [31] tried to directly determine the profitability of technical trading system including price, volume and relative strength indicators on individual stock issues. The study showed that the trading system has the ability to beat a simple buy-and-hold strategy over a significant period of time that cannot be attributed to chance alone.

Brock, Lakonishok and LeBaron [32] found that the moving average and the trading range break technical indicators did possess some predictive power, and that the returns that they generated were unlikely to be generated by the four popular null models: a random walk with drift, AR(1), GARCH-M and Exponential GARCH. Hsu [33] found that significantly profitable rules and strategies were available for the samples from relatively “young” markets (NASDAQ Composite and Russell 2000), but not for those of more “mature” markets (DJIA and S&P 500).

Neftci [34] investigated statistical properties of Technical Analysis in order to determine if there was any objective foundation for the attractiveness of technical pattern recognition. The paper examined whether formal algorithms for buy and sell signals similar to those given by Technical Analysts could be made and whether the rules of Technical Analysis were useful in prediction in excess of the forecasts generated by the Weiner-Kolmogorov prediction theory. The article showed that most patterns used by technical analysts needed to be characterized by appropriate sequences of local minima and/or maxima and if defined correctly, Technical Analysis could be useful over and above the Weiner-Kolmogorov prediction theory.

Using genetic programming to investigate whether optimal trading rules could be revealed by the data themselves, Neely, Weller, and Dittmar [35] discovered strong evidence of economically significant out-of-sample excess returns after the adjustment for transaction costs for the exchange rates under consideration. Similarly, Allen and Karjalainen [36] used genetic programming to discover optimal trading rules for the S&P 500 index and found that their rules did exhibit some forecasting power.

Lo, Mamaysky and Wang [4] found that certain technical patterns, when applied to many stocks over many time periods, did provide incremental information, especially for Nasdaq stocks.

1.2 Research Objective

The objective of this thesis is to test the profitability of Technical Analysis in the Singapore and Malaysian stock markets. There are several motivations for doing this. First, there is a huge debate about how to define a technical indicator in terms of when a buy or sell signal is generated. There are various parameters that can take arbitrary values. For instance, if one is using a moving average indicator, what should be the number of days for which the moving average is calculated? Most of the previous studies chose one fixed value and then evaluated how profitable that indicator is. The problem with this approach is that it leads to data snooping. Sullivan, Timmermann and White **[37]** point out that such an approach leads to selection bias whereby an arbitrary rule is bound to work even on a table of random numbers. This thesis attempts to address this problem by starting with a universe of trading rules that include various combinations of the parameters. This in turn eliminates the need to specify a fixed arbitrary value for the parameters. Such an approach was used on a limited scale by Brock, Lakonishok and Lebaron **[32]** and later by Sullivan, Timmermann and White **[37]** to find out if there really exists a superior rule in the entire universe of trading rules. In this thesis, I will first find out the best performing rule of each technical indicator class in an in-sample period, and then later test it in an out-of-sample period.

Second, this thesis attempts to define technical indicators in the way they are used by practitioners in reality. Many studies only take into account the historical prices and ignore other valuable indicators like volume, which is extensively used by analysts. Another important concept that is frequently ignored is that of a neckline, which tells when to initiate a position. This thesis will try to make the definitions as practically relevant as possible.

Third, this thesis improves the non-parametric kernel regression algorithm developed by Lo, Mamaysky and Wang **[4]** to identify technical chart patterns like Head and Shoulders etc by using local polynomial regression. This method solves some of the limitations of kernel regression and makes the pattern recognition algorithm more accurate.

Finally, as far as I am aware, no such exhaustive study has been conducted on Singapore and Malaysian stock markets and thus, the research will add to the fruitful discussion between the practitioners and the academia in the Asian markets.

To sum up, this thesis contributes to the existing research by eliminating data snooping bias while testing the performance of technical indicators, by defining technical indicators more accurately, by improving the pattern recognition algorithm initially developed by Lo, Mamaysky and Wang **[4]** and by exploring the relatively untested Asian markets in an exhaustive manner.

This thesis is structured as follows –

- Chapter 2 gives a description of the technical indicators and patterns and the parameters used.
- Chapter 3 describes the chart pattern detection algorithm.
- Chapter 4 describes the empirical data, statistical test and results.
- Chapter 5 is the Conclusion and Future Work, followed by Appendices and Bibliography.

Chapter 2 Technical Indicators and Chart Patterns

Technical Analysis is "the science of recording, usually in graphic form, the actual history of trading (price changes, volume of transactions, etc.) in a certain stock and then deducting from that pictured history the probable future trend" [3].

The general goal of Technical Analysis is to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data. To aid in this, many signal generating indicators and chart patterns are used. In this thesis, I will focus on the most common class of indicators that have been used and tested extensively in the literature. These are Filter Rules, Moving Averages, Support and Resistance, Channel Breakouts, Momentum Strategies, Head and Shoulders, Inverse Head and Shoulders, Broadening Tops and Bottoms, Triangle Tops and Bottoms, Rectangle Tops and Bottoms and Double Tops and Bottoms. There are many other technical indicators that could have been used, but I have restricted my current analysis to those that have been mentioned extensively in literature.

The universe of trading rules is constructed by specifying the parameters on which each class of trading rule depends and then choosing sample values for these parameters. I have mostly followed Sullivan, Timmermann and White [37] and Hsu [33] as far as choosing of parameters is concerned, though I have modified the chart pattern detection algorithm by including volume information and neckline so that it is in sync with the way these patterns are used by practitioners.

This chapter will define each trading rule class and its parameters. A list of the parameter values is given in Appendix A.

2.1 Filter Rules

Fama and Blume [8] explain the standard filter rule:

An x per cent filter is defined as follows: If the daily closing price of a particular security moves up at least x per cent, buy and hold the security until its price moves down at least x per cent from a subsequent high, at which time simultaneously sell and go short. The short position is maintained until the daily closing price rises at least x percent above a subsequent low at which time one covers and buys. Moves less than x percent in either direction are ignored.

A subsequent high is defined as the highest closing price achieved while holding a long position; similarly a subsequent low is defined as the lowest closing price achieved while holding a short position. Following a filter rule strategy, a trader is always in the market (either long or short). To allow for a neutral position, an additional parameter y can be introduced, whereby a long (short) position is liquidated if the price decreases y percent from a high (low). Another liquidation strategy is to hold a position for a fixed number of days c once a signal is generated, and ignore all the signals generated during this period.

Figures 1, 2 and 3 below show the buy/sell signals generated if a filter rule is implemented. The blue line is the price series of the Straits Times Index. The area shaded in green indicates a long position; the area shaded in red indicates a short position and the area in white a neutral position. The parameter values are indicated at the bottom of the figure.

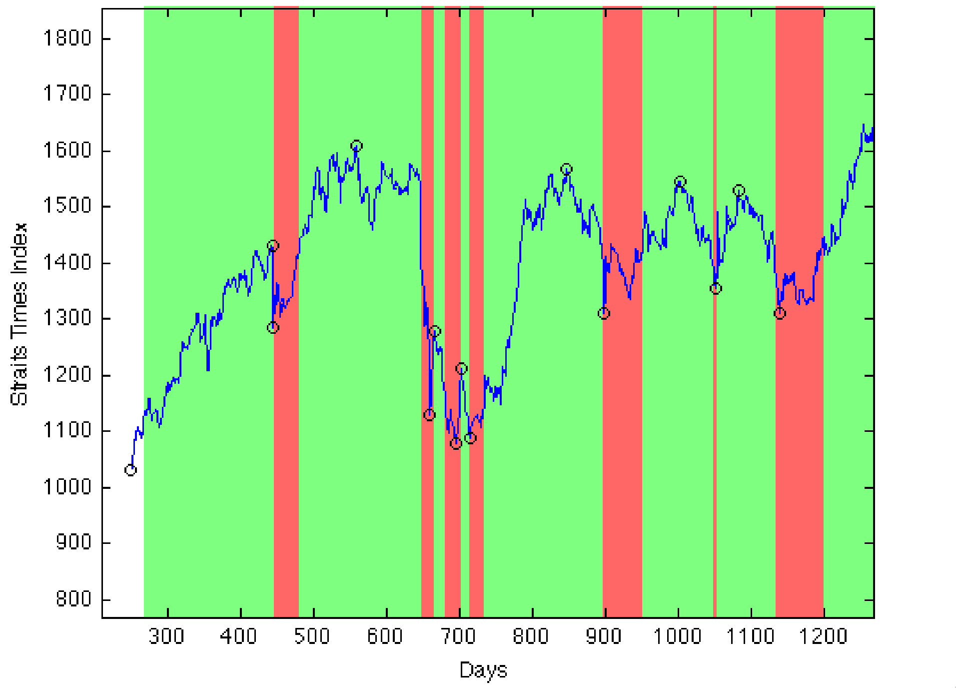


Figure 1 - Filter Rule – x = 0.1

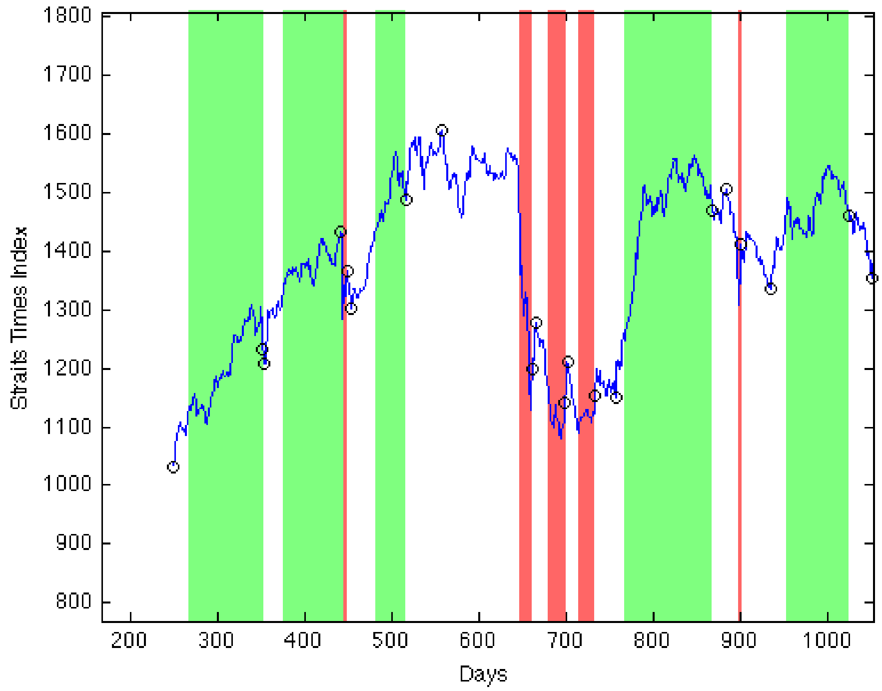


Figure 2 - Filter Rule – x = 0.1, y = 0.5

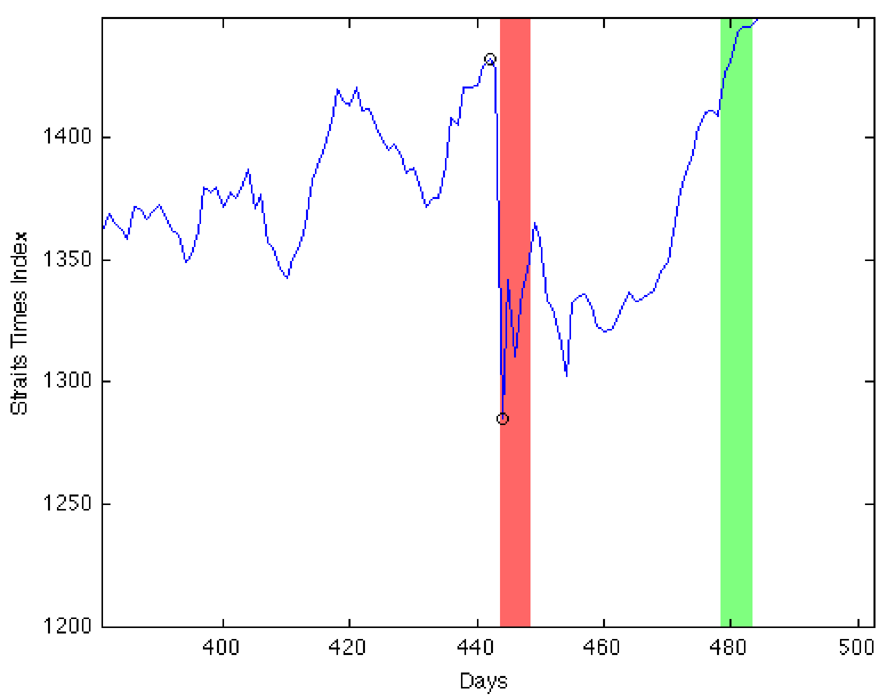


Figure 3 - Filter Rule – x = 0.1, c = 5

2.2 Moving Averages

Moving average rules are among the most popular rules discussed in the literature (for e.g., see Achelis [38] and Pring [39]). They smooth a data series and make it easier to spot trends, something that is especially helpful in volatile markets. A simple *n*-day moving average is the average of the previous *n* days' closing prices, So, mathematically, $MA = \frac{p_1 + p_2 + ... + p_n}{n}$, where p_i is the *i*-th day closing price. The standard moving average rule generates signals as explained by Gartley [40].

