The statistical properties of technical trading rules

By

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Abstract

A portfolio of 200 heterogeneous technical trading rules is tested for their directional predictabilities on the DJIAI from 1988 to 1999.

We also explore several nonparametric techniques designed for brain research, and detected possibly other forms of dependencies more significant than the traditional linear autocorrelation for the time series.

The overall conditional mean directional predictability is 46%. 36 percent of the rules have more than 50% directional predictability, and the top 20 percent rules has a 73% directional predictability, whereas the bottom 80 percent has a directional predictability of 40%. Buy signals consistently generate higher predictability than sell signals but do not commensurate with their respective risk levels. The relationship between two sub-periods is not stable, while the difference between the conditional mean directional predictability of buy only and sell only signals is highly significance.

The belief that most successful rules have a directional predictability of 25% to 50% coincides with the mode of distribution.

We observe counter intuitive relationship between volatility and directional predictability. The results of directional predictability in a downtrend concur with the argument that buy-and-hold strategy is not a suitable benchmark.

Attempts are made to tackle the issues of small sample bias, data snooping, size of test window, bootstrap or t-test, and homogeneity. Issues are discussed on empirical testing for their real world applications, statistical and non-statistical interpretations; also randomness test; physical or biological science approach.

Key words
Technical trading rules; Technical analysis; Nonparametric analyses; Directional predictability; Belief; Down trend; Volatility; Empirical testing.

J.E.L. Classification
G12, G14

Contents

Preface

My first encounter with technical analysis was shortly after my Master Degree's dissertation at the Institute of European Finance, University of Wales, when I spotted a newspaper advertisement by the Citibank group recruiting for technical analysts. It was at first fascinating, but then skepticism prevailed, as it was at that time, too simple and without rationales to me to be of value.

It was not until 1989, during my study at the New York Institute of Finance, that I noticed all major brokerage houses had their own technical analysis departments that rekindled my interest. From then on, I collected as many books and articles on technical analysis as I can to the size of thousands.

Subsequently, it was clear to me that one need to empirically test technical trading rules of any sort prior to using them in real life trading, and not just blindly follow those in the books which are mostly in the form of "selected" examples without rigorous testing.

Nowadays, financial television channels such as Bloomberg and CNBC; have frequent interviews with technical analysts from major brokerage houses and investment boutiques; to the extent that it is sometimes almost on a daily basis.

With the affordability of computing power and the availability of large financial time series data; opportunity abound, and hence the start of this project.

Acknowledgements

I am indebted to my employer, Permodalan Sabah Bhd. for the funding of this project.

I wish to thank my supervisor Professor Terence C. Mills who always responds promptly, provides good advice and has given me much needed encouragement despite his heavy schedule.

My thanks also go to Lo Lian Jin for her excellent assistance in the setting up and maintenance of the Trade Station software, collection of some technical trading rules, and in following up to some of my computational works; and not forgetting my long serving personal secretary Florence Ombong for her assistance on the completion of this thesis.

A word of appreciation also goes to the following libraries: Loughborough University, London Business School, University of Chicago and the Chicago City's library, University of Malaya and University of Sabah Malaysia. The Chicago City library houses one of the most comprehensive collections of non-academic literature on technical analysis and financial trading. This is not surprising given the high concentration of futures markets in Chicago and the related financial trading using mostly technical analysis. Indeed, Chicago is regarded by some as the Holy Land of financial trading.

I also wish to pay a tribute to my late cousin sister "See Lia" who passed away on the September 11th at the former World Trade Center. Her success in Wall Street had inspired much of my continuous interest in financial investment and trading.

A special thank to two of my colleagues at Turtleglen Fund Ltd. (a derivative Hedge Fund) for their financial trading insights, in particular, the Turtle trading methodology: they are David William Hunt (past Vice President and Secretary of the Australian Technical Analysis Association) and Russell J. Sands (one of the original 21 "turtles" trained by the legendary financial trader Richard J. Dennis).

To my stockbroker Lim Guan Gin - a first class honours degree holder in mathematics and a very successful financial trader - for some of his views and experience on technical analysis, trading and probability.

Credit for this thesis's completion should go to Lilian, Soon Tee and May for their cheerful willingness and understanding for a few years' worth of evenings and weekends, and during my occasional absence on short study leave.

The usual disclaimers apply. All else belong to nonlinearity.

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Certificate of originality

This is to certify that I am responsible for the work submitted in this thesis, that the original work is my own except as specified in acknowledges or in footnotes, and that neither the thesis nor the original work contained herein has been submitted to this or other institution for a higher degree.

______________________________________ (Signed)

______________________________________ (Date)

Chapter 1

Introduction: rationale, purpose, scope, justifications and contributions

1.1 Why quantitative?

1.1.1 Merits

There are basically three types of argument for the use of quantitative methods in investment and trading. The first one is that it helps to eliminate and reduce the emotional aspect of decision making and hence, leaving the cognitive biases to be replaced by systematic and often automatic investment and trading decisions. This argument is evidenced by the success of those systematic trading and investment funds (see for example, Edmonds, 1998). To give an example, one of the key ideas in behavioral finance is the Prospect Theory originally conceptualized by Kahneman and Tversky (1979) which suggests that people respond differently to equivalent situations; depending upon whether it is presented in the context of a loss or a gain. Typically, they become more distressed at the prospect of losses than they are made happy by equivalent gains. This loss aversion means that people are willing to take more risks to avoid losses than to realize gains! (Please refer to Robert Schiller's website-www.econ.yale.edu/schiller- for a survey on some of the key ideas in behavioral finance or the chapter of investor psychology in LeBaron and Vaitilingam, 2002 for a summary). The Prospect Theory in our view could be the theoretical underpinning for the success of some of the widely used technical trading rules such as the "Supports and Resistances" and warrant further investigation.

Secondly, it also reduces a lot of subjectivities which are to be replaced by objectivity expressed clearly in numbers and in statistical terms such as the probability of a certain event occurring; and can be understood by all levels of the investment and trading hierarchy. A good example of this is the Efficient Portfolio Theory by Harry Markowitz (1959) which is a technique for optimal risk diversification and it is useful no matter how many market participants use them. Another example is identifying market inefficiency such as the seminal work of Fama and French (1992) which showed that it had been possible for a long time to earn very substantial extra returns by investing in stocks with small capitalizations and stocks with high book to price ratios

Last and not least, it can extract information more efficiently and in greater speed (time is money) which is often the decisive factor in implementing trading decisions such as arbitrage and so forth before the trading opportunities are disappeared in front of the monitor screen. This view is shared by many others such as Van Vliet and Hendry (2004): "Human traders – using strategies that combine technical and fundamental indicators with gut instincts and market savvy – are quite possibly an endangered species. They are being replaced by quantifying trading systems capable of watching hundred of securities and derivatives simultaneously and, at the exact second that conditions are most favourable, executing hundred of strategies in a millisecond."

1.1.2 Limitations

Obviously, quantitative investing and trading also have their fair share of criticisms. Amount them, "quants" are described as those who try to drive based on what appears in their rearview mirrors. The instability of the system based on the assumption of static relationships is another important drawback. An obvious compromise would be to employ quantitative methods where they are most beneficial and use qualitative judgments where it is beyond quantitative boundary. The Bayesian technique is an example of a synthesis of the two. As Forcardi et al. (2004) put it: "The ability to incorporate exogenous insight, such as a portfolio manager's judgment, into formal models is important; such insight might be the most valuable input the model uses." They further conjecture that with the availability of more powerful computers and recent advances in Markov Chain Monte Carlo methods will contribute to a growing use of a variety of Bayesian models.

1.2 Fundamental analysis and irrational exuberance

The fundamental side has been quite efficient for a long time, as compared to quantitative which has not been that objective until the advancement and affordability of technology. While earning do drive stock price, they are not the only deciding factor. Stocks can fall despite increase in earnings. This can be due to changes in business outlook, valuation that exceed earning potential, or products and/or technologies become obsolete, or the competitive advantages of a firm is deteriorating.

Quantitative analysis can sometimes detect changes more quickly than fundamental analysis where the information would not arrive until company conference calls and earning announcements. The old market adage of "buy on rumors and sell on facts" is a typical example. The market's "irrational exuberance" can be hard to exploit by fundamental analysis. Markets over reactions and under reactions are at odd with fundamental analysis. The dotcom fiasco of the late 1990s is a classic example. Even in time of booms and bursts, stocks do not necessarily move in straight lines. Stocks and markets prices can move far more often than what changes in fundamentals of companies and markets may suggest. Meanwhile, quantitative analysis can exploit the changes in price trends and volatilities, rather than suffering from it. Thus, quantitative analysis may has a place in making a profit in the financial markets due to the irrational exuberance of greed and fears of market participants; and may we venture to assume also markets inefficiencies?

Not every market participant shares and receives the same information, at the same time, and act upon the information (i.e. buy or sell) at the same time, and with the same magnitude. And so it boils down to timing, and hopefully the "quants" can then provide better timing strategies for profit opportunities.

The remaining chapters will endeavor to provide some answers by tackling some issues on whether quantitative analyses such as technical trading rules can add value to market participants in general.