In an uptrend, long commitments are retained as long as the price trend remains above the moving average. Thus, when the price trend reaches a top, and turns downward, the downside penetration of the moving average is regarded as a sell signal. Similarly, in a downtrend, short positions are held as long as the price trend remains below the moving average. Thus, when the price trend reaches a bottom, and turns upward, the upside penetration of the moving average is regarded as a buy signal.

Numerous variations of the simple moving average rule exist. The most common one is where more than one moving average rule is applied to generate signals. For example, a fast moving average and a slow moving average can be used to generate signals. When the fast moving average crosses the slow moving average from below, a buy signal is generated and when it crosses from above, a sell signal is generated.

If the market is trending sideways, then simple moving average rules generate lots of noise signals, which can turn out to be costly because of transaction costs. Thus, various filters are employed by traders to filter out the noise. Following White [37], I will use two filters: a fixed percentage band filter *b* and a time delay filter *d*.

The fixed percentage band filter requires the buy or sell signal to exceed the moving average by a fixed multiplicative amount, *b*. The time delay filter requires the buy or sell signal to remain valid for a pre-specified number of days, *d*, before action is taken. Note that only one filter is imposed at a given time.

Once again, a liquidation strategy is to hold a given long or short position for a pre-specified number of days, *c*.

Figures 4 and 5 below show the signals generated by a moving average rule.

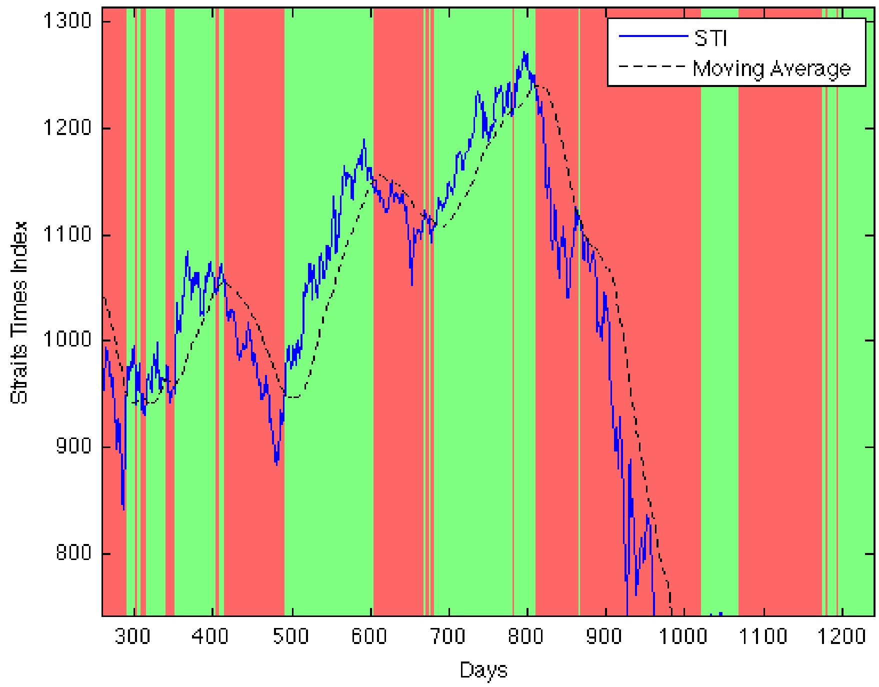


Figure 4 - Simple Moving Average - n = 50

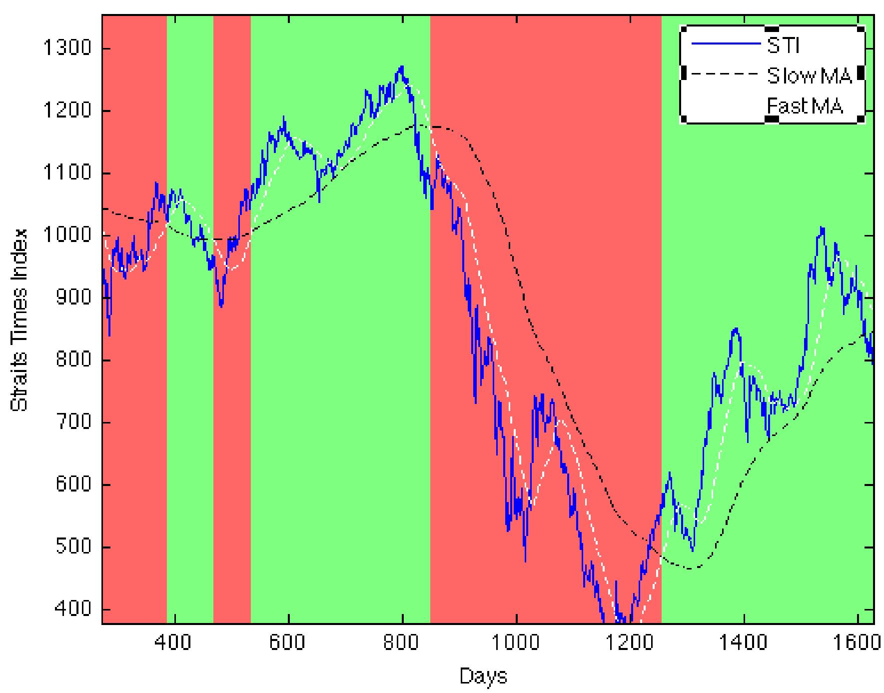


Figure 5 - Crossover Moving Average - n = 200, m = 50

2.3 Support and Resistance

The concepts of support and resistance are undoubtedly two of the most highly discussed attributes of Technical Analysis. Support and Resistance represent key junctures where the forces of supply and demand meet. Support is the price level at which demand is thought to be strong enough to prevent the price from declining further. The logic dictates that as the price declines towards support and gets cheaper, buyers become more inclined to buy and sellers become less inclined to sell. By the time the price reaches the support level, it is believed that demand will overcome supply and prevent the price from falling below support. Resistance is the price level at which selling is thought to be strong enough to prevent the price from rising further. The logic dictates that as the price advances towards resistance, sellers become more inclined to sell and buyers become less inclined to buy. By the time the price reaches the resistance level, it is believed that supply will overcome demand and prevent the price from rising above resistance.

A simple trading rule based on the notion of support and resistance is to buy when the closing price exceeds the resistance level over the previous n days, and sell when the closing price is less than the support level over the previous n days. A support level is identified if there are at least 2 minimas within 2% of each other in the previous n days. Similarly, a resistance level is identified if there are at least 2 maximas within 2% of each other.

As with the moving average rules, a fixed percentage band filter, b, and a time delay filter, *d*, can be included. Also, positions can be held for a pre-specified number of days, *c*.

2.4 Channel Breakouts

A channel breakout occurs when a stock (or any other financial instrument) is trading in a tight channel, then starts trading at a price higher or lower than the channel. A channel rule can be implemented as follows: a channel is said to occur when the high over the previous *n* days is within *x* percent of the low over the previous *n* days. The trading strategy is to buy when the closing price exceeds the channel and sell when the price closes below the channel. Similar to the moving average rule, a band filter *b* can be used to filter out false trading signals. The liquidation strategy is to hold the position for a pre-specified number of days *c*.

2.5 Momentum Strategies in Price

Momentum strategy is an investment strategy that aims to capitalize on the continuance of existing trends in the market. This strategy looks to capture gains by riding "hot" stocks and selling "cold" ones. To participate in momentum investing, a trader will take a long position in an asset, which has shown an upward trending price, or short sell a security that has been in a downtrend. The basic idea is that once a trend is established, it is more likely to continue in that direction than to move against the trend.

To implement a momentum strategy, typically a momentum measure is applied. In this thesis, following Hsu [33], I will use the rate of change (ROC).

Specifically, the m-day ROC is defined as $(q(t) - q(t-m)) / q(t-m)$, where *q(t)* is the closing price. Pring [1] recommends 3 oscillators: simple, moving average and crossover moving average. The simple oscillator is just the *m*-day ROC; the moving average oscillator is the *w*-day moving average of the *m*-day ROC with $w \le m$; the crossover moving average oscillator is the ratio of the $w1$-day moving average to the $w2$-day moving average (both based on *m*-day ROC) with $w1 < w2$. An overbought/oversold level, *k* is needed to determine when a position should be initiated. When the oscillator crosses the overbought level from below, a long position is initiated; when it crosses the oversold level from above, a short position is initiated. The liquidation strategy is again to hold the position for fixed number of days *c*.

2.6 Head and Shoulders

The head-and-shoulders pattern is not only the most famous, but also one of the more common and, by all odds, considered the most reliable of the major patterns (e.g. Osler and Chang [41] and Mcallen [42]). It can appear in two ways, as normal head-and-shoulders or as inverted head-and-shoulders.

The normal head-and-shoulders pattern consists of four parts: the two shoulders, the head and the break-out. It starts with a strong upward trend during which the trading volume becomes very heavy, followed by a minor recession on which trading volume decreases. This is the left shoulder. The next section starts with another high-volume rally which reaches a higher level than the top of the left shoulder, and then another downturn on less volume which take prices down to somewhere near the bottom level of the preceding recession. It can be higher or lower but in any case below the top of the left shoulder. This is the head. Then comes a third increase, but this time during much less volume than that of the first two increases, which fails to reach the height of the head before another decline sets in. This is the right shoulder. Finally, a decrease of the stock price in this third recession down through a line, called the neckline, drawn across the bottoms of the declines on both sides of the head. The break out is confirmed when the stock price closes k percent below the neckline. The break out of the head-and-shoulders pattern is a signal for selling the stock.

Head-and-shoulders pattern can be characterized by a sequence of five consecutive local extrema $E1, \ldots, E5$, located such that[1]:

$$HS = \left\{ \begin{array}{l} E1 \text{ a maximum} \\ E3 > E1,\ E3 > E5 \\ E1 \text{ and } E5 \text{ within } r \text{ percent of their average} \\ E2 \text{ and } E4 \text{ within } r \text{ percent of their average} \end{array} \right\}$$

[1] Details of the detection algorithm are given in the next chapter

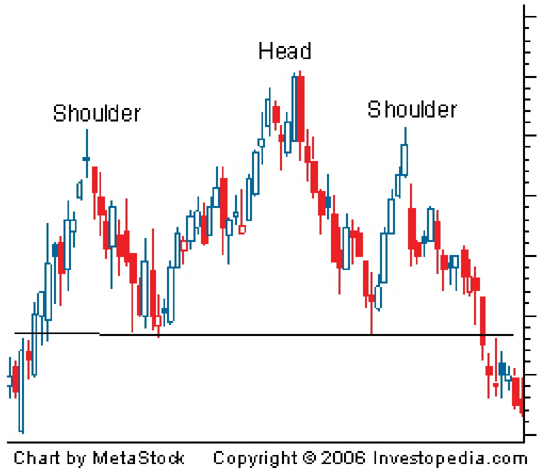


Figure 6 - Head and Shoulders[2]

The inverted head-and-shoulders pattern looks the same as the normal one apart from the obvious fact that it is turned upside down. The break out of the inverted head-and-shoulders pattern is a signal for buying the stock.

Inverse Head-and-shoulders pattern can be characterized by a sequence of five consecutive local extrema $E1,\ldots,E5$, located such that

$$IHS = \left\{ \begin{array}{l} E1 \text{ a minimum} \\ E3 < E1,\ E3 < E5 \\ E1 \text{ and } E5 \text{ within } r \text{ percent of their average} \\ E2 \text{ and } E4 \text{ within } r \text{ percent of their average} \end{array} \right\}$$

[2] The charts are provided by www.investopedia.com

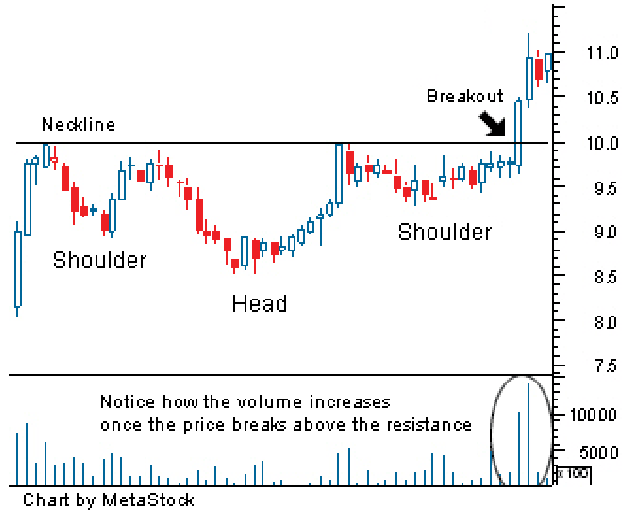


Figure 7 - Inverted Head and Shoulders

A band filter *b* is imposed so that a signal is generated once the price moves *b* percent below the neckline. For liquidation, two strategies are applied: one is the fixed day liquidation whereby a position is liquidated after a pre-specified number of days *c*. The other strategy that is frequently used by practitioners is the stop-loss and fixed-profit strategy. The fixed profit price is the closing price that declines *d* times the head trough difference below the neckline. A stop loss price is used to limit the losses and is the closing price that is *s* times the right trough. So, a position is liquidated if the closing price exceeds the stop loss price or it goes below the fixed-profit price.

For the remaining patterns explained below, same filter and liquidation strategies will be applied.

2.7 Broadening Tops and Bottoms

The broadening patterns start with very narrow fluctuations and then widen out between diverging boundary lines. The tops start with a maximum and the bottoms start with a minimum.

The trading activity during a broadening formation usually remains high and irregular throughout its construction. The appearance of this pattern suggests that the market is approaching a dangerous stage indicating that new commitments should not be made and any holdings should be cashed in at the first good opportunity. It is reasonable to assume that the prices, if they break away from the

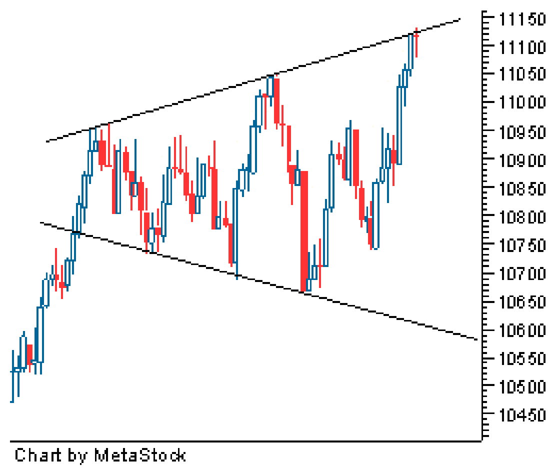


Figure 8 - Broadening Top

formation, will go down. Thus, by all means, the broadenings are sell signals.

Broadening tops (BTOP) and bottoms (BBOT) are characterized by a sequence of five consecutive local extrema $E1$, ...,$E5$ such that:

$$BTOP = \left\{ \begin{array}{l} E1 \text{ a maximum} \\ E1 < E3 < E5 \\ E2 > E4 \end{array} \right\}$$

$$BBOT = \begin{Bmatrix} E1 \text{ a minimum} \\ E1 > E3 > E5 \\ E2 < E4 \end{Bmatrix}$$

2.8 Triangle Tops and Bottoms

Historically, triangles have developed at periods of major trend changes and they are therefore considered as important since these are the periods which are most relevant for an investor to realize. Triangles normally signal a consolidation in the market, terminating an up or down move only temporary and preparing for another strong move in the same direction at a later stage.

The triangle tops are composed by a series of price fluctuations, starting at a maximum, where every new fluctuation is smaller than the last one. This creates a down-slanting line touching the tops of the fluctuations as well as an up-slanting line touching the bottoms. Together, the two lines form a triangle. In the run of this price fluctuation, trading activity shows a decreasing trend. The smaller the fluctuations get, the volume turns into an abnormally low daily turnover. The sign whether to buy or sell comes when the price breaks out of the triangle. This occurs in a notable pick up in volume. If the price increases, it will likely continue doing so and it is therefore a clear buy signal. The opposite goes for a decline. It is very rare that the chart contains any information in which direction the price is going to break out. The investor normally has to wait and see until the action suddenly occurs.

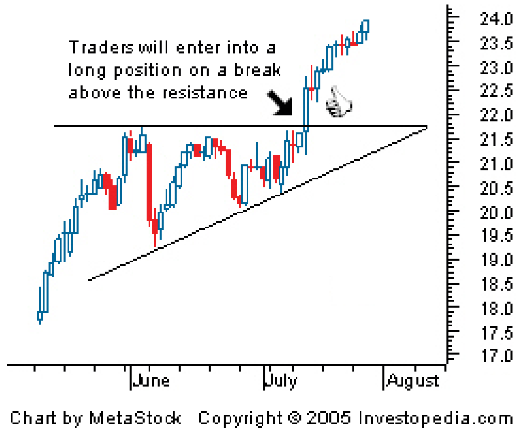


Figure 9 - Triangle Top

Triangle bottoms are built up in the same way as the tops, with the only difference that they start with a minimum. The buy or sell sign and decision are the same as for the tops.

Figure 10 - Triangle Bottom

Triangle tops (TTOP) and bottoms (TBOT) are characterized by a sequence of five consecutive local extrema $E1$, ...,$E5$ such that:

$$TTOP = \begin{Bmatrix} E1 \text{ a maximum} \\ E1 > E3 > E5 \\ E2 < E4 \end{Bmatrix}$$

$$TBOT = \begin{Bmatrix} E1 \text{ a minimum} \\ E1 < E3 < E5 \\ E2 > E4 \end{Bmatrix}$$

2.9 Rectangle Tops and Bottoms

A rectangle consists of a series of sideways price fluctuations which is called the trading area. It has been given this name since it can be bounded both at the top and at the bottom by horizontal lines. These lines are allowed to slope in either direction if the departure from the horizontal line is trivial. In the same way as for triangles, the rectangle top starts with a maximum and the bottom starts with a minimum. The trading volume development within the patterns follows the same rules as for triangles, i.e. the activity decreases as the rectangle lengthens. Also in terms of break outs and indications of directions the same rules as for triangles apply. If the price increases, it will likely continue doing so and is therefore a clear buy signal. The opposite goes for a decline.

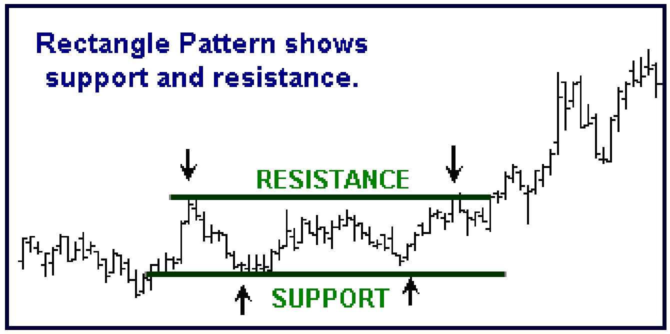


Figure 11 - Rectangle Top

Rectangle tops (RTOP) and bottoms (RBOT) are characterized by a sequence of five consecutive local extrema $E1$, ...,$E5$ such that:

$$RTOP = \begin{Bmatrix} E1 \text{ a maximum} \\ \text{Tops within 0.75 percent of their average} \\ \text{Bottoms within 0.75 percent of their average} \\ \text{Lowest top } > \text{ Highest bottom} \end{Bmatrix}$$

$$RBOT = \begin{Bmatrix} E1 \text{ a minimum} \\ \text{Tops within 0.75 percent of their average} \\ \text{Bottoms within 0.75 percent of their average} \\ \text{Lowest top } > \text{ Highest bottom} \end{Bmatrix}$$

2.10 Double Tops and Bottoms

The doubles normally occur very rarely and they are difficult to exploit in the sense that they cannot be detected until prices have gone quite a long way away from them. They can never be told in advance or identified as soon as they occur.

The definition of the doubles is also slightly more involved. The double tops is formed when a stock's price increases to a certain level under heavy trading and then falls back during a decrease in activity. It should then bounce back to approximately the same level as the first top during less heavy trading as last increase. Then, finally, it turns down a second time. The distance between the two tops must not be too small. Lo, Mamaysky and Wang [4] suggest a minimum of 23 trading days. The double tops give a signal of selling the stock since the second down turn indicates a consequential decline.

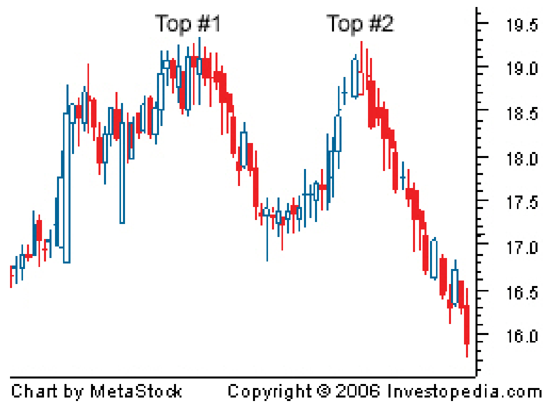


Figure 12 - Double Top

The double bottoms are the same pattern turned upside down and it is a signal of buying the stock.

Double tops (DTOP) and bottoms (DBOT) are characterized by an initial local extremum $E1$ and a subsequent local extrema E_a and E_b such that:

$$E_a = \max\left\{P_{t_k} : t_k > t_1, k = 2, \ldots, n\right\}$$
$$E_b = \min\left\{P_{t_k} : t_k > t_1, k = 2, \ldots, n\right\}$$

and

$$DTOP = \left\{ \begin{array}{l} E1 \text{ a maximum} \\ E1 \text{ and } E_a \text{ within 1.5 percent of their average} \\ t_a - t_1 > 22 \end{array} \right\}$$

$$DBOT = \left\{ \begin{array}{l} E1 \text{ a minimum} \\ E1 \text{ and } E_a \text{ within 1.5 percent of their average} \\ t_b - t_1 > 22 \end{array} \right\}$$

Where t_1, t_a and t_b are the times for the local extremas $E1$, E_a and E_b.

Chapter 3 Chart Pattern Detection Algorithm

Technical indicators like filter rules and moving averages are easier to implement than technical chart patterns like Head and Shoulders etc. This is because chart patterns are primarily visual, and so it is difficult to quantify them. For a long time, these patterns remained untested until Lo, Mamaysky and Wang [4] developed a pattern recognition algorithm using kernel regression in an attempt to quantify them. In this thesis, I have attempted to improve their algorithm by using local polynomial regression. I will first describe the kernel regression method together with its limitations and then will move on to the more robust local polynomial regression method.

3.1 Smoothing Estimators

The natural starting point for any regression, linear or nonlinear, is the regression equation, which is assumed to mirror the behaviour of the underlying variables. For a series of stock prices $\{P_t\}$, the most fundamental equation which captures the nonlinearity is:

$$P_t = m(X_t) + \varepsilon_t \tag{1}$$

where $m(X_t)$ is an arbitrary fixed but unknown nonlinear function of a state variable X_t and ε_t is white noise. When determining stock prices using time series data the state variable is usually set equal to time, i.e. $X_t = t$. However, I will use the expression $X_t = x_t$ to keep my derivations more in line with Lo, Mamaysky and Wang [4].

Financial theorists have not yet been able to agree upon a parametrical model for the movement of stock prices, i.e. they have not been able to determine the shape of $m(X_t)$ analytically. The function $m(X_t)$ thus has to be estimated non-parametrically from available data. Lo, Mamaysky and Wang [4] define pattern recognition as the method of constructing a smooth function $\hat{m}(\cdot)$ to approximate a time-series of prices $\{P_t\}$. The dot indicates that the form of the regression equation does not have to be specified in advance and is thus non-parametric. The fact that the regression equation does not have to be specified, but can be drawn from any data, is an advantage since it does not limit the spectrum of possible patterns which can be found in the data.

One method to estimate the nonlinear function $\hat{m}(\cdot)$ is smoothing, which can be described as a technique to reduce the regression errors by averaging data in some sophisticated way. Kernel regression, orthogonal series expansion, projection pursuit, nearest-neighbour estimates, average derivative estimators, splines and neural networks are all examples of smoothing estimators [4]. The reader can refer to Hardle [43], Bishop [44] and Lo [45] for a detailed description of these techniques.

In a general parametrical regression, the $\hat{m}(\cdot)$ is determined by repeated sampling. By repeating the sampling of $X_t = x_0$ it is possible to determine an estimator of $m(x_0)$ such that:

$$\hat{m}(x_0) = \frac{1}{n}\sum_{i=1}^{n} p_i = \frac{1}{n}\sum_{i=1}^{n}\left[m(x_0) + \varepsilon_t^i\right] = m(x_0) + \frac{1}{n}\sum_{i=1}^{n}\varepsilon_t^i = m(x_0) \tag{2}$$

since $\frac{1}{n}\sum_{i=1}^{n}\varepsilon_t^i$ is negligible for large n. Unfortunately, when using time series, we cannot allow ourselves to repeat the sampling for a given time t, since only one observation per time-period is available [46]. However, Lo, Mamaysky and Wang [4] describe a method to avoid this problem. If $\hat{m}(\cdot)$ is assumed to be sufficiently smooth in a small interval around x_0, then, in a small neighbourhood around x_0, $\hat{m}(\cdot)$ will be nearly constant and can be estimated by averaging the P_t*'s* corresponding to those X_t*'s* around x_0.

It is obvious that the P_t*'s* closest to x_0 provide more information about $m(x_0)$ than the P_t*'s* further away. Weighting the observations according to some weighting schedule depending on the distance between x_0 and x_t thus improves the estimate. More formally the smoothing estimator of $m(x)$ can be described as:

$$\hat{m}(x) = \frac{1}{T}\sum_{t=1}^{T}\omega_t(x)P_t \tag{3}$$

where the weights $\{\omega_t(x)\}$ are larger for observations closer to x. The performance of the estimate is to a large extent dependent on the length of the neighbourhood in which $m(\cdot)$ is assumed to be linear and the applied weights. If the neighbourhood is too small and the weights decline too rapidly the regression will be too volatile and too much noise will be captured. On the other hand, if the neighbourhood is too large and the weights too constant, valuable information will be lost. Thus, the weights have to be chosen to balance these two considerations.