1.3 Background

This thesis starts off as a "***reverse engineering***" project, whereby a large portfolio of technical trading rules are randomly assembled and tested across different financial markets on over a dozen of variables. Those trading rules which consistently performed well or badly are then analyzed. Some of the initial results are studied and presented here.

1.4 Objectives

To investigate whether technical trading rules in general can provide valuable information, and add value to the process of financial trading. In particular:

1.4.1 Predictability

To investigate the distributional properties of directional predictabilities in general of published technical trading rules in the practitioners' community. Specifically, whether there is a more than 50 percent chance of directional predictability.

1.4.2 Efficient market?

To analyze the differences if any, between buy and sell signals, and discuss its implication for the efficient market hypothesis.

1.4.3 Stability

To test the stability of results between two distinct periods.

1.4.4 Volatility and predictability

To find out what is the relationship between volatility and directional predictability for the buy signals and sell signals and what the implication for the efficient market hypothesis is.

1.4.5 80/20 rule

To compare the performance of the top 20 percent and bottom 80 percent of the technical trading rules.

1.4.6 Belief

To find out what proportion of the directional predictabilities fall within the 25 to 50 percent region as some practitioners believe that most profitable technical trading rules have a directional predictability that fall in to that region. In other words, profitable technical trading rules with less than 50% predictability. This indeed is a statement that is counter intuitive, and warrant further investigation.

1.4.7 Downtrend

Do published technical trading rules in general, in the practitioners' community perform differently in the presence of a downtrend and uptrend financial time series?

1.4.8 Benchmark

Is buy-and-hold strategy a suitable benchmark for the performance of technical trading rules? Since technical trading rules can profit from a downtrend but not a buy-and-hold strategy.

1.4.9 Nonparametric dependencies

Dependency and stationarity are two important concepts in predictability. However, driven by the lack of strong evidence on dependency in financial time series when using the traditional linear techniques; we wonder whether would techniques from other discipline help? For this, we employ several nonparametric techniques developed for brain research to test the two concepts for the time series.

1.4.10 Distributional and temporal properties

To test whether the time series conform to the usual stylized facts of distributional and temporal properties of daily returns by using the traditional linear techniques.

1.5 Scope

If one is to subscribe to our definition of technical trading rules that they are simple rules that involve the study of past and present prices and volume data to derive an investment or trading decision; then there are as many technical trading rules as one can imagine. As such our sphere of investigation revolves around the following:

(a) Within the space of those published technical trading rules.

(b) Randomly selected.

(c) The two main sources are from: (i) Regular magazine publications of "Technical analysis of stocks and commodities" and "Futures". (ii) Books on technical analysis.

(d) Study only directional predictability rather than profitability (the rationales for the study of directional predictability are elaborated in chapter 5 of methodology and issues on empirical testing).

1.6 Justifications

Financial economists: (a) Neftci (1991) demonstrates that technical trading rules can be formalized as non-linear predictors, and non-linearity is increasing found in financial time series. (b) Empirical studies so far, such as the seminal work of Brock et al (1992) and the recent work of Mills (1997a) and Taylor (2000), amount many others, find that technical trading rules provide evidence that standard statistical models sometimes fail to explain the dynamics of financial time series, notably those of stock indices and prices, and the foreign exchange rates. We shall discuss the findings in greater details later.

Market participants: Surveys show that, (a) 90 percent of foreign exchange market participants in London placed some weight on technical analysis when making forecasts (Taylor and Allen, 1992). (b) The worldwide foreign exchange turnover in April 2004 was US$3.1 trillion *daily* which was much more than the total non-gold reserve of all industrial countries (The Economist, 2004). (c) Experienced traders tend to use technical analysis more than less experienced traders (Cheung et al., 1999). (d) The number of systematic traders using some sort of technical trading rules far outnumber their discretionary counter parts; and the vast majority of commodity trading programs that have existed for more than one to two decades are systematic traders and it is very unusual to find consistently successful discretionary traders (Edmonds, 1998).

The above evidences present tremendous academic and economic significances which merit our immediate attention (please refer to chapter 3 for more details).

Popularity: A recent search by using Yahoo through the internet in November 2004 reveals the following URL statistics indicating the popularity of technical analysis as compared to econometrics:

Technical analysis: 20,500,000
Technical trading rules: 2,460,000
Econometrics: 1,590,000
Financial econometrics: 500,000

1.7 Data

A decade of daily prices from 1988 to 1998 on open, close, high and low together with volumes from the Dow Jones Industrial Average Index are used. Besides testing the traditional stylized facts of distributional and temporal properties; we also explore some nonparametric techniques on analyzing time series data that had been used for neural and brain research. The initial results appear to be encouraging and the techniques have potential for further research (chapter 4).

1.8 Methodology and contributions

Expected values and distributional properties of directional predictabilities of a portfolio of 200 randomly collected technical trading rules from various published sources are generated.

The importance but relatively less discussed issues on small sample bias, size of test window, homogeneity and data snooping are addressed, as well as the comparative results of bootstrap and t-test, and the limitations of traditional statistical techniques are discussed (chapter 5).

1.9 Major results and contributions

The results are generally robust and pervasive.

A comprehensive literature review was carried out, and several issues discussed and suggestions forwarded (chapter 3). While the traditional tests on the distributional and temporal properties did not reveal any unexpected result; several nonparametric techniques adopted from neural brain science research indicate much stronger dependencies than the traditional linear autocorrelation (chapter 4).

We attempted to tackle several shortcomings of previous studies on technical trading rules by employing new methodological designs. With the increasing complexity and sophistication for empirical testing, a series of issues on empirical testing of technical trading rules which are often overlooked, are highlighted and discussed (chapter 5).

Expected values of technical trading rules in general, on the various aspects of directional predictability are mostly well within expectations; whereas the distributional properties provide empirical evidences which give further insights in to the statistical properties of technical trading such as financial traders' belief (chapters 6 and 7).

In chapter 8, we discover the counter-intuitive relationship between directional predictability and volatility; and also presented empirical supports on earlier argument by researchers that buy-and-hold strategy is not an appropriate benchmark for the performance of technical trading rule.

Finally, in chapter 9, we summarize and conclude our contributions and discuss some important issues such as whether is there a free lunch for technical trading rules? Are there values for those unprofitable technical trading rules? A thought on whether forecasting is a physical or evolutionary science? And so forth.

1.10 Notes on reading of this thesis

(a) For the ease of reading, we use the notation % to express the percentage of directional predictability in order to differentiate from other percentage calculations. (b) The words predict and forecasts are used interchangeably even though there is a subtle difference in the modern literature on the econometrics of forecasting. (c) The terms technical trading rules and trading rules; and rules and strategies are also used interchangeably. (d) The words investors and traders are also used interchangeably. After all, what are short and long terms are very much the objectives, constraints and preferences of each investor and trader.

1.11 Concept

We use experience and creativity to study the subject, rather than starting from the view point of existing consensus view. In other words, not to view within the existing box, but rather, to view out of the box.

1.12 Computation

All the technical trading rules' results are generated by the "Trade Station version 4" software marketed by Omega Research Inc. (1996 a,b,c,d,e,f). This particular software has the ability to go online and track the market, as well as incorporating fundamental information. Since 2003/2004 it has been used by the City University of New York's business school as a research and teaching tool. The school is the largest of its kind in the United States of America. For the nonparametric analyses, we use Microsoft's Excel to programme and generate the results. All else are performed by the 'Stat Pro" software written by Albright et al (1996) and EView (version 3.1).

Chapter 2

A primer on technical analysis

This Chapter provides a snapshot of technical analysis. Most of the 200 technical trading rules used in this study are invariably using one of the concepts illustrated in this chapter, or it variants, or a combination of the concepts and/or their variants.

Technical analysis is the study of past market behaviour based on prices and volumes to determine the current state or condition of the market. There are an infinite number of technical analysis techniques or as many as one can imagine.

2.1 Chartist

More than 50 years after its original publication, "Technical Analysis of Stock Trends" by Edwards and Magee (2001) is still regarded by many as the definitive work of technical chart analysis of the financial markets. In Chapter One of that book, they define Technical Analysis as:

> "... the science of recording, usually in graphic form, the actual history of trading (price changes, volume of transactions, etc.) in a certain stock or in "the averages" and then deducing from that pictured history the probable future trends."

They went on to emphasize that "prices move in trends and trends tend to continue until something happens to change the supply-demand balance." In Chapter Seventeen of the same book, they concluded as follows:

> "... it doesn't matter what creates the supply and the demand. The fact of their existence and the balance between them are all that count. No man ... can hope to know and accurately appraise the infinity of factual data, mass moods, individual necessities, hopes, fears, estimates, and guesses which, with the subtle alterations ever proceeding in the general economic framework, combine to generate supply and demand. But the summation of all these factors is reflected virtually instantaneously in the market. The technical analyst's task, then, is to interpret the action of the market itself to read the flux in supply and demand mirrored therein. For this task, charts are the most satisfactory tools thus far devised ... the minutiae of daily fluctuations – ask yourself constantly, "What does this action really mean in terms of supply and demand?" "

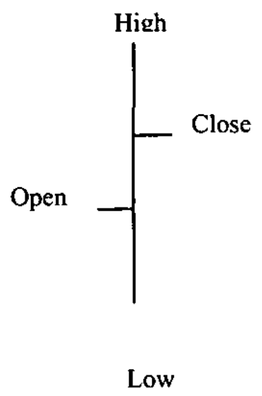
2.1.1 Starting point: some basics

The starting point of most technical studies is a price chart of the market. The majority of price charts, called bar charts, plot price versus time and, some include volume and open interest on the horizontal axis.