3.2 Kernel Regression and Determination of the Estimation Weights

Several methods to determine the regression weights have been proposed in the literature. Hardle [43] describes a conceptually simple approach called kernel regression estimator. The kernel is defined as a continuous, bounded and symmetrical real function K which integrates to one:

$$K(u) \geq 0, \quad \int K(u)du = 1 \tag{4}$$

In order to provide flexibility in terms of the choice of weights so that the above described trade-off between too small and too high weights can be balanced, the kernel is scaled by a factor h so that:

$$K_h(u) = \frac{1}{h} K(u/h), \quad \int K_h(u)du = 1 \tag{5}$$

The regression weights are then given by:

$$\omega_{t,h}(x) = K_h(x - X_t) / g_h(x) \tag{6}$$

$$g_h(x) = \frac{1}{T} \sum_{t=1}^{T} K_h(x - X_t) \tag{7}$$

Substituting these weights into the smoothing estimator function yields a kernel estimator $\hat{m}_h(x)$ of $m(x)$:

$$\hat{m}_h(x) = \frac{\sum_{t=1}^{T} K_h(x - X_t) Y_t}{\sum_{t=1}^{T} K_h(x - X_t)} \tag{8}$$

Hardle [43] shows that $\hat{m}_h(x)$ asymptotically converges to *m(x)*. This convergence holds for a wide range of kernels *K* such as Uniform, Biweight, Triweight, Epanechnikov and Gaussian [47]. The perhaps most commonly used kernel is the Gaussian kernel where the kernel *K* is given by the Gaussian distribution scaled by *h*:

$$K_h(x) = \frac{1}{h\sqrt{2\pi}} e^{-\frac{x^2}{2h^2}} \tag{9}$$

3.3 Selection of Bandwidth

As with any non-parametric method, selection of bandwidth is key to the success of $\hat{m}_h(x)$ in approximating $m(\cdot)$. If the bandwidth is too low, we run the risk of over-fitting the data and the approximation will be choppy; if the bandwidth is too high, there will be too much averaging and thus an approximation that is too smooth.

In order to gain a better understanding of the effect of bandwidth in enabling a kernel regression algorithm to capture the true trend in noisy data, let us look at a simple example. I have added random noise to a sine function and visualized how well the kernel regression algorithm can capture the underlying sine function for different bandwidth parameters. The equation used to generate the noisy data is

$$y = \sin(x) + \varepsilon, \quad x \in (0, 2\pi) \tag{10}$$

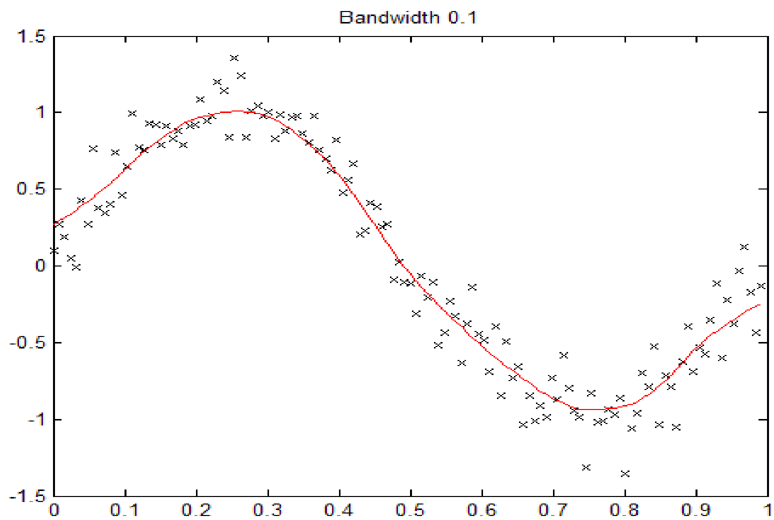


Figure 13 - Bandwidth = 0.1

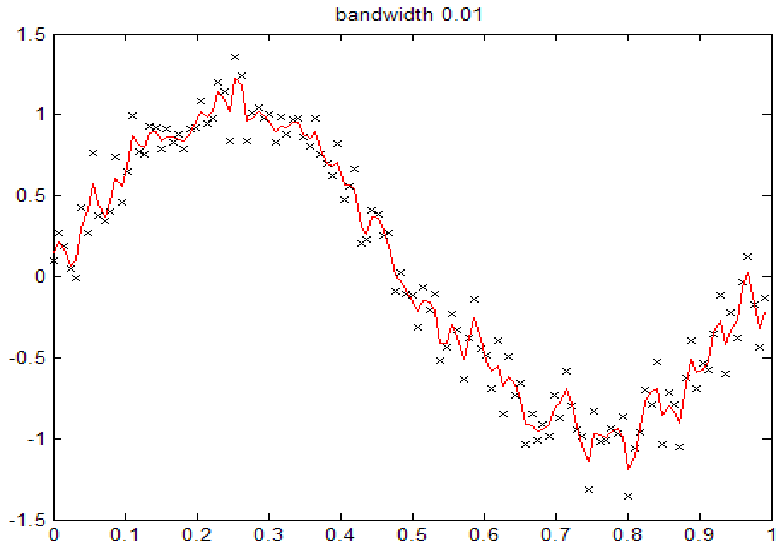


Figure 14 - Bandwidth = 0.01

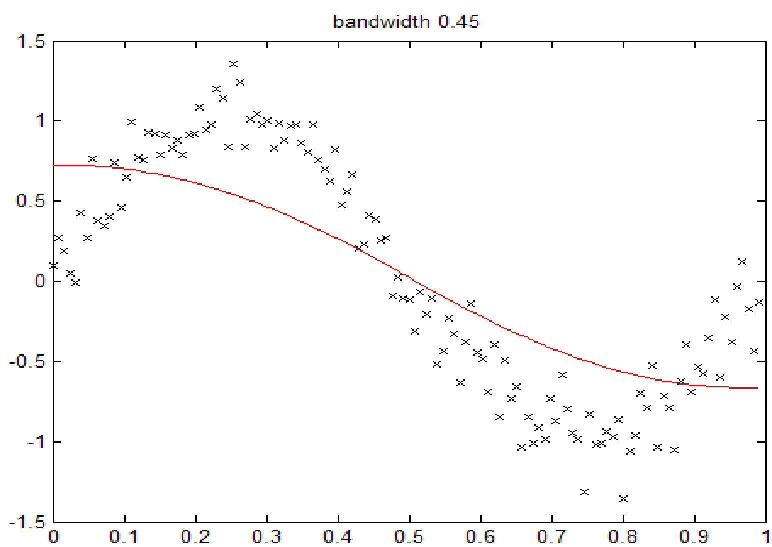


Figure 15 - Bandwidth = 0.45

As can be seen in Figure 13, the kernel regression function to a large extent mirrors the underlying sine-function, without any parameterization of the actual shape of the underlying form. This implies that the kernel method finds an underlying trend without us specifying the shape of it.

Figures 14 and 15 demonstrate the importance of the bandwidth parameter. When the bandwidth is too low (0.01), too little weight is given to distant observations and thus the approximation is too noisy. When the bandwidth is high (0.45), too much weight is given to distant observations and thus the approximation is too smooth. Thus, an arbitrary approach to set the bandwidth is not desirable. We in turn need an automatic algorithm for setting the bandwidth. Several methods to automatically determine the optimal bandwidth have been suggested. Mittelhammer, Judge and Miller [48] derive that the bandwidth $h^* = 1.059\sigma n^{-1}$, where σ is the standard deviation of the data, works reasonably for the Gaussian kernel if the data is normally distributed. A more robust method, known as the cross-validation method is proposed by Green and Silverman [49]. The method is independent of the distribution of the data and has better finite sample properties.

The cross-validation method is a non-parametric version of the standard method applied for parametric regression. The general procedure for determining a regression equation is to train the equation in-sample and then evaluate it out-of-sample. Since a non-parametric regression normally is used on a single data set no new observations are available. Instead, the cross-validation method creates an out-of-sample by omitting one observation at the time and run a regression on the remaining observations [6]. Formally, this can be described as minimizing the cross-validation function:

$$CV(h) = \frac{1}{T}\sum_{t}^{T}(P_t - \hat{m}_{h,t})^2, \text{ where } \hat{m}_{h,t} = \frac{1}{T}\sum_{x \neq t}^{T} w_{x,h} Y_x \tag{11}$$

The estimator $\hat{m}_{h,t}$ is the kernel estimator applied to the data set with the *t*-th observation omitted [49]. By selecting the bandwidth *h* that minimizes the cross-validation function *CV* (*h*), the asymptotic mean-squared error is minimized [50].

The result obtained by using the CV function to compute the bandwidth for equation (11) is shown below:

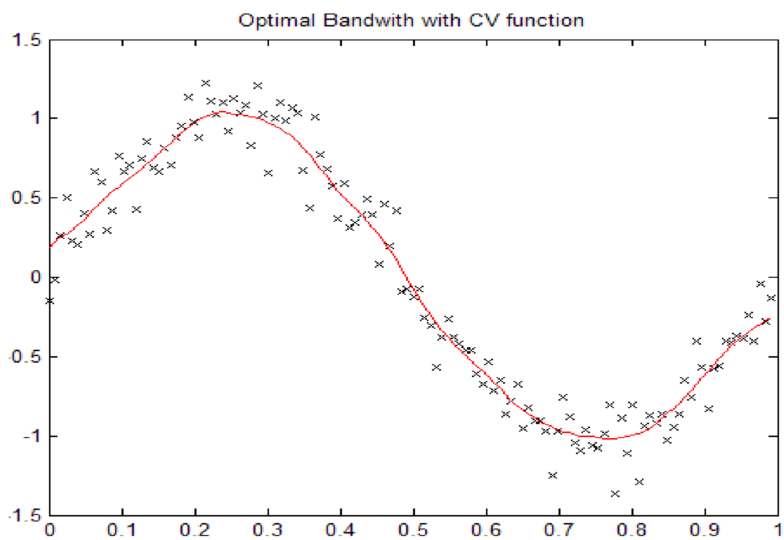


Figure 16 - Bandwidth with CV function

However, the bandwidth computed by minimizing the cross-validation function tends to overfit the data [51]. To resolve this, Lo, Mamaysky and Wang [4] apply an ad-hoc approach where they multiply the bandwidth computed above by a fixed parameter, which they deduced by discussing with several Technical

Analysts.

In this thesis, I propose an automatic bandwidth selection approach that adds a penalizing factor to the cross-validation function so as to compensate for the over-fitting. The new function to minimize is thus:

$$CV(h) = \frac{1}{(T - \sum_{x \neq t}^{T} w_x)} \sum_{t}^{T} (P_t - \hat{m}_{h,t})^2, \text{ where } \hat{m}_{h,t} = \frac{1}{T} \sum_{x \neq t}^{T} w_{x,h} Y_x \qquad (12)$$

3.4 Limitations of Kernel Regression

Although kernel regression is useful for its intuitiveness and simplicity, it suffers from well-known deficiencies, like boundary bias and lack of local variability in the degree of smoothing. This can induce significant errors in the function approximation, especially for stock market data where the degree of local variability is high. A popular alternative that overcomes these particular deficiencies is local polynomial regression [52].

3.5 Local Polynomial regression

Local polynomial regression uses weighted least squares (WLS) regression to fit a d^{th} degree polynomial ($d \neq 0$) to the data. An initial kernel regression fit to the data is computed to determine the weights assigned to the observations. Kernel regression, as described previously, is just a special form of local polynomial regression with $d = 0$. Hastie and Loader [53] showed that local polynomial regression addresses the boundary problem present in kernel regression.

Additionally, local polynomial regression addresses the problem of potentially inflated bias and variance in the interior of the x's if the x's are non-uniform or if substantial curvature is present in the underlying, though undefined, regression function.

Consider fitting y_i at the point x_i. First, a kernel fit is obtained for the entire dataset in order to obtain the kernel hat matrix W(ker). The kernel weights give weight to y_j based on the location x_j from x_i. With local polynomial regression, these become the weights to be used in weighted least squares regression.

Let d represent the degree of polynomial that needs to be fit at a point x. We obtain the estimate $\hat{y}$ at $\hat{x}$ by fitting the polynomial

$$\beta_0 + \beta_1(X_i - x) + \ldots\ldots\ldots + \beta_d(X_i - x)^d \tag{13}$$

using the points (X_i, Y_i) and the weighted least squares procedure.

The value of the estimate at a point x is $\hat{\beta}_0$, where the $\hat{\beta}_i$ minimize

$$\sum_{i=1}^{n} K_h(X_i - x)(Y_i - (\beta_0 + \beta_1(X_i - x) + \ldots\ldots\ldots + \beta_d(X_i - x)^d))^2 \tag{14}$$

Because the points that are needed to estimate the model are all centered at x, the estimate at x is obtained by setting the argument in the model equal to zero. Thus, the only parameter left is the constant term $\hat{\beta}_0$.