2.1.1.1 Bar charts

These are the most commonly used method of charting the market. They consist of open, high, low and close prices of the day or week or month, with the opening price on the left hand side of the horizontal bar and closing price on the right hand side of the horizontal bar as in figure 2.1.

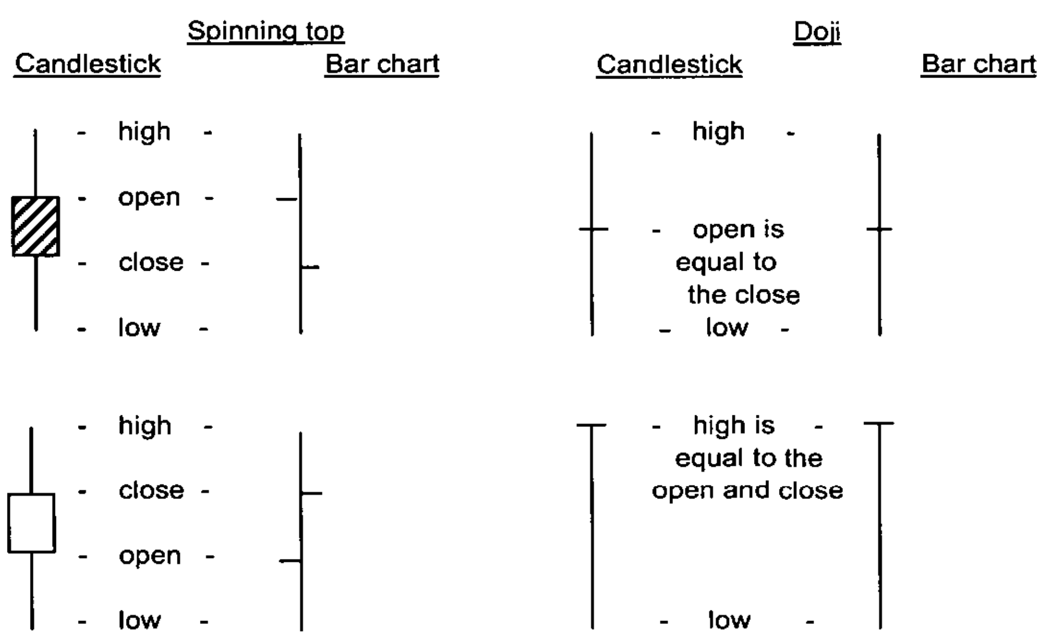
Figure 2.1 Bar of a period



2.1.1.2 Japanese candlestick charts

Two common candlestick patterns in candlestick and bar chart form are shown in figure 2.2.

Figure 2.2 The spinning top and doji in a candlestick and bar chart formation for comparison.



2.1.1.3 Point and figure charts

A point and figure chart depicts price versus movement, and is an excellent way to study how the market moves through different price levels. These charts are calculated in the following manner:

(a) Determine the size of box. A box may contain either an X which represents a price moving up, or an O, which represents a price moving down.

(b) Determine the minimum price reversal for the market. This is the number of boxes required to change the vertical column from an X to an O, or vice versa. The commonly accepted number is a three box reversal.

(c) The chart is started by recording the first minimum reversal move up or down. A move that continues in the same direction is recorded with an X or an O until a minimum reversal occurs. The reversals are recorded independently of time.

Figure 2.3 Sample price move to construct a point and figure chart

Price	X	0	0.30 point movements for a price change
98.50			begin
98.70			No
98.50			No
98.80	X		yes: 98.50 to 98.80
98.60			No
98.90	X		yes: continuation from 98.50
99.05	X		yes: continuation from 98.50
97.00		0	yes: 99.05 – 97.00
96.85		0	yes: continuation from 99.05
97.10			No
96.95			No
97.20	X		yes: 96.95 – 97.20

Point and figure chart formations can be traded just like time chart. Each market will have various box sizes, depending on the volatility of the market and the time frame of the trader. The more volatile the market and the longer the time frame of the trader, the larger the box size.

2.1.1.4 Market profile

This is a method for looking at the market in a unique price and time basis. The trader must be cognizant of where buyers and sellers agree or disagree on price. This is determined by how often a price will occur during a time period. The time periods are signified by different letters. For instance, the A period might refer to the 8.00 a.m. to 8.30 a.m. time period, and the B period would then refer to the 8.30 a.m. to 9.00 a.m. time interval. Consider a 4 period chart, and assign a letter for each price within each period's price range, letter A for the 1st period, B for the 2nd, and so on (see figure 2.4).

Figure 2.4 Construction of a market profile graphic

Price	1	2	3	4
168				
167				D
166		B	C	D
165	A	B	C	D
164	A	B	C	D
163	A	B	C	D
162	A			
161	A			
160				
159				

Price				
168				
167	D			
166	B	C	D	
165	A	B	C	D
164	A	B	C	D
163	A	B	C	D
162	A			
161	A			
160				
159				

In short, the profile graphic provides a substantial amount of price information per unit of time, allowing the trader to identify pattern and dynamics which would not be readily apparent using other methods.

2.1.1.5 Volume, and open interest

Price, volume and open interest provide important information about the market for the technical analyst, and are used in many technical studies such as in conjunction with the study of support and resistance levels.

2.1.1.6 Three phase of a market

Technical analysts believe markets continually exhibit three distinct phases of congestion, trending, or random behavior.

a. Congestion: Market is at an equilibrium level and buyers and sellers agree on price.

b. Trending : Perceptions and fundamentals change and the market moves higher or lower.

c. Random : Market is in disarray with no discernible congestion range or trend.

Trader must determine the state of the market as theoretically, it is possible to make money in the first two phases but mathematically impossible in third phase. For example, if the market is in a congestion phase, selling the tops and buying the bottoms should result in profitable trades. If market is trending, buying in a bull trend or selling in a bear trend should result in profitable trading.

There is a common perception that markets are in the congestion or random phases as much as 80 percent of the time depending upon what type of market. For example, currency markets have historically manifested much broader and longer-lasting trends.

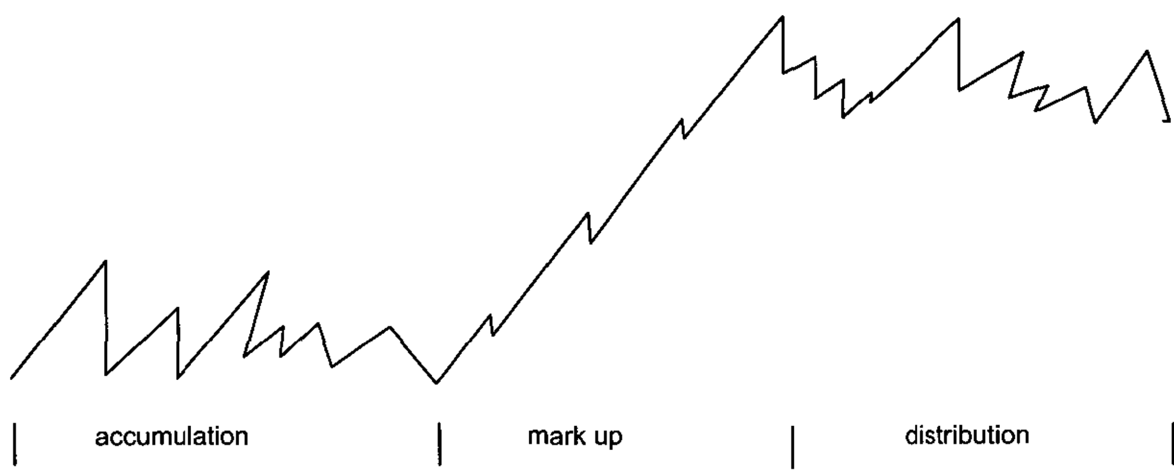
2.1.1.7 Dow Theory and the three trends and phases of the markets

Charles Dow is credited with the idea that market averages discount all information, and are better indicators of the overall trend of the market than individual stocks. Dow believed there were three trends to the market, which be called the primary, secondary, and minor trends, and used the analogy of the tide, the wave, and the ripple. The primary move was considered the major move in the market, with the secondary and minor trends the actions and reactions of the major move. An important consequence to this idea is that the trader should always beware of the major move, and try to trade in the direction of the major trend.

The primary or major trend exhibits three phases called the accumulation, mark up, and distribution. The accumulation phase occurs when the market is trading near its lows and interest is minimal. Knowledge investors begin to accumulate. The mark-up phase occurs when the market starts to move higher and public interest and participation begins to increase. The distribution phase occurs when the market has reached higher levels and is now fairly valued or overvalued.

Public participation and awareness is now at the highest level, but the more knowledgeable investors are distributing their holdings to the public. The three phases are shown in figure 2.7.