According to standard weighted least squares theory, the solution in matrix notation can be written as:

$$\hat{\beta} = (X_x{}^T W_x X_x)^{-1} X_x{}^T W_x Y \qquad (15)$$

where Y is the nx1 vector of responses;

$$X_x = \begin{pmatrix} 1 & X_i - x \ldots & (Xi - x)^d \\ \vdots & \ddots & \vdots \\ 1 & X_n - x \ldots & (X_n - x)^d \end{pmatrix}, \qquad (16)$$

And W_x is a $n \times n$ matrix with weights along the diagonal, calculated using the kernel regression approach.

As mentioned before, the local polynomial regression solves the problem of boundary bias in kernel regression which arises because of the asymmetric contribution of observations to the kernel summation near the boundary. By fitting local polynomials at the boundary values, the estimator does not flatten out because of the lack of available data past the boundary the way the kernel estimator (which fits a local constant) does [54]. This reduction in bias though leads to an increase in variance in the overall estimate. This is not necessarily a bad tradeoff in trying to find a smoothing estimate for stock market data as we want to guard some of the local variability inherent in the financial time series.

An example to illustrate this boundary bias is shown in figure 17. Equation (10) is used to create sample data. Then kernel regression estimator and local polynomial regression estimator of order 2 is applied to the data. One can see that the local polynomial estimate (shown in black) does a much better job of estimating the

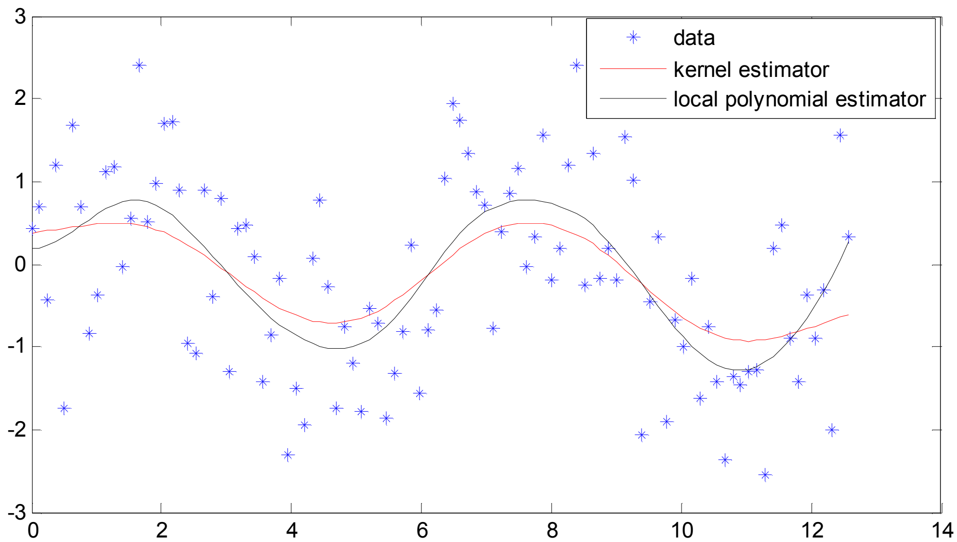


Figure 17 - Comparison of kernel and local polynomial regression estimate

values at the boundary than the kernel estimate (shown in red).

3.6 The Identification Algorithm

Once we have obtained a mathematical representation $\hat{m}(\cdot)$ of $\{P_t\}$ with which geometric properties can be characterized in an objective manner, we can construct an algorithm for automating the detection of technical patterns. The algorithm can be broken into three stages:

1. Define each technical pattern in terms of its geometric properties, for example, local extrema (maxima and minima).

2. Construct a local polynomial regression estimator $\hat{m}(\cdot)$ of a given time series of prices so that its extremas can be determined numerically.

3. Analyse $\hat{m}(\cdot)$ for occurrences of each technical pattern.

As Lo, Mamaysky and Wang pointed out, it is the first step that is likely to be the most controversial because it is here that the skills of a professional Technical Analyst come to play. Technical Analysts may argue that the approximations obtained by the algorithm are poor compared to the kinds of patterns professional analysts can identify. However, while any automated procedure for pattern recognition may miss some of the more subtle nuances that human cognition is capable of discerning, it still can provide a reasonable approximation to some of the cognitive abilities of the human analyst, and thus we can employ such an algorithm to investigate the empirical performance of those aspects of Technical Analysis for which the algorithm is a good approximation. From a practical perspective, there may be significant benefits to developing an algorithmic approach to Technical Analysis because of the leverage that technology can provide. As with many other successful technologies, the automation of technical pattern recognition may not replace the skills of a Technical Analyst but can amplify them considerably [4].

Let each stock in our data set represent a series of prices $\{P_1, \ldots, P_T\}$ where T is the number length of the time-series corresponding to the given stock. Each series of prices is divided into windows of length n on a rolling basis. The parameter n represents the number of historical data points needed to detect a pattern. Lo, Mamaysky and Wang [4] set $n = 35$ to limit themselves to short-term patterns. I have used $n = 50$ to detect short-term patterns because I have further imposed the condition that the pattern should break the neckline before it is considered complete.

Within each sub-window, a local polynomial estimate $m_h(\tau)$ is obtained using the prices in that window, where τ represents each observation in the sub-window. The bandwidth is set to one which minimizes the cross-validation function as described earlier.

The procedure yields an estimate of $m_h(\tau)$ which is a differentiable function of τ. Local extrema are then identified by finding τ such that $Sgn(m_h'(\tau) = -Sgn(m_h'(\tau+1)$, where Sgn is the signum function. Once such is detected, we look for the corresponding extrema in the interval $[\tau-1, \tau+1]$ in the original price series $\{P_t\}$. If the closing price remains the same for several days and we detect $m_h'(\tau)=0$, we use the next observation where $m_h'(\tau)\neq 0$ as a base of comparison.

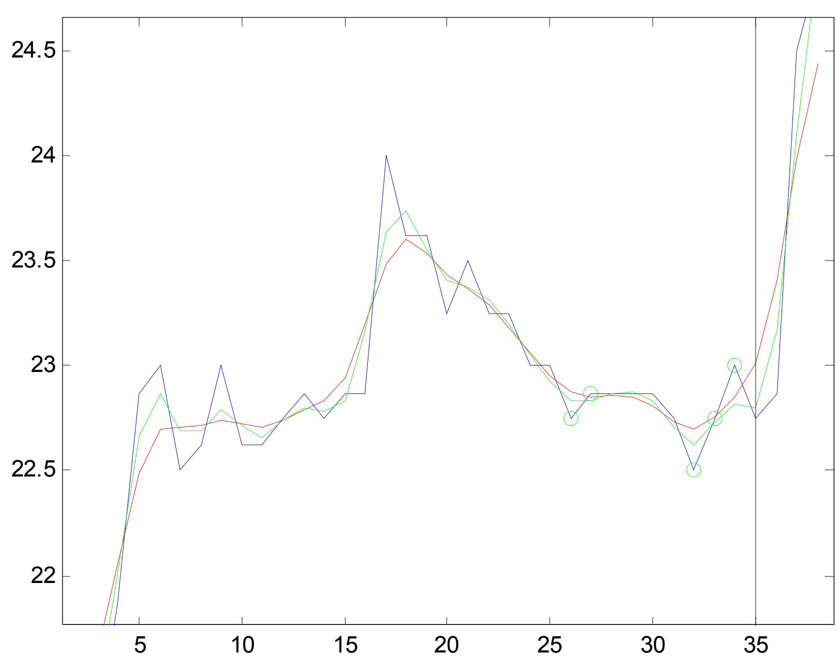
An important advantage of using this regression approach to identify patterns is the fact that it ignores extremas that are "too local." For example, a simpler alternative is to identify local extrema from the raw price data directly, that is, identify a price P_t as a local maximum if $P_{t-1} < P_t$ and $P_t > P_{t+1}$ and vice versa for a local minimum. The problem with this approach is that it identifies too many extremas and also yields patterns that are not visually consistent with the kind of patterns that Technical Analysts find compelling [4].

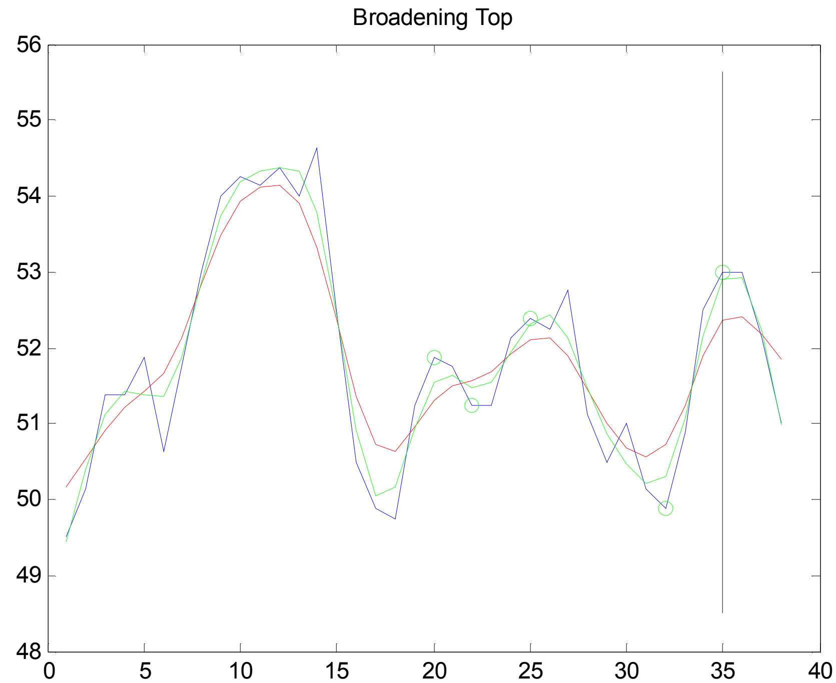
Once we have identified all of the local extrema in the window $[t, t+l-1]$, we can proceed to check for the presence of the various technical patterns defined earlier. This procedure is then repeated until the end of the sample is reached.

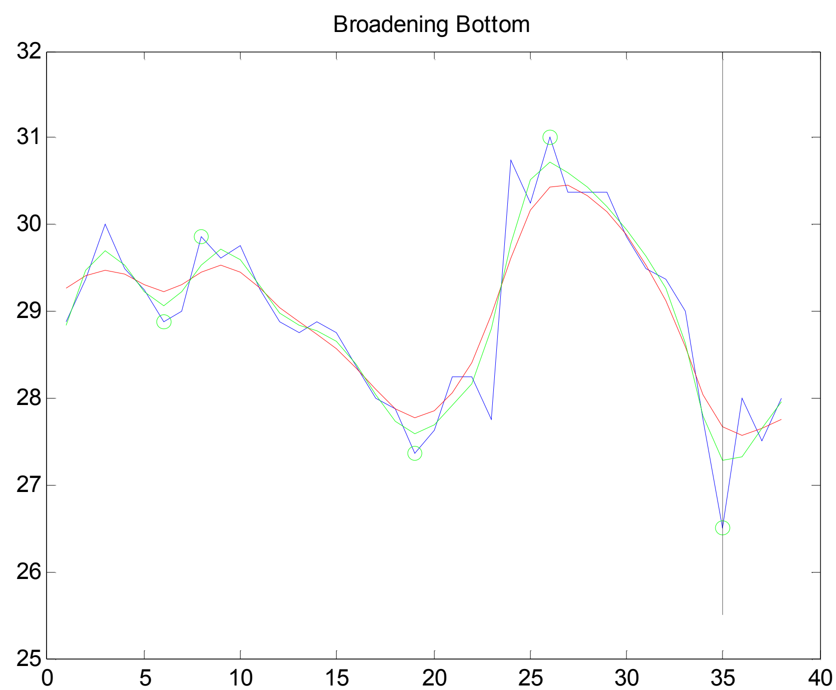
The figures below show the detection of patterns by the algorithm. The curve in blue is the actual price series, the curve in green is the kernel regression estimate and the curve in red is the local polynomial regression estimate.