Figure 2.7 Dow theory and three phases of the market



2.2 Technical analysis in the 21st century

With the affordability of computing technology and internet; much has changed in the ways charts are calculated and drawn. Together with advancements in investment technology, such as financial econometrics (i.e. time series econometrics, artificial neural networks, and genetic algorithms etc.), has produced a new brand of technical analysts who can be more appropriately described as system or black-box traders. This new phenomenon is well summed up by Kaufman (1998) in his book entitled "Trading Systems and Methods."

2.2.1 Current status

Over 20 business schools in the United States are now teaching credit courses in technical analysis; and almost all investment banking firms and brokerage houses have a technical analysis division within their research department. Across the Atlantic, City University in London also started to conduct courses in technical analysis in recent years. Nowadays, technical analysts are frequently interviewed along with others in the financial media. A sample of technical analysis courses provided by Golden Gate University of USA is given in tables 2.1 and 2.2.

Market Technicians Association, the largest association of professional technical analysts in the United States, recommends two books for its level one Chartered Market Technician program: 1. Murphy, J.J. (1999) *Technical analysis of the financial markets,* New York Institute of Finance. 2. Pring, M.J. (2002) *Technical analysis explained,* 4^{th} Edition, McGraw Hill.

Most empirical results in this thesis are generated by Omega's "Trade Station" software. It is noteworthy to mention that Baruch College, City University of New York (the largest business school in the United States), started to use "Trade Station" at its Subotnick Financial Services Center in year 2003 for teaching and research.

Table 2.1 A sample of technical analysis courses provided by Golden Gate University, USA.

FI 352 Technical Analysis of Securities – 3 Units
Examines empirical evidence concerning non-efficient markets in which technical analysis is thought to apply. Topics include trend analysis, turning-point analysis, charting techniques, volume and open interest indicators, contrary opinion theories, and technical theories such as Dow theory and Elliott waves.
Prerequisite: FI 203 (or FI 100) or FI 300A.
FI 354 Wyckoff Method I – 3 Units
Studies the Richard D. Wyckoff method, a complete, time-tested and effective approach to market analysis and trading. The action sequence is a unique active-learning way to acquire the skills and judgment needed to apply the Wyckoff method. Prerequisite: FI 352 or consent of instructor.
FI 355 Wyckoff Method II – 3 Units
Continues the study of the Richard D. Wyckoff method, a complete, time-tested and effective approach to market analysis and trading. The action sequence is a unique active-learning way to acquire the skills and judgment needed to apply the Wyckoff method. Prerequisite: FI 352 and FI 354, or consent of instructor.
FI 498P Behavioral Finance (with Applications In Technical Market Analysis) – 3 Units

Introduces theories and research on cognitive biases, emotions and herd effects that influence decisions in portfolio management, manager-client communications and market timing and technical analysis. Exercises to improve managerial judgments involving risk and uncertainty. Examination of how technical market analysis can systematically utilize the crowd psychology that lies beneath all the numbers. Prerequisite: FI 203.
FI 498S Building Efficient Trading Systems – 3 Units
Guides you through the construction of your own trading system. In the process, a number of technical methods will be examined in depth: charting, fractal and number driven. Guest speakers will include some prominent traders.

Table 2.2 A sample of technical analysis courses provided by Golden Gate University, USA at graduate level.

- **Technical Analysis (MSc Elective)**
  - Course Outline
  - Slides
    - Lecture 1-Forecasting Essentials
    - Lecture 2-Statistical Indicator
    - Lecture 3-Pattern Recognition
    - Lecture 4-Neural Networks
    - Lecture 5-Behavioural Finance
    - Lecture 6-Elliot Wave Theory
  - Supporting Material
    - Using Metastock
    - Useful Datastream marco
    - Equity Data
  - Links
    - StockCharts.com
    - Technical Analysis from A to Z

2.3 Further topics on technical analysis

Technical analysis is the study of past market behaviour based on prices and volumes to determine the current state or condition of the market. There are an infinite number of technical studies or as many as one can imagine. This section shall cover a bit more on some of the more popular and well known traditional kinds of technical analysis.

In the non-academic literature, numerous books have been written on the subject and among them, a few are regarded as classics such as Edward and Magee (2001), and Murphy (1999). The former explain how technical analysis is based on the following assumptions:

(a) Market value is determined solely by the interaction of demand and supply.

(b) Although there are minor fluctuations in the market, stock prices tend to move in trends that persist for long period of time.

(c) Shift in demand and supply cause reversals in trends.

(d) These shifts in demand and supply can be detected in charts.

(e) Many chart patterns tend to repeat themselves.

From the above assumptions, we can see that technical analysis is rooted in basic economic theory. A stock's price is determined through the interaction of demand and supply.

A downward trend in stock prices can be caused by weakening demand or increasing supply and vice-versa in an upward trend. However, a technical analyst does not need to know why demand or supply is shifting. To trade profitably, one need only recognize a shift in the trend and position themselves appropriately. Technical analysts rely heavily on charts to detect these shifting trends and that is why they are sometimes called "chartists".

Murphy (1999), on the other hand, cited three premises underlying the philosophy or rationale of technical analysis which are broadly similar to that of Edward and Magee (2001) as follows:

(a) Market action discounts everything.

(b) Prices move in trends.

(c) History repeats itself.

We will only go through the traditional technical analysis briefly. Some of the modern technical analysis is similar to some of the rudimentary time series techniques due to the availability and affordability of computing power and the large number of academics joining the investment community.

Broadly, technical analysis can be separated into subjective and objective analysis. Subjective analysis refers to studies that are subject to interpretation and therefore may not be easily verified using mathematical methods. We shall go through this group of technical analysis very quickly as our interests fall on the objective analysis.

2.3.1 Subjective technical analysis

2.3.1.1 Support and resistance points

A support point is a place where buying overcomes selling and, consequently, the market tends to rise. A resistance point is a place where selling overcomes buying, and therefore, the market drops. Support and resistance are important concepts in understanding many studies employed in technical analysis. Recent academic studies by Osler (2000, 2001) made considerable advances in understanding these concepts.

2.3.1.2 Trend lines

Diagonal trend lines are drawn to both portray and project the trend of the market, and also help to indicate the possible end of a trend.

2.3.1.3 Channels

The trading range between the trend line and the line parallel to it is called a channel.

2.3.1.4 Robert Edwards and John Magee

These two pioneer technical analysts categorize and document the different chart formations in their book, *Technical analysis of stock trends* (with the 8th edition in print now). Briefly, the chart patterns are Triangle Rectangle, Head and Shoulders, Double Top, Double Bottom, Pennant, Flag, Wedge, Ascending Triangle and so forth

2.3.1.5 Richard Wyckoff

He used a combination of price, wave, and point and figure charts, and developed a comprehensive way of analyzing the market. He looked at relatively simple formations and developed his own terminology, such as spring or shake out. Price objective could be obtained from different charts through measuring the horizontal length of a price pattern.

2.3.1.6 W. D. Gann

Some of his ideas were grounded in empirical studies, while others were more mystical in nature. He contended that certain law governed not only the market, but nature as well, and were therefore universal in scope. One of his most important contributions was the concept of combining price and time. Gann believed crucial price movements happened when price and time converged, and time was the ultimate indicator because all of nature was governed by time.

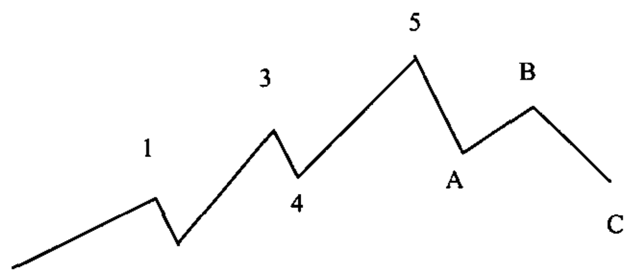
2.3.1.7 Leonardo Fibonacci

One of his most famous ideas is the Fibonacci series which is the sum of two previous numbers. The ratio of two consecutive numbers in the series approaches 0.618 which is called the golden mean. Many technical studies, such as the Elliott Wave theory, are based on some of the Fibonacci series.

2.3.1.8 Wave theory – Elliott Wave

R. N. Elliott believed the market moved in five distinct waves on the upside and three distinct waves on the down side as in Figure 2.8. Waves one, three, and five represent the "impulse" or minor up-waves in the major bull move. Waves two and four represent the "corrective" or minor down waves in the bull move. Waves A and C represent the minor down waves in the major bear move, and wave B represents the one up wave in the major bear move.

Figure 2.8 Elliott Wave Pattern



2.3.1.9 Percentage retracements

Percentage retracements refer to the market reacting from high or low by a certain percentage. The more popular retracements include the 25%, 33%, 38% and 50% levels which are derived from the importance of the common fractions 1/4, 1/3, 3/8, and 1/2. The 3/8 is an important fraction because of its relationship with the golden mean of 0.62 (1-0.62 =0.38).

These percentage levels, when measured from the high (or low) of a move, should act as a support (or resistance) level when the market retraces from the high (or low).

2.3.1.10 Contrary opinion

When market opinion becomes one sided, and most of the public is either bullish or bearish, an important change of trend may be developing. The reasoning is, if everyone is long and therefore bullish on the prospect of the market, there is no one left to buy, and so, the market can only go lower as some investors begin to sell, and vice versa.

2.3.1.11 Astrology

Many people are reluctant to link up astrology and trading. However, some studies do show some correlation between the moon and market activities. Since we know that the sun and moon may have a great effect on our weather and peoples' moods; it merits further investigation.

2.3.2 Objective technical analysis

This refers to studies that can be analyzed, and the results verified, using statistics or other mathematical methods. In some respects, it is similar to some of the time series econometrics except on a less sophisticated level. Most of the 200 technical trading rules used in this study are invariably using one of the following concepts or its variants; or a combination of the following concepts and/or their variants.

Filtering is an important process in technical analysis, both subjectively and objectively. This is the selection of data which meets certain criteria, and eliminating data which does not. For example, a trader may wait until the market closes below the neckline on a head and shoulders pattern.

2.3.2.1 Moving average

2.3.2.1.1 Simple moving averages

A simple moving average is the average of a series of prices during a specified period. The general formula is:

$$M_n = \frac{\sum_{i=1}^{n} P_i}{n}$$

Where i = specific period

p_i = price at period i

n =the number of period

One reason for using a moving average is to reduce some of the noise inherent in the short-term movements, and thus, better depict the major trend of the market. A long (buy) signal is generated upon the original time series crossing above the moving average and vice versa.

2.3.2.1.2 Weighted moving average

A weighted moving average places weights on each time period of the moving average. The simple moving average is also a weighted moving average, with equal weight for each period. The calculation is:

$$m_n = \sum_{i=1}^{n} w_i p_i$$

Where n = number of periods

p_i = price in period i

i = specific period

w_i = weight of period i

2.3.2.1.3 Exponential moving average

This is another variation on a moving average. The exponent moving average uses the price data and does not drop off older price data, like the simple and weighted moving averages. However, the recent price action is weighted more heavily than the earlier prices. The calculation is

$$e_n = e_{i-1} + [r(p - e_{i-1})]$$

Where p = price in period i

i = specific period

r = constant for smoothing

n = number of periods

e_{i-1} = exponential moving average value in the previous period

To arrive at the first exponential moving average value, simply substitute the market price in the first period as the first exponential value, and then begin calculating the exponential average for period two as described earlier. The n is the number of periods used to calculate the first exponential moving average (EMA). Firstly, let us illustrate how a second EMA is calculated. Assume that the previous or the first EMA is 100, the current price is 105, and the constant r for smoothing is 0.2, then the 2nd or current EMA is:

$$e_n = e_{i-1} + (r(p - e_{i-1}))$$

$$e_n = 100 + (0.2 \text{ X } (105 - 100))$$
$$= 100 + 1$$
$$= 101$$

This is the 2nd EMA value. But how does one generate the first EMA? Because one needs an EMA (i.e. e_{i-1}) in order to generate the first EMA.

There are two approaches: (a) Use the current market price as the first EMA (i.e. the n is 1), or (b) Use a n day simple moving average to approximate the previous day's EMA (i.e. e_{i-1}).

EMA is increasingly preferred by technical analysts over other moving average methods for at least two reasons: (a) EMA represents an excellent compromise between the overly sensitive weighted moving average and the overly sluggish simple moving average. Compared to other averaging techniques, EMA follows the trend of current data smoothly, minimizing jumps and lags. (b) Computationally, EMA is the simplest of all moving average techniques since it requires the least data handling and the least data history. EMA requires only two data periods; they are the current raw data and the immediate past EMA value.

2.3.2.1.4 Trading with moving averages

Trading systems designed with moving averages are generally trend-following systems. Three of the commonly known trading rules for moving averages are:

a) Buy when the market closes above the moving average or combination of averages. Sell when the market closes below the moving average or contribution of averages.
b) Buy when the short-term moving average crosses above the long-term moving average, and vice versa.
c) Buy when the short-term and long-term average both point up, and vice versa.

2.3.2.2 Envelopes and bands

Since technical analysts think of the market (or a stock) as being either in a state of equilibrium or disequilibrium, a market that trades within a narrow range might be considered a market in a state of equilibrium. From a fundamental perspective, the supply and demand forces are balanced. A market breaking out of a range, or envelope or band would be one in a state of disequilibrium, or out of balance. A market out of balance searches for a new equilibrium level by probing new highs or lows. There are many ways to construct a band. One way to create a band is by using moving average of the highs and lows.

Many of the trade-offs mentioned in the moving average section, such as shorter and longer time frames, would apply equally well with envelopes and bands. These methods are normally used as a trend following system, but they may also be used in counter trend trading. In this case, a break above the band would be construed as a sell signal, and a break below the band would be a buy signal.

2.3.2.3 Oscillators

Oscillators cover a broad class of indicators which measure movement about an equilibrium level, usually designed as zero. An oscillator is often used to identify overbought and oversold conditions. Another use for oscillators is to establish confirmations and non confirmations of market movements. Some use oscillators in trend following methods similar to moving average system.

2.3.2.3.1 Moving average oscillators

This is one of the most common types of oscillators measuring the difference between two moving averages. The oscillator becomes zero when the two moving averages cross. An oscillator measures absolute amounts and so each market will have different values for the purpose of trading, depending on the price and volatility of the market.

2.3.2.3.2 Line oscillators and the moving average convergence divergence (MACD)

A line oscillator is a simple moving average of the moving average oscillator values (i.e. a moving average of an oscillator). A line oscillator smoothes the data to a greater degree, because it is a moving average of the difference of two moving averages.

The MACD is similar to the line oscillator, but is calculated with an exponential moving average instead of a simple moving average.

2.3.2.4 Momentum

Momentum measures the change in price with time. It is calculated by taking the difference in price of two time periods, as shown in the formula:

Momentum i = $P_i - P_{i-t}$

Where P = price

i = specific time period

t = number of time periods in the past

The momentum value provides an indication of the rate of change in the market. A large positive change in the value means the market is rapidly moving higher, which may imply there is good internal strength to the market and vice versa.

2.3.2.5 Rate of change

Whereas the momentum indicator is an absolute measure of price change, the rate of change is a relative measure of price change. The rate of change is calculated by dividing the present price by the price in previous period.

Rate of change = P_i / P_{i-t}

Where P = price

i = specific time period

t = number of time periods in the past

2.3.2.6 Stochastic

This is another type of oscillator widely used by many market technicians, and developed by George Lane. They are a form of oscillator which place significance on where the closing price is, relative to the high and low for the period. The theory behind stochastic is simple. Rising prices are often accompanied by closes near the highs of the range, while falling prices are often accompanied by closes near the lows of the range. Prices which close near the middle of the range suggest a listless or trendless market.

One stochastic value is called the %K value and is calculated as follows:

$$\%k = \frac{C_i - L_n}{H_n - L_n} x100$$

Where C_i = closing price in current period

L_n = lowest low during the n time periods

H_n = highest high during the n time periods

i = specific time period

n = number of periods

The % D value is simply the moving average of the %K value. The moving average can be calculated in any way such as the simple or exponential calculation. The formula for the simple moving average calculation is:

$$\%D = \frac{\sum_{i=1}^{n} \%K_i}{n}$$

Where i = specific time period

n = total number of periods

$\%K_i$ = the % K value for period i

The % K value react more quickly; or is faster than the % D value, because the % D value is a moving average of the % K value. Stochastic values below 30 percent suggest the market is oversold, whereas values above 70 percent imply the market is overbought. Many types of rules can be developed to trade stochastic. For example, one rule is to sell when the fast (%K) crosses the slow (1%D), and both are pointing down but above the 70% level. A buy signal would be generated when the fast crosses the slow, and both point up but are below the 30 percent level.

2.3.2.7 William % R

Larry Williams is credited with developing the % R oscillator. This is similar to the stochastic as the calculation shows:

$$\%R = \frac{H - C}{H - L}$$

Where H = highest high of the period

C = close of the current period

L = lowest low of the period

2.3.2.8 Wilder's relative strength index (RSI)

RSI is used in a similar way as the other oscillators. The calculation is:

RSI = 100 - 100 / (1 + R)

Where R = U/D

U = average of the days closing higher during the interval.

D = average of the days closing lower during the interval

A 14-day interval is frequently used, but any numbers of days can be used for the interval. The oversold and overbought areas are usually considered in the 30 percent and 70 percent areas respectively, but again it depends on the type of market and the results of empirical tests.

2.3.2.9 Volatility systems

Volatility and time are some of the most commonly used measurements in trading. However, volatility, like time, is not always well understood. There are many ways to calculate volatility; one of them is the percentage price change of the market. For example, if the market moves from 100 to 110, the volatility or percentage change is 10 percent [(110 – 100)/100 = 0.10].

Volatility trading systems are based in the premise that, if the market moves a certain percentage from a previous price level, it has broken out of a trading range and is a buy or sale. This type of system is called a volatility breakout system. There are many variations on this, but the general idea is to catch a move which break out above or below a band or envelope of prices. One way of determining the bands or breakout ranges is to use the moving averages of the highs or lows of the market. Another way is a volatility band around the price data.