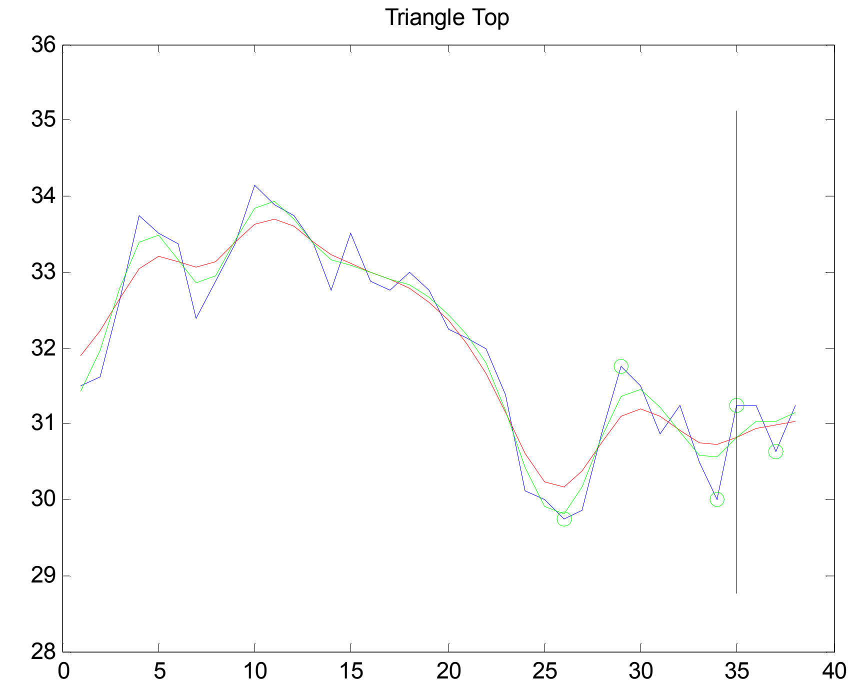
Head and Shoulders

Inverse Head and Shoulders




Broadening Top
56
55
54
53
52
51
50
49
48
0
5
10
15
20
25
30
35
40


Broadening Bottom
32
31
30
29
28
27
26
25
0
5
10
15
20
25
30
35
40


Triangle Top
36
35
34
33
32
31
30
29
28
0
5
10
15
20
25
30
35
40


Rectangle Top
43
42.5
42
41.5
41
40.5
40
39.5
39
5
10
15
20
25
30
35

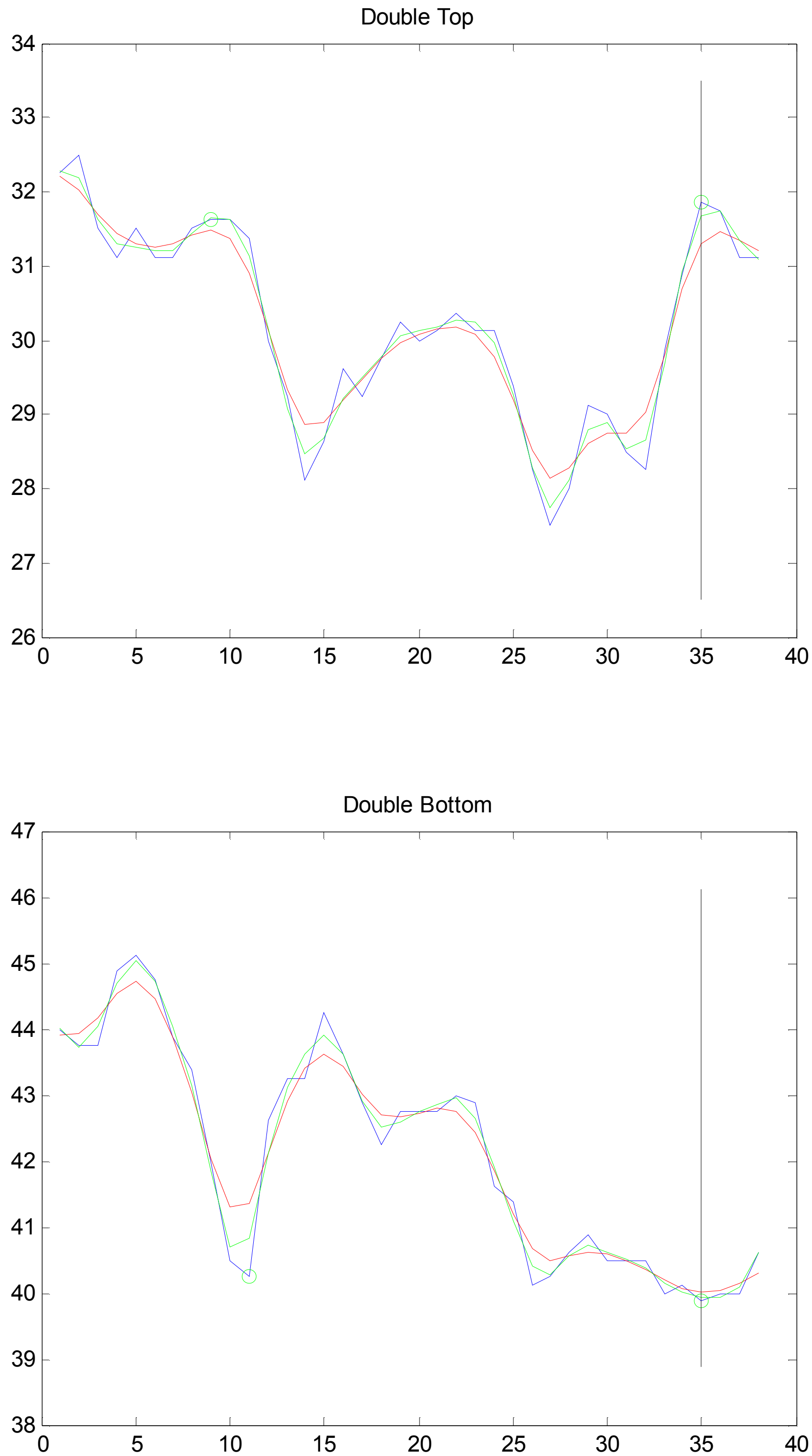


Figure 18 - Chart Patterns

Chapter 4 Empirical Data, Statistical Tests and Results

4.1 Empirical Data

As the aim of this research project is to test the profitability of Technical Indicators in the Singapore and Malaysian market, I have chosen the Straits Times Index (STI) and the Kuala Lumpur Composite Index (KLCI) to test the indicators.

The Straits Times Index is the benchmark index for the Singapore Exchange. It is a market value-weighted index of the stocks of 30 companies that are deemed representative of the Singapore market.

The Kuala Lumpur Composite Index (KLCI) is a capitalization-weighted stock market index. Introduced in 1986, it is now known as the FTSE Bursa Malaysia KLCI. It comprises the 30 largest companies listed on the Malaysian exchange by full market capitalization.

For the STI, the daily closing prices and volume information from 1 Jan 1989 to 31 Dec 2009 were taken, a total of 21 years. This is further subdivided into in-sample period comprising prices from Jan 1989 to Dec 2003, a total of 15 years and out-of-sample period from Jan 2004 to Dec 2009 comprising a total of 6 years.

Similarly, for KLCI, the daily closing prices and volume information from 1 Jan

1989 to 31 Dec 2009 were taken.

The data was obtained from Yahoo Finance and Bloomberg and was cross checked to screen for errors. In case of minor inconsistencies, an average of the two values was taken.

4.2 Statistical Test

The daily closing prices of STI are used to compute the daily returns

$$r_t = S_k * \ln(\frac{P_{t+1}}{P_t}) - r_0 - (Transaction\ Cost) \tag{17}$$

This is in accordance with the financial literature where log returns are used instead of discrete returns (for e.g, Gray and French [55] , Campbell [56], Kon [57] and Fama [58]). One of the benefits of using log returns is that it is additive, so the return over n days is just the sum of n daily returns. The S_k is the signal generated by the k^{th} trading rule. There are 3 values of the signal: 1 for a buy/long signal, 0 for a neutral signal and -1 for a sell/short signal.

The returns are then compared to the results of a benchmark rule. The benchmark rule in this case is the null rule which is always out of the market and thus $r_0 = 0$.

The transaction costs are assumed to be 0.5% for 1 way trade as suggested by Wong, Manzur and Chew [30] for institutional investors.

The average return for the period tested is given by

$$\bar{r} = \frac{\sum_{t=1}^{n} r_t}{n} \tag{18}$$

where n is the sample period.

It must be mentioned that the technical chart pattern rules generate considerably fewer trading signals than the other rules. The resulting mean returns may not be directly comparable with the returns of other rules. As such, I have adopted the modified approach suggested by Hsu [18] which is: the investor holds double positions when there is a buy signal, one position when there is neutral signal and no position for a sell signal.

Let μ be the mean of the daily returns and σ be the standard deviation. Since, it is expected that the returns will be positive, we test the hypothesis:

H_0: $\mu = 0$ vs

H_1 : $\mu > 0$

using the test statistic : $T = \dfrac{\bar{r}}{s/\sqrt{n}}$

Here, s is the sample standard deviation. The test statistic T follows standard normal distribution $N(0,1)$ if H_0 is true. Hence, for an α level of significance, if $T > z_\alpha$, we will reject H_0: $\mu = 0$ and conclude that the return is significantly larger than zero. This can also be deduced using the p-value, which is the probability of obtaining a test statistic at least as extreme as the one that was actually observed, assuming that the null hypothesis is true. Thus, if the p-value obtained is less than

α, we can reject the null hypothesis.

In addition, for meaningful assessment of trading, both risk and return should be considered. A trading strategy that reduces risk is useful even though the return observed is not the maximum. A measure that shows how well the return of an asset compensates the investor for the risk taken is the Sharpe ratio. The Sharpe ratio for a financial asset in general is calculated according to:

$$SR = \frac{\mu - r_f}{\sigma} \tag{19}$$

where μ and σ are the return and standard deviation for an asset and r_f the risk free rate, e.g. the rate of a government bond. A high Sharpe ratio indicates a high return in relation to the risk, which is desirable.

For both Singapore and Malaysian markets, the 3 month Treasury bill rate is considered as proxy for risk free rate.

4.3 Results

4.3.1 In-sample Profitable Rules

I first examine the profitability of the trading rules for the in-sample period of 1989 to 2003. For each class of indicators, the best performing rule is found based on the largest mean return together with a high Sharpe ratio. The criteria for a high Sharpe ratio is that it should not be less than 80% of the value for the rule with the highest Sharpe ratio. Table 2 lists the mean return for the best performing rule together with the annual returns (mean return * 252), the Sharpe ratios and the *p*-values for both STI and KLCI.

Table 1 - Returns and p-values for the best performing rules of each class

	STI				KLCI			
Class	Mean Return	Annual Returns	Sharpe Ratio	*p*-value	Mean Return	Annual Returns	Sharpe Ratio	*p*-value
FR	0.0576	14.52	0.89	0.0000	0.1235	31.13	0.78	0.0000
MA	0.0659	16.60	0.74	0.0002	0.1285	32.38	0.91	0.0003
SR	0.0601	15.15	1.12	0.0029	0.1046	26.35	0.86	0.0031
CB	0.0723	18.21	0.94	0.0001	0.0991	24.97	0.82	0.0019
MSP	0.0449	11.32	1.23	0.0045	0.0965	24.31	1.1	0.0045
HS/IHS	0.0391	9.85	1.16	0.0209	0.0101	2.53	1.02	0.6684
BTOP/ BBOT	0.0329	8.30	0.71	0.1071	-0.0047	-1.19	0.77	0.9060
TTOP/ TBOT	0.0349	8.79	0.83	0.0940	0.0651	16.41	0.63	0.0681
RTOP/ RBOT	0.0574	14.48	0.91	0.0093	0.0110	2.78	0.67	0.7463
DTOP/DBOT	0.0150	3.78	0.80	0.4889	-0.0083	-2.09	0.98	0.8306

From the table above, we can see that the class of technical indicators (FR, MA, CB, SR, MSP) fare much better than the class of technical chart patterns (HS/IHS, BTOP/BBOT, TTOP/TBOT, RTOP/RBOT, DTOP/DBOT) in terms of maximum mean return. The technical indicators are all significant at 1% i.e. *p*-value is less than 0.01, whereas most of the chart patterns are not significant at this level.

In terms of comparing the returns in the two stock markets, the returns in the Kuala Lumpur Index are generally higher than those of Straits Times Index. It would be interesting to see if the pattern holds true in the out-of-sample period too. However, the Sharpe ratio in general is lower suggesting that the Malaysian market is more volatile than the Singapore market.

The parameters of the best-performing rule of each class are listed in Appendix B.

4.3.2 Out-of-sample comparison with buy-and-hold strategy

To test the profitability of Technical Analysis, I will compare the returns of the best rules identified in the preceding section with that of the buy-and-hold strategy in out-of-sample data. Buy and hold is a long-term investment strategy based on the view that in the long run financial markets give a good rate of return despite periods of volatility or decline. It is frequently considered as the benchmark strategy against which other trading strategies are evaluated. Many studies have carried out the comparisons between Technical Analysis and buy-and-hold, for example, Fama and Blume [8]. However, in most of these studies, transaction costs were not taken into account. As the transaction costs in Singapore are of the order of 0.5% per transaction [30] for large institutional investors which is quite high, the profitability of Technical Analysis only makes sense when these costs are taken into account.

Tables 2-11 give the out-of-sample annual returns for the best performing rule for each class and the returns for the buy-and-hold strategy.