2.3.2.10 Velocity and acceleration

The velocity is a measure of how quickly the market price moves from one point to another. The formula is:

Velocity = d/t

Where d = distance moved

t = time of move

In trading, the distance is measured by price, so a market that moved from 100 to 105 in one day would have a velocity of 5/1 = 5 points/day. The acceleration is a measure of how quickly are velocity changes. The formula for acceleration is:

Acceleration = v/t

Where v = change in velocity

t = time

Both the above indicators provide measurements of how fast the market moves.

2.3.2.11 Volume and open interest

Volume and open interest can be used with price data to confirm a market move. The general rules are:

Price	Volumes	Open Interest	Significance
up	up	up	bullish
up	down	down	bearish
down	up	up	bearish
down	down	down	bullish

These rules are based on the belief that volume drives the market. If the market is moving in a certain direction, high volume and open interest confirm strong momentum in the direction the market is moving.

2.3.2.12 Commitment of traders report

This report is a good source to determine the types of traders holding position in the market. The report indicates whether hedgers or speculators are long or short the market.

2.3.2.13 On balance volume (OBV)

Joseph Granville developed the OBV indicator, and it attempts to measure the influence of both price and volume on the market. It is calculated by adding the volume of the day if the price change for the day is positive and subtracting volume of the day if the price change is negative. A cumulative total of the volume is kept and plotted against the price.

If the OBV is rising, then this confirms an up-move, but if it is dropping, a potential down-move is possible.

2.3.2.14 Donchian method

Richard Donchian developed a simple, but effective trading method called the four-week rule:

a) Buy when the market makes new highs over the past four weeks.
b) Sell when the market makes new lows over the past four weeks.

This system is a trend following method and works well in trending markets. However, the results, like any other trend following method, can be less comforting in choppy and random markets.

2.3.2.15 Cycles

Cycles theories as applied to the markets can be complex and challenging and is a relatively new area in technical analysis. The authors are of the opinion that time-series economists are more familiar in this subject and we shall only discuss briefly the rationale of cycles in the context of trading and investing.

The stock market has many cycles which affect it, such as tax selling at year end, dividend pay outs cycles, and economic cycles. On a shorter horizon, the daily U shaped intra-day cycles and the "triple witching hours" of financing derivatives expiring on the third Friday of every month are some of the examples.

For soft commodities, the wheat market is affected by major long-term weather patterns lasting ten years or more, and by shorter-term, seasonal weather patterns which may affect the supply of wheat. As for perennial crops (such as cocoa), it is affected by more new planting at the peak of a cycles and resulting in greater supply several years later when the new planting comes into production. But perennial crop cycles are getting shorter as new varieties of species with shorter gestation period and higher yield are introduced, coupled with the improvement in crop production technology such as pests control, more effective input of fertilizers, harvesting techniques and so forth.

With the advances in computing and telecommunicating technologies, many feel that the business or economic cycles would also be getting shorter in the future.

Each one of these cycles has a different period and amplitude, which affects the stock markets in varying ways at different times. When the cycles in any market are in synchronicity, a pronounced bottom or top, such as the Great Crash of 1929, may happen.

When the market is out of sync, there may be no significant trend, and the cycles may be harder to define. Some observed cycles are Kondratieff cycle, business cycle and circadian timing cycles. Cycles are a fascinating way of looking at the market because many of the ideas are related to other natural phenomena in mathematics, physics, biology, and a host of other subjects.

2.3.2.16 Pattern recognition

Pattern recognition is the study of recurring formations or patterns. These patterns can be quite simple or intricately complex. All the topics covered in subjective or objective analysis could easily be placed under pattern recognition. However, there is a distraction between patterns in this section and those in the subjective section, the patterns covered in this section can be objectively measured and tested to see how they have performed in the past. Patterns need to be identified by at least one or more variables.

2.3.2.16.1 Price patterns

Point and figure charts are a good start for looking at price patterns.

2.3.2.16.2 Price and time patterns

These are the most common charting methods used for evaluating markets. Most of the rules in pattern recognition are based on price and time together. For example, the January effect suggests that if the stock market is higher at the end of January, the market will probably be up for the rest of the year. The price has to be at certain place within a certain time.

2.3.2.17 Price, time and volume

These patterns can become even more complex because now there are three variables. The OBV study described in the objective analysis section is an example. Other relationships, such as buying the market when the price and volume increase, or selling the market when price and volume decrease.

2.3.2.18 Gaps

Gaps occur when the opening price is either some values way about (gap up) or below (gap down) the closing price of previous trading session. A major gap up or down is a sign of bullishness or bearishness respectively. Be careful when analyzing gaps. Some market gap more than others, such as the currencies, because they are actively traded 24 hours a day. Other markets, like the stock market, do not gap as readily because the markets may only be open at certain times of the day.

2.3.2.19 Inside day

An inside day occurs when the high and low of the most recent period are contained by the high and low of the previous period. Therefore, the high of the recent day is less than the high of the previous day, and the low of the recent day is greater than the low of the previous day. Some traders believe an inside day represents an equilibrium point from which the market will make an important move. A breakout above the previous high or below the previous low will provide a possible answer to the eventual direction of the market.

2.3.2.20 Key reversal day

A key reversal day pattern may provide the initial indication of a change in trend. A sell signal is generated when the high of the current day is above the high of the previous day, and the close of the current day is below the close of the previous day. A buy signal occurs when the low of the current day is below the low of the previous day, and the current day close is above the close of the previous day.

2.3.2.21 Island reversals

An island reversal occurs when a market gaps above previous highs and gaps down on the next or subsequent days, leaving an island formation. Some possible trading rules might be: sell if the market gaps below an island and buy if the market gaps above an island.

2.3.2.22 Consecutive closes

Buy or sell if the market closes higher or lower a specific number of times. This type of pattern may suggest the beginning of a trend.

2.3.2.23 Complex pattern recognition

So far we have discussed some relatively simple pattern. What about more complex pattern such as head and shoulders. (This is being tackled by Lo et al, 2000, using algorithm) or Elliott Wave formation. The process of finding a simple pattern such as rectangle or triangle requires a lot of rules to make sure every nuance is caught. Even simple patterns have an infinite number of possibilities or variations.

2.3.2.24 Japanese candlestick chart patterns

These are the simple time and price pattern recognition as shown in figure 2.2.

2.4 Concluding remarks

Look no further - it is all in the price!

The philosophy underlying technical analysis could very well summed up briefly by Edward and Magee (2001): "No man, no organization (and we mean this verbatim et literatim) can hope to know and accurately to appraise the infinity of factual data, mass, moods, individual necessities, hopes, fears, estimates and guesses which, with the subtle alternations ever proceeding in the general economic framework, combine to generate supply and demand. But the summation of all these factors is reflected virtually instantaneously in the market."

It is interesting to note that there are dozens of universities in the United States of America conducting courses in technical analysis for under and post graduate studies. The Trade Station software used for this thesis is also employed by the largest business school in USA at the City University of New York, starting 2003/4, for teaching and research purposes. Across the Atlantic, City University took the lead in teaching technical analysis recently.

Chapter 3

Review of academic literature

3.1 Plan and rationale for the core reviews

We make no attempt to review all subjects that can be related to the study of technical analysis, but to review technical trading rules in general and then place particular emphasis on those areas which we feel are more relevant in the investigation of technical trading rules. Broadly, they are (a) the theoretical underpinnings, (b) the study of behavioral finance, (c) practices and, (d) methodologies and evidence. We shall also touch briefly on the data generating process of financial time series since the understanding is fundamental for the design of technical trading rules. We also review the recent findings in high frequency data for the same reason. Some mentions on the study of volume and momentum based strategies are also included as there are voluminous literature and considerable advances have been made in these two areas in recent years, and they also fit into the description of our definition on technical trading rules. That is the study of past and present prices and volume for forecasting.

We shall not elaborate much on the empirical evidence as they are subject to (a) the types of trading rules used, (b) the markets under study in terms of countries and financial instruments traded, (c) the time period chosen and (d) the methodologies involved, which for some studies, appear to have a number of drawbacks as we shall discuss later.

3.2 Introduction

3.2.1. Historical backdrop

The early studies of trading rules applied to US equity prices by Alexander (1961, 1964) and Fama and Blume (1966) provide evidence of an efficient equity market based on their statistical studies and interpretations, and the subsequent much publicized book of a Yale professor by the name of Malkiel (1981) entitled "Random walk down wall street" in various editions had discouraged academic research into technical analysis for many years. Technical analysis has only enjoyed somewhat of a renaissance in the academic community since the efficient market hypothesis has come under serious seize. This interest has also been rekindled by Neftci (1991) who demonstrates that technical trading rules require some form of non-linearity in prices to be successful, and non-linearity is being increasingly found in financial time. With the application of bootstrap technique, Brock et al. (1992) demonstrate the potential of some popular technical trading rules against some standard time series models; and that provided a template for subsequent debates and more empirical works on technical analysis.

3.2.2 Definition of technical trading rules

We define technical trading rules as *simple* rules that involve the study of *present and past price* and *volume* data only to infer the direction of future prices and to derive an investment or trading decision. As such, there are three basic components to our definition. Although there are much similarities with time series econometrics, but the word simple would exclude them in our definition as they are considered to be comparatively more sophisticated. Some of the standard financial econometrics models such as the common factor analysis using size and book to market ratio etc. (for instance, Fama and French, 1992) are also not included. In a strict sense, volume and momentum strategies may not belong to the traditional study of technical analysis; they are however, fall within our definition here. We are also adamant about the inclusion in view of the voluminous literature in both volume and momentum strategies in recent years as we are of the opinion that this study would not complete without their inclusion.

A popular trading rule used by most researchers is the Double (or Dual) Moving Average Crossover initiated by Brock, Lakonishok and LeBaron (1992) – hereinafter referred as BLL. This rule separates days when returns are expected to be low from days when returns are expected to be high. A financial trader oblivious to transaction costs and risk would buy (sell) when a high (low) return is expected. The two moving averages of lengths S (short) and L (long) are calculated at time t from the most recent price observations:

$$MA_{t,S} = S^{-1}\sum_{j=1}^{S} P_{t-S+j}, \qquad MA_{t,L} = L^{-1}\sum_{j=1}^{L} P_{t-L+j}$$

and their relative position is measured by

$$R_t = \frac{MA_{t,S} - MA_{t,L}}{MA_{t,L}}$$

When the short average is above (below) the long average, recent prices are higher (lower) than older prices, and it is supposed to indicate an upward (downward) trend. When the two averages are equal, it is supposed to indicate a sideway movement or no trend. Consequently, where B is the bandwidth between the two averages (the third parameter besides S and L):

Buy if $R_t \geq B$,

Sell if $R_t \leq -B$,

Neutral if $-B \leq R_t \leq B$

There are as many technical trading rules as one can imagine. For example, Sullivan et al. (1999) uses the idea of moving average and expand it into a universe of 2049 trading rules by varying the parameters and their combinations. Technical trading rules generally provide a one-step-ahead trading signal such as the moving average described above and do not generally provide an n-step-ahead point forecast.

3.2.3 Technical and fundamental analysis

Oscar Wilde (1893) once described a cynic as someone who knows the "price" of everything but the "value" of nothing. Such a simple description of knowing what and what not could well sum up the current dichotomy between the philosophies underlying technical analysts and fundamentalists, where the former focus mostly on prices and volumes and the latter focus on the values of stock markets for their respective decision making.

3.2.4 Technical analysis and technical jargon

Perhaps some of the prejudice against technical analysis can be attributed to semantics as pointed out by Campbell et al. (1997). Their argument is that because fundamental analysis is based on quantities familiar to most financial economists – for example, earnings, dividends and other accounting terms – it possesses a natural bridge to the academic literature.

In contrast, the vocabulary of the technical analyst is completely foreign to the academic and often mystifying to the general public. Campbell et al. (1997) give the following example, which might be found in any recent academic finance journal: "The magnitude and decay pattern of the first twelve autocorrelations and the statistical significance of the Box-Pierce Q-statistics suggest the presence of a high-frequency predictable component in stock returns."

They contrast this with the following statement of technical analyst: "The present 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."

Campbell et al. (1997) conclude that both statements have the same meaning: Using historical prices, one can predict future prices to some extent in the short-run. But because the two statements are so laden with jargon, the type of response they elicit depends very much on the individual reading them.

3.3 Theoretical underpinnings

There have been several theoretical developments on predictability which have a profound impact on the study of trading rules thus far. The notable ones are that of Acar (1998) and Neftci (1991).

3.3.1 Mathematically well-defined and nonlinearity

According to Neftci (1991), for a trading rule to be mathematically well defined it has to be able to issue signal that are Markov times which can not depend on future information. Markov times are defined as random time periods, whose value can be determined by looking at the current information set (p.535). Using the notion of Markov times, he shows that the moving average rule can generate Markov times such that it is mathematically well defined. Because of this characteristic, the moving average rule is of interest to both academics and practitioners since it generate trading signal mechanically without depending upon financial traders' subjective judgments which invariably incorporate assumptions on future price movements. Note that various patterns or trend crossings in technical analysis such as "head and shoulders" and "triangles" did not appear to generate Markov times. In addition, he also demonstrates that if the underlying time series process is nonlinear; then the moving average rule might capture some information ignored by Wiener-Kolmogorov (also known as Gaussian noise) prediction theory. Since nonlinearity is increasingly found in financial time series; his finding has rekindled the investigation of technical trading rules.

3.3.2 Relationship between stochastic processes and technical trading rules

Acar and Satchell (1997) derive the probability distribution of realized returns from a simple moving-average rule given that asset returns are Markovian. Acar (1998) also attempts to specify the theoretical relationship between the magnitude of observed serial correlation coefficient, and profitability of trading rule. In other words, how trading rule's returns are related to the characteristics of the underlying time series. Prior to his seminal study, very little is known about the expected returns of trading rules in the finance literature, although there exit some theoretical works for trading rules under the assumption of a random walk with drift. For examples, Praetz (1976), Bird (1985) and Sweeney (1986) for the filter rule; Cox and Rubinstein (1985) for the option strategy; Black and Perold (1992) for the stop-loss and constant proportion insurance strategies.

However, random walk may not be a fair representation of reality and that motivated Acar (1998) to establish the expected return of directional forecasts for any Gaussian stochastic process which describes numerous classes of models. The type of trading rules used for his investigation was restricted to autoregressive models and linear technical trading rules which are well defined in the Neftci (1991) sense. Note that moving average and most other oscillators technical trading rules do not provide an h-step-ahead point forecast, but a one-step-ahead trading signal.

According to Acar (1998), if trading rule is written as $F_t = f(P_t, P_{t-1}, \ldots)$, then the rule produces the binary stochastic process B_t, is defined as

Sell: $B_t = -1$ iff $F_t \leq 0$

Buy: $B_t = +1$ iff $F_t \geq 0$.

B_t is completely defined by the rule and only in the trivial case of a buy (sell) and hold strategy is it deterministic, taking the value of $+1$ or -1 irrespective of the underlying process. The study of the binary process B_t is of limited interest for trading purpose. What is more important is the returns process implied by the decision rule. Denoting the return at time t made by applying the rule F_{t-1} as R_t, then

$$R_t = B_{t-1} r_t = \begin{cases} -r_t & \text{if } B_{t-1} = -1, \\ +r_t & \text{if } B_{t-1} = +1. \end{cases}$$

The major conclusions made by Acar's (1998) various mathematical propositions and proofs could be summarized as follows:

(a) Many technical trading rules can be classified as autoregressive forecast and are thus implicitly linear rules. This is especially the case for moving average and momentum type of indicators.

(b) The expected return following a linear trading rule is zero if the underlying process is a random walk without drift.

(c) If the underlying process is a random walk with drift, the expected return of a trend following trading rule is a positive function of the drift and a negative function of risk, if risk is measured in terms of volatility.

(d) If the underlying process exhibits positive (negative) autocorrelation but no drift, the expected return of a trend-following (contrarian) strategy is a positive function of volatility.

(e) If the underlying process is Gaussian and using a linear forecast, minimizing the mean squared error is a sufficient but not necessary condition to maximize expected returns.

Acar and Satchell (1998) also show that although both buy and hold and active strategies should exhibit zero returns under the random walk assumption; however, when more than one directional strategy is used, the distribution of returns is no longer normal. When two forecasts are used, the distribution is a mixture of two normal laws, and the mixture coefficient would depend upon the correlation coefficient between the two forecasts.

3.3.3 Behavioral finance: causes for trend and reversal

Behavioral finance approaches financial issues with the help of ideas borrowed from psychology. It casts doubt on the predictions of modern finance such as the notion of efficient markets and microstructure finance (for instance, expected utility maximization and rational expectations). Prospect theory and related psychological concepts form the basis for a new theory of finance. In asset pricing, for instance, it has been used to interpret the anomalies in the speculative dynamics of stock returns such as under and overreaction to news. Through detailed surveys and archival studies of trading behavior; a great deal has been learned about the conduct of investors, analysts, money managers and so forth. The behavioral approach has also stimulated interest in the determinants and the quality of executive decision making such as excessive risk aversion, unjustified optimism and so forth (Kahneman, 2002).

Beginning of the 2000s, works are published on the behavioral approach in attempting to explain the success of trading rules. This is in line with the growing interest in behavioral finance of the day. Zielonka's (2004) clinical study suggests that the popularity of technical analysis is associated with its relation to the cognitive biases of humans.

In the study of speculative dynamics of stock prices, there are three theoretical groups of (not mutually exclusive) behavioral causes for trend and reversal:

(a) Biased forecast of future profit potential (El-Galfy and Forbes, 2004),
(b) Biased forecast of risk and/or risk attitudes that are in conflict with utility theory (Kahneman and Tversky, 1979), and
(c) Non-rational trading behavior that reflect (falsely imagined) technical patterns in prices, superstition, emotion, or fashion, and that it is not linked to forecasts of business fundamental in any way (Hwang and Salmon, 2004).

El-Galfy and Forbes (2004) reexamines the issue of whether financial analyst forecasts of corporate profits are rational. Over the years, numerous studies have documented excessive optimism (hype) as well as other biases in analyst predictions. However, the prominent work of Keane and Runkle (1998) dispute those findings and that motivated El-Galfy and Forbes to inspect the key assumptions in Keane and Runkle's modeling strategy, and they extend the research in multiple ways. The revised estimates for the US from 1983 to 1997 unmistakably show that analyst earnings forecasts are not rational with respect to publicly information.