Table 2 - Out-of-sample returns - FR

STI	KLCI

Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	-26.17	12.40	-9.20	14.05
2005	-7.81	13.58	3.09	-0.45
2006	18.56	24.23	-3.19	20.52
2007	2.33	13.51	10.40	25.74
2008	-10.88	-61.87	9.22	-49.32
2009	1.74	40.80	-26.89	35.28
Mean Return	-3.71	7.11	-2.76	7.64

Table 3 - Out-of-sample returns - MA

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	0.68	12.40	1.74	14.05
2005	6.14	13.58	-8.34	-0.45
2006	24.35	24.23	13.30	20.52
2007	-11.42	13.51	8.28	25.74
2008	67.47	-61.87	33.71	-49.32
2009	22.32	40.80	23.50	35.28
Mean Return	18.25	7.11	12.02	7.64

Table 4 - Out-of-sample returns - SR

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	-6.88	12.40	18.14	14.05
2005	-5.87	13.58	-2.84	-0.45

2006	19.70	24.23	16.74	20.52
2007	-3.14	13.51	4.67	25.74
2008	45.04	-61.87	23.18	-49.32
2009	21.44	40.80	-5.04	35.28
Mean Return	11.71	7.11	9.14	7.64

Table 5 - Out-of-sample returns - CB

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	8.18	12.40	1.88	14.05
2005	2.55	13.58	-6.09	-0.45
2006	10.49	24.23	7.76	20.52
2007	7.21	13.51	10.45	25.74
2008	50.45	-61.87	41.44	-49.32
2009	-33.75	40.80	23.60	35.28
Mean Return	7.52	7.11	13.17	7.64

Table 6 - Out-of-sample returns - MSP

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	-1.02	12.40	9.58	14.05
2005	-2.91	13.58	-1.49	-0.45
2006	6.03	24.23	0.40	20.52
2007	-13.20	13.51	-14.34	25.74
2008	-1.74	-61.87	-12.80	-49.32

2009	-4.46	40.80	-15.54	35.28
Mean Return	-2.88	7.11	-5.69	7.64

Table 7 - Out-of-sample returns - HS/IHS

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	-7.00	12.40	-1.27	14.05
2005	0.01	13.58	-11.49	-0.45
2006	35.73	24.23	19.68	20.52
2007	-9.64	13.51	11.85	25.74
2008	-45.93	-61.87	-0.25	-49.32
2009	-17.86	40.80	-5.92	35.28
Mean Return	-7.45	7.11	2.10	7.64

Table 8 - Out-of-sample returns - BTOP/BBOT

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	12.32	12.40	12.98	14.05
2005	8.04	13.58	-0.59	-0.45
2006	23.76	24.23	22.02	20.52
2007	2.17	13.51	24.97	25.74
2008	-56.80	-61.87	-44.41	-49.32
2009	7.20	40.80	33.59	35.28
Mean Return	-0.55	7.11	8.09	7.64

Table 9 - Out-of-sample returns - TTOP/TBOT

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	9.02	12.40	3.87	14.05
2005	4.24	13.58	0.25	-0.45
2006	2.45	24.23	14.32	20.52
2007	16.05	13.51	19.43	25.74
2008	-22.06	-61.87	-20.16	-49.32
2009	4.68	40.80	-0.03	35.28
Mean Return	2.39	7.11	2.95	7.64

Table 10 - Out-of-sample returns - RTOP/RBOT

	STI		KLCI	
Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	16.97	12.40	2.88	14.05
2005	1.46	13.58	0.44	-0.45
2006	19.54	24.23	14.72	20.52
2007	-12.76	13.51	9.38	25.74
2008	-47.57	-61.87	-41.63	-49.32
2009	30.89	40.80	33.59	35.28
Mean Return	1.42	7.11	3.23	7.64

Table 11 - Out-of-sample returns - DTOP/DBOT

	STI		KLCI	

Year	Return with TC (%)	Buy-and-hold (%)	Return with TC (%)	Buy-and-hold (%)
2004	12.32	12.40	12.97	14.05
2005	14.20	13.58	-0.59	-0.45
2006	23.76	24.23	22.03	20.52
2007	11.64	13.51	24.97	25.74
2008	-56.80	-61.87	-44.41	-49.32
2009	41.68	40.80	33.59	35.28
Mean Yearly Return	7.80	7.11	8.09	7.64

As can be deduced from the tables above, none of the rules except Moving Averages, Support Resistance and Channel Breakout out-perform buy-and-hold significantly in both the indices. In fact, for some rules like FR, MSP, the mean returns are negative. This is largely due to the fact that FR and MSP generate a lot of signals, and when there are transaction costs involved, the net returns tend to be low.

Even in the case of MA, SR and CB, where the mean yearly return is greater than buy and hold in both the markets, the results are inconclusive. This is because, for MA rules, the best rule only outperforms buy-and-hold in 2 out of 6 out-of-sample periods for STI and 1 out of 6 periods for KLCI. Similarly, for SR rules, the best rule only outperforms buy-and-hold in 1 out of 6 out-of-sample periods for STI and 2 out of 6 periods for KLCI. In the case of CB, its 1 in 6 for STI and 1 in 6 for KLCI.

Overall, none of the classes considered in this thesis seem to offer any performance improvement over buy-and-hold strategy in both Singapore and Malaysian markets when tested out-of-sample. The finding stands in marked contrast to all the research conducted earlier that have found profitable rules in the class of indicators considered in this thesis. The in-sample conclusion that returns in KLCI are higher than those of STI also does not hold in the out-of-sample period.

Chapter 5 Conclusion and Future Work

In this thesis, an attempt was made to evaluate the profitability of Technical Analysis by testing the most commonly used indicators and chart patterns. It was found that none of the indicators significantly out-perform the buy-and-hold strategy when tested out-of-sample. That is not to say that Technical Analysis as a whole is out of merit. This research only focused on a subset of indicators that are used by practitioners. The study can be further enhanced by considering more complex trading strategies that combine many simple indicators to generate signals. Hsu [18] found that complex trading strategies fare much better than simple rules.

In addition, instead of creating a universe of technical rules by specifying parameter values and then finding the best rule in-sample, a genetic algorithm can be applied to search for the most profitable rule in the entire rule space. In this way, the span of technical rules considered will be much larger, and the results will be more conclusive.

Also, in this thesis, a local polynomial regression estimate to automate the recognition of technical chart patterns was implemented. Casual inspection by me and a discussion with some of the Technical Analysts led me to the conclusion that the local polynomial regression estimate does a better job at capturing the patterns in the price series. It captures the extremas in regions where the prices are volatile, as compared to the kernel regression estimator that tends to smooth too much in such areas. It also performs well at the boundaries. By including the neckline and volume information, the definition of patterns are closer to those used by analysts. However, the algorithm can be further improved by generalizing it to detect patterns in a price series of any length. Currently, consecutive maximas and minimas are analysed to detect a pattern. This method is adequate for short price series but it may fail to capture trends in longer series where there may be spurious extremas in between.

Appendix A: Parameter Values of Technical Indicators and Chart Patterns

A.1 Filter Rules

x = change in security price (x*price) required to initiate a position

y = change in security price (y*price) required to liquidate a position

e = used for an alternative definition of extrema where a low(high) can be defined as the most recent closing price that is less(greater) than the n previous closing prices

c = pre-specified number of days a position is held, ignoring all other signals during that time

x = 0.005, 0.01, 0.015 , 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, 0.5 (24 values)

y = 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.04, 0.05, 0.075, 0.1, 0.15, 0.2 (12 values)

e = 1, 2, 3, 4, 5, 10, 15, 20 (8 values)

c = 5, 10, 25, 50 (4 values)

y must be less than x, so there are 185 x-y combinations.
There are 24 x values, so there are 24 simple filter rules. For each value of x, there are 185 x-y combinations, 24*8 = 192 x-e combinations, 24*4 = 96 x-c combinations.

Number of filter rules = x + xy + x*e + x*c
= 24 + 185 + 192 + 96
= 497

A.2 Moving Averages

n = number of days in a moving average

m= number of fast-slow combinations of n

b = fixed band multiplicative value

d = number of days for the time delay filter

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250 (15 values)

b = 0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05 (8 values)

d = 2, 3, 4, 5 (4 values)

c = 5, 10, 25, 50 (4 values)

Fast moving average is less than slow moving average, so number of fast-slow combinations are 105.

Number of MA rules = (n + m) + (b*(n + m)) + (d*(n + m)) + (c*(n + m))

= 15 + 105 + 960 + 480 + 480 = 2049

A.3 Support Resistance

n = number of days in the support and resistance range

b = fixed band multiplicative value

d = number of days for the time delay filter

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 5, 10, 15, 20, 25, 50, 100, 150, 200, 250 (10 values)

b = 0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05 (8 values)

d = 2, 3, 4, 5 (4 values)

c = 5, 10, 25, 50 (4 values)

Number of SR rules = (1 + c)*n + b*(1 + c)*n + d*c*n

= 50 + 400 + 150 = 610

A.4 Channel Breakouts

n = number of days for the channel

x = difference between the high price and low price (x*high price) required to form the channel

b = fixed band multiplicative value

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 5, 10, 15, 20, 25, 50, 100, 150, 200, 250 (10 values)

x = 0.005, 0.01, 0.02, 0.03, 0.05, 0.075, 0.10, 0.15 (8 values)

b = 0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05 (8 values)

c = 5, 10, 25, 50 (4 values)

b must be less than x, so there are 43 x-b combinations

Number of CB rules = n*x*c + n*c*x-b

= 320 + 1720 = 2040

A.5 Momentum Strategies in Price

m= rate of change(ROC) over the past m days

w= number of days in a moving average

k = overbought/oversold level

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 2, 5, 10, 20, 30, 40, 50, 100, 125, 250 (10 values)

w= 2, 5, 10, 20, 30, 40, 50, 100, 125, 250 (10 values)

b = 0.05, 0.1, 0.15, 0.2 (4 values)

c = 5, 10, 25, 50 (4 values)

There are 10 m values, thus 10 simple oscillators. For moving average oscillators, w<=m. Thus, there are 55 of them. For crossover moving average oscillators, w1<w2, so there are 45 ratios.

Number of MSP rules = (m + m-w combinations + w1-w2 combinations)*b*c

= (10 + 55 + 45)*4*4 = 1760

A.6 Head and Shoulders and Inverse Head and Shoulders

n = number of days in the pattern detection window

x = differential rate of shoulders or troughs

b = multiplicative band

r = stop loss rate

d = parameter for fixed liquidation price

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 50 (1 value)

x = 0.005, 0.01, 0.015, 0.03, 0.05 (5 values)

b = 0, 0.005, 0.01, 0.02, 0.03 (5 values)

r = 0.005, 0.0075, 0.01, 0.015 (4 values)

d = 0.25, 0.5, 0.75, 1 (4 values)

c = 5, 10, 25, 50 (4 values)

Given 1 value of n, 5 values of x, and 5 values of b, there are 25 (n, x, b) combinations. For each combination, there are 4 fixed hold and 4*4=16 stop loss and fixed liquidation price methods.

Number of HS rules = 25*(4 + 16) = 500

A.7 Broadening Tops and Bottoms

n = number of days in the pattern detection window

b = multiplicative band

r = stop loss rate

d = parameter for fixed liquidation price

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 50 (1 value)

b = 0, 0.001, 0.003, 0.005, 0.075, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 (15 values)

r = 0.005, 0.0075, 0.01, 0.015 (4 values)

d = 0.25, 0.5, 0.75, 1 (4 values)

c = 5, 10, 25, 50 (4 values)

Given 1 value of n, 15 values of b, there are 75 (n, b) combinations. For each combination, there are 4 fixed hold and 4*4=16 stop loss and fixed liquidation price methods.

Number of Broadening rules = 15*(4 + 16) = 300

A.8 Triangle Tops and Bottoms

n = number of days in the pattern detection window

b = multiplicative band

r = stop loss rate

d = parameter for fixed liquidation price

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 50 (1 value)

b = 0, 0.001, 0.003, 0.005, 0.075, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 (15 values)

r = 0.005, 0.0075, 0.01, 0.015 (4 values)

d = 0.25, 0.5, 0.75, 1 (4 values)

c = 5, 10, 25, 50 (4 values)

Given 1 value of n, 15 values of b, there are 75 (n, b) combinations. For each combination, there are 4 fixed hold and 4*4=16 stop loss and fixed liquidation price methods.

Number of Triangle rules = 15*(4 + 16) = 300

A.9 Rectangle Tops and Bottoms

n = number of days in the pattern detection window

x = parameter of bounds

b = multiplicative band

r = stop loss rate

d = parameter for fixed liquidation price

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 50 (1 value)

x = 0.005, 0.0075, 0.01 (3 values)

b = 0, 0.001, 0.003, 0.005, 0.075, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 (15 values)

r = 0.005, 0.0075, 0.01, 0.015 (4 values)

d = 0.25, 0.5, 0.75, 1 (4 values)

c = 5, 10, 25, 50 (4 values)

Given 1 value of n, 3 values of x, and 15 values of b, there are 45 (n, x, b) combinations. For each combination, there are 4 fixed hold and 4*4=16 stop loss and fixed liquidation price methods.

Number of Rectangle rules = 45*(4 + 16) = 900

A.10 Double Tops and Bottoms

n = number of days in the pattern detection window

x = parameter of bounds

b = multiplicative band

r = stop loss rate

d = parameter for fixed liquidation price

c = pre-specified number of days a position is held, ignoring all other signals during that time

n = 50 (1 value)

x = 0.005, 0.01, 0.015, 0.03, 0.05 (5 values)

b = 0, 0.001, 0.003, 0.005, 0.075, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 (15 values)

r = 0.005, 0.0075, 0.01, 0.015 (4 values)

d = 0.25, 0.5, 0.75, 1 (4 values)

c = 5, 10, 25, 50 (4 values)

Given 1 value of n, 5 values of x, and 15 values of b, there are 75 (n, x, b) combinations. For each combination, there are 4 fixed hold and 4*4=16 stop loss and fixed liquidation price methods.

Number of Double Tops and Bottoms rules = 75*(4 + 16) = 1500

Appendix B: Parameter Values of Best Performing Rules in each class

B.1 Filter Rules

STI : x = 0.01

KLCI : x = 0.005

B.2 Moving Averages

STI : slow moving average = 40, fast moving average = 15, b = 0.01

KLCI : slow moving average = 50, fast moving average = 5, b = 0.015

B.3 Support Resistance

STI : n = 50

KLCI : n = 20, b = 0.001

B.4 Channel Breakout

STI : n = 5, x = 0.005, c = 5

KLCI : n = 20, x = 0.1, b = 0.01, c = 50

B.5 Momentum Strategies in Price

STI : m = 2, k = 0.05, c = 5

KLCI : m = 20, w1 = 5, w2 = 0, k = 0.05, c = 50

B.6 Head and Shoulders/Inverse Head and Shoulders

STI : n = 50, x = 0.015, c = 25

KLCI : n = 50, x = 0.03, b = 0.03, c = 50

B.7 Broadening Tops and Bottoms

STI : n = 50, b = 0.005, c = 50

KLCI : n = 50, b = 0.075, c = 50

B.8 Triangle Tops and Bottoms

STI : n = 50, c = 50

KLCI : n = 50, b = 0.05, c = 50

B.7 Rectangle Tops and Bottoms

STI : n = 50, x = 0.01, b = 0.04, c = 50

KLCI : n = 50, x = 0.0075, b = 0.04, c = 50

B.7 Double Tops and Bottoms

STI : n = 50, x= 0.005, r = 0.005, d = 0.25

KLCI : n = 50, x= 0.005, r = 0.005, d = 0.25

References

[1] M.J. Pring, *Technical Analysis Explained*.: New York,NY:McGraw-Hill, 2002.

[2] S. Nison, *Japanese Candlestick Charting Techniques*.: New York Institute of Finance, New York, 1991.

[3] Robert Edwards and John Magee, *Technical Analysis of Stock Trends*, 7th ed.: John Magee Inc., 1997.

[4] A.W. Lo, H. Mamaysky, and J. Wang, "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference and Empirical Implementation," *Journal of Finance*, pp. 1705-1765, 2000.

[5] Burton Malkiel, *A Random Walk Down Wall Street*.: W.W. Norton, New York, 1996.

[6] John Campbell, Andrew W. Lo, and Craig A. MacKinlay, *The Econometrics of Financial Markets*.: Princeton University Press, Princeton, N.J, 1997.

[7] E. F Fama, "Efficient Capital Markets: A Review of Theory and Empirical Work.," *Journal of Finance*, pp. 383-417, 1970.

[8] E. F. Fama and M. E. Blume, "Filter Rules and Stock Market Trading.," *Journal of Business*, pp. 226-241, 1966.

[9] J.L. Treynor and R Ferguson, "In Defense of Technical Analysis," *Journal of Finance*, pp. 757-773, 1985.

[10] D. P. Brown and R. H. Jennings., "On Technical Analysis," *Review of Financial Studies*, pp. 527-551, 1989.

[11] B. D. Grundy and M. McNichols, "Trade and the Revelation of Information through Prices and Direct Disclosure," *Review of Financial Studies*, pp. 495-526, 1989.

[12] A. Shleifer and L. H. Summers, "The Noise Trader Approach to Finance," *Journal of Economic Perspectives*, pp. 19-33, 1990.

[13] A. Beja and M. B. Goldman, "On the Dynamic Behavior of Prices in Disequilibrium," *Journal of Finance*, pp. 235-248, 1980.

[14] K. A. Froot, D. S. Scharfstein, and J. C. Stein, "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation," *Journal of Finance*, pp. 1461-1484, 1992.

[15] A. B. Schmidt, "Why Technical Trading May Be Successful? A Lesson from the Agent-Based Modeling," *Physica A,* pp. 185-188, 2002.

[16] W. C. Clyde and C. L. Osler, "Charting: Chaos Theory in Disguise?," *Journal of Futures Markets*, pp. 489-514, 1997.

[17] Cheol-Ho Park and Scott H. Irwin, "The Profitability of Technical Analysis: A Review," AgMAS Project Research Report No. 2004-04 2004.

[18] Andrew Lo and A. C. MacKinlay, *A Non-Random Walk Down Wall Street.*: Princeton, NJ: Princeton University Press, 1999.

[19] S. H. Irwin and B. W. Brorsen, "A Note on the Factors Affecting Technical Trading System Returns," *Journal of Futures Markets*, pp. 591-595, 1987.

[20] B. W. Brorsen and S. H. Irwin, "Futures Funds and Price Volatility," *The Review of Futures Markets*, pp. 118-135, 1987.

[21] R. S. Billingsley and D. M. Chance, "Benefits and Limitations of Diversification Among Commodity Trading Advisors," *Journal of Portfolio Management*, pp. 65-80, 1996.

[22] L Menkhoff, "Examining the Use of Technical Currency Analysis," *International Journal of Finance and Economics*, pp. 307-318, 1997.

[23] Y. W. Cheung, M. D. Chinn, and I. W. Marsh, "How Do UK-Based Foreign Exchange Dealers Think Their Market Operates?," *NBER Working Paper*, 2000.

[24] Y. W. Cheung and M. D. Chinn, "Currency Traders and Exchange Rate Dynamics: A Survey of the US Market," *Journal of International Money and Finance*, pp. 439-471, 2001.

[25] S Smidt, *Amateur Speculators*.: Ithaca, NY: Graduate School of Business and Public Administration, Cornell University, 1965a.

[26] Group of Thirty, *The Foreign Exchange Market in the 1980s.*: New York, NY: Group of Thirty, 1985.

[27] M. P. Taylor and H. Allen, "The Use of Technical Analysis in the Foreign Exchange Market.," *Journal of International Money and Finance*, pp. 304-314, 1992.

[28] Y. H. Lui and D. Mole, "The Use of Fundamental and Technical Analyses by Foreign Exchange Dealers: Hong Kong Evidence," *Journal of International Money and Finance*, pp. 535-545, 1998.

[29] Y. W. Cheung and C. Y. P. Wong, "The Performance of Trading Rules on Four Asian Currency Exchange Rates," *Multinational Finance Journal*, pp. 1-22, 1997.

[30] Wing-Keung Wong, Meher Manzur, and Boon-Kiat Chew, "How rewarding is technical analysis? Evidence from Singapore stock market," *Applied Financial Economics,13:7,* pp. 543 - 551, 2003.

[31] S.W. Pruitt and R.E. White, "The CRISMA Trading System: Who Says Technical Analysis Can't Beat the Market?," *Journal of Portfolio Management*, vol. 14, no. 3, pp. 55-58, 1988.

[32] W. Brock, J. Lakonishock, and B. LeBaron, "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *Journal of Finance*, pp. 1731-1764, 1992.

[33] Po-Hsuan Hsu and Chung-Ming Kuan, "Reexamining the Profitability of Technical Analysis with Data Snooping Checks," *Journal of Financial Econometrics*, vol. 3, no. 4, pp. 606-628, 2005.

[34] S. N. Neftci, "Naïve Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of Technical Analysis," *Journal of Business*, pp. 549-571, 1991.

[35] C. J. Neely, P. A. Weller, and R. Dittmar, "Is Technical Analysis Profitable in the Foreign Exchange Market? A Genetic Programming Approach," *Journal of Financial and Quantitative Analysis*, pp. 405-426, 1997.

[36] F. Allen and R. Karjalainen, "Using Genetic Algorithms to Find Technical Trading Rules," *Journal of Financial Economics*, pp. 245-271, 1999.

[37] Ryan Sullivan, Allan Timmermann, and Halbert White, "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap," *The Journal of*

Finance, vol. 54, no. 5, pp. 1647-1691, Oct 1999.

[38] Steven Achelis, *Technical Analysis from A to Z*, 2nd ed.: McGraw-Hill, 2000.

[39] M.J. Pring, *Study Guide for Technical Analysis Explained : The Successful Investor's Guide to Spotting Investment Trends and Turning Points*, 1st ed.: McGraw-Hill, 2002.

[40] H.M. Gartley, *Profits in the Stock Market*. Washington: Lambert-Gann Publishing, 1935.

[41] Carol L. Osler and Kevin P. H. Chang, "Head and Shoulders: Not Just a Flaky Pattern," FRB of New York Staff, 4, 1995.

[42] Fred Mcallen, *Charting and Technical Analysis*.: CreateSpace, 2010.

[43] Wolfgang Hardle, *Applied Nonparametric Regression*, 1st ed.: London, UK: Press Syndicate of the University of Cambridge, 1990.

[44] Christopher M. Bishop, *Neural Networks for Pattern Recognition*, 1st ed.: Oxford University Press, USA, 1996.

[45] A.W. Lo, "Neural Networks and Other Nonparametric Techniques in Econometrics and Finance," *Blending Quantitative and Traditional Equity Analysis*, 1994.

[46] Jeffrey D. Hart and Thomas E. Wehrly, "Kernel Regression Estimation Using Repeated Measurements Data," *Journal of the American Statistical Association*, pp. 1080-1088, Dec 1986.

[47] C.-K. Chu and J. S. Marron, "Choosing a Kernel Regression Estimator," *Statistical Science*, pp. 404-419, 1991.

[48] Ron C. Mittelhammer, George G. Judge, and Douglas J. Miller, *Econometric Foundations*, 1st ed.: London, UK: Cambridge University Press, 2000.

[49] P.J. Green and B.W. Silverman, *Nonparametric Regression and Generalized Linear Models: A Roughness Penalty Approach*.: London, UK: Chapman & Hall.

[50] Badi H. Baltagi, *A Companion to Theoretical Econometrics*.: Oxford, UK: Blackwell Publishers Ltd, 2001.

[51] Michael Brockmann, Theo Gasser, and Eva Herrmann, "Locally Adaptive

Bandwidth Choice for Kernel Regression Estimators," *Journal of the American Statistical Association*, pp. 1302-1309, 1993.

[52] Jianqing Fan, Nancy E. Hickman, and M.P. Wand, "Local Polynomial Kernel Regression for Generalized Linear Models and Quasi-Likelihood Functions," *Journal of the American Statistical Association*, vol. 90, 1995.

[53] T. Hastie and C. Loader, "Local Regression: Automatic Carpentry," *Statistical Science* , no. 8, pp. 120-143, 1993.

[54] Jeffrey S. Simonoff., "Smoothing Methods in Statistics," *Psychometrica*, pp. 163-164, 1997.

[55] J. Brian Gray and Dan W. French, "Empirical Comparisons of Distributional Models for Stock Index Returns," *Journal of Business Finance & Accounting*, 1990.

[56] John Y. Campbell, "A Variance Decomposition for Stock Returns," National Bureau of Economic Research, Cambridge, 3246, 1990.

[57] Stanley J. Kon, "Models of Stock Returns--A Comparison," *The Journal of Finance*, pp. 147-165, 1984.

[58] Eugene F. Fama and Kenneth R. French, "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, pp. 427-465, 1992.

[59] L Bachelier, "Théorie de la Spéculation. Doctoral Dissertation in Mathematics," University of Paris , 1900.

[60] Y. W. Cheung and C. Y. P. Wong, "A Survey of Market Practitioners' Views on Exchange Rate Dynamics," *Journal of International Economics, 51(2000): 401-419.*

[61] J. Koza, *Genetic Programming: On the Programming of Computers by Means of Natural Selection*.: Cambridge, MA: MIT Press, 1992.

[62] L. Blume, D. Easley, and M. O'Hara, "Market Statistics and Technical Analysis: The Role of Volume," *Journal of Finance*, pp. 153-181, 1994.

[63] P. H. K. Chang and C. L. Osler, "Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts," *Economic Journal*, pp. 636-661, 1999.

[64] B LeBaron, "Technical Trading Rule Profitability and Foreign Exchange Intervention.," *Journal of International Economics*, pp. 125-143, 1999.

[65] P. A. Samuelson, "Proof That Properly Anticipated Prices Fluctuate Randomly," *Industrial Management Review*, pp. 41-49, 1965.

[66] B Mandelbrot, "Forecasts of Future Prices, Unbiased Markets, and 'Martingale' Models.," *Journal of Business*, pp. 242-255, 1966.

[67] J. A. Frankel and K. A. Froot, "Chartist, Fundamentalists, and Trading in the Foreign Exchange Market," *American Economic Review*, pp. 181-185, 1990.

[68] M. C. Jensen, "Some Anomalous Evidence Regarding Market Efficiency," *Journal of Financial Economics*, pp. 95-101, 1978.