Hwang and Salmon (2004) develop a new method to measure herding behavior by investors and they define herding as imitation and suppression (or absence) of private information. They investigate how the cross-sectional variation in factor sensitivities such as betas evolves over time. The idea is to quantify deviations from equilibrium beliefs expressed in market prices. For instance, when investors herd around the market consensus, the cross-sectional variance of stock betas is expected to fall. It is striking to note that herding goes down and that market efficiency improves during periods of market stress (see also Burstein, 1999).

3.4 Methodologies and empirical evidence

The study of technical trading rules has improved since the earlier 1990s upon the limitations of earlier studies. With advances in statistical theories and the affordability and growth of computing power: (a) the number of trading rules tested has increased, (b) standard statistical tests or sophisticated bootstrap based statistics are performed, (c) parameter optimization and out of sample verification are conducted and (d) risks and transaction costs are factored in for the performance assessment. Broadly, one can categorize these investigations into eight major groups: (a) Standard statistical studies, (b) Model-based bootstrap, (c) Genetic programming, (d) Reality check, (e) Chart pattern, (f) Nonlinear model, (g) Combined studies, and (h) Others.

3.4.1 Standard statistical studies

Studies under this category usually consider various technical trading rules and incorporate risks and transaction costs in to testing procedures. Trading rules were optimized based on a specific performance criterion and out-of-sample tests were performed. A representative study of this kind is Lukc ct al. (1988). They used 12 trading rules (namely channels, moving averages, momentum oscillators, filters and a combined rule) applied across 12 futures markets (agricultural commodities, metals and financials), over the period of 1975-1984.

Parameters were optimized over a three years period and then used for the next year trading. At the end of the next year, new parameters were optimized again and so on. Thus, the optimized parameters were adaptive and the simulated results were out-of-sample. The current contract was rolled over to the next contract prior to the first notice date in order to overcome the discontinuity of futures price series. Two tailed test were performed to test the null hypothesis that gross returns generated from technical trading rules are zero, while one-tailed t-test were conducted to test the statistical significance of net returns after transaction costs. In addition, Jensen's α (alpha) was measured by using the capital asset pricing model (CAPM) to determine whether net returns exist above β (beta) or returns to risk.

Overall, studies under this category indicate that technical trading rules generated statistically significant economic profits in various speculative markets, especially in the foreign exchange markets and futures markets. However, there are increasing evidence by recent studies that trading profits seem to gradually decrease over time. For examples, Olson (2004) reported that risk-adjusted profits of moving average crossover rules for an 18-currency portfolio declined from over 3% between the late 1970s and early 1980s to about zero percent in the late 1990s, while Kidd and Brorsen (2004) provided some evidence of reduction in returns in the 1990s by managed futures funds which predominantly used technical trading rules. He posited that the reduction in returns may had been caused by structural changes in the markets such as a decrease in price volatility and an increase in large price changes occurring while markets were closed.

Taylor (2000) studied a wide range of speculative market indices and individual stock prices and found that small transaction costs would eliminate the profitability of technical trading rules. For instance, an average breakeven one-way transaction cost of 0.35% across all data series in his study. In addition, there are two interesting empirical evidence came out from the study regarding technical trading rules:

(a) Test statistics calculated from technical trading rules correlate more highly with a linear combination of many autocorrelations than they do with the first-lag autocorrelation. Therefore, the predictability detected in his study by technical trading rules is typically dependence that extends over many time lags;
(b) Tests based upon technical trading rules have less empirical power than standard statistical tests to reject hypothesis that returns are produced by some type of uncorrelated stochastic process.

3.4.2 *Model-based bootstrap studies*

A representative of this category is the seminal work of Brock et al. (1992). The basic idea in this approach is to compare returns conditional on buy (or sell) signals from the original time series to conditional returns from simulated time series generated by widely used traditional statistical models. According to Brock et al. (1992), there are several advantages of using bootstrap methodology: (a) bootstrap method allows a joint test of significant for different technical trading rules by constructing bootstrap distributions, (b) traditional t-test assumes normal, stationary and time-independent distributions of data series which are not found in financial time series; and since bootstrap is distribution free, it may provide more powerful inference than the t-test and (c) bootstrap procedure allows estimation of confidence intervals for the standard deviations of technical trading rules and thus, the risk levels of rules can be more vigorously examined.

Brock et al. (1992) used technical trading rules to develop two new test methodologies. They first tested and rejected the null hypothesis that returns from the Dow Jones Industrial Average index are independent and identically distributed. For examples, firstly, technical trading rules identify buy and sell days more or less than what they should be under the assumption of a normal distribution. Secondly, the difference between average returns on buy and sell days is a considerable 19% per annum across a 90 year period. The second test was used to evaluate the null hypothesis that returns are generated by a specific stochastic process, and they showed that the null is rejected for several standard statistical time series models.

There are four major conclusions reached by Brock et al. (1992): (a) buy signals consistently generate higher returns than sell signals, (b) returns following sell signals are negative, which is not easily explained by any of the existing equilibrium models, (c) returns following buy signals are less volatile than returns following sell signals, and thus risk does not commensurate with return, and (d) returns from technical trading rules are not consistent with some of the popular statistical time series models.

Bessembinder and Chan (1995, 1998) follow up the works of Brock et al. (1992). After including dividend yields in the calculations, they find that negative average returns on sell days only occur before 1939. They also estimate that realistic transaction costs are more than twice the amount of gross trading profits. Consequently, the predictability of the Dow Jones Industrial Average Index could be explained in terms of transaction costs, varying risk premia, bandwagon effects and/or other explanations. The bandwagon concept is rejected by evidence that there is much useful information in CRSP indices that are not followed by the market, as there is in the Dow Jones index.

As in most of the studies on predictability, the model-based bootstrap studies vary across markets in terms of countries and instruments, sample period, trading rules used and methodologies applied. Generally, for stock indices either in terms of spot or futures in emerging markets, technical trading rules are profitable even after transaction costs. For examples, Bessembinder and Chan (1995), Raj and Thurston (1996), Ito (1999), Ratner and Leal (1999), Coutts and Cheung (2000), and Gunasekarage and Power (2001). However, in developed markets, profits generally are negligible after transaction costs or have declined over time. For examples, Hudson et al. (1996), Mills (1997a), Bessembinder and Chan(1998), Ito (1999), and Day and Wang (2002).

For the foreign exchange markets, Levich and Thomas (1993), LeBaron (1999), Neely (2002), and Saacke (2002) all report substantial profits of moving average rules.

For the stock markets, LeBaron (2000) up dated the work of Brock et al. (1992) and found what other researchers had already shown in the dramatic changes in the conditional means. In contrast to the means, variance appeared to be stable over time. In addition, the rules that were used in Brock et al. (1992) could have been replaced with simple momentum based strategies which show similar performance using both measures of predictability such as mean and variance. So, has the dynamic of stock prices changed in recent years, or is it due to the data mining of previous study? Results in Sullivan et al. (1999) suggest that it was a change in the data, since their test attempts to adjust for data mining in the previous (Brock et al., 1992) sample. However, as LeBaron (2000) points out, no test for data mining is perfect, as it depends on simulating the snooping process that might have been occurring. He concludes that the disappearing profits may have to do with technology, better price information, and lower transaction costs, or possibly a greater attention is now given to technical trading rules.

3.4.3 *Genetic programming studies*

Genetic programming may become an alternative approach to test technical trading rules since traditional studies use pre-determined parameters of technical trading rules before the test, while genetic programming optimized rules in an ex-ante sense that parameters are not determined before the test; and thus, not ex-post. According to Koza (1992), genetic programming is a computer-oriented search procedure for problems based on the Darwinian principle of survival of the fittest. Broadly, a computer is used to randomly generates a set of potential solutions to the problem and then allows them to evolve over many successive generations under a given performance criterion. Those potential solutions such as technical trading rules that satisfy the fitness criterion are to survive, while those fail to meet the criterion are to be replaced, and this process will carry on for usually about 20 generations until the improvement in performance is negligible or marginal. Mutations may be incorporated randomly in to the selection process. The procedure differs in one respect with natural selection in that human would not survive for more than one generation and thus the selected candidate or potential solution is suppose to be more robust than what could otherwise happen in nature.

Neely et al. (1997), Allen and Karjalainen (1999), Ready (2002), and Wang (2000) and others attempt to avoid data snooping problems by testing ex-ante technical trading rules optimized by genetic programming on out-of-sample data. Overall, technical trading rules optimized by genetic programming appear to be unprofitable in stock markets, particularly in recent periods. In contrast, they perform better in foreign exchange markets with their performance decreasing over time. For the grain futures markets, they are only partially profitable (Robert, 2003).

3.4.4 Reality check studies

This type of studies assesses data snooping bias that is associated with an in-sample search for profitable trading rules. White (2000) develops a statistical procedure called the Bootstrap Reality Check that tests the null hypothesis that the best trading rule performs no better than a benchmark strategy. The best rule is searched by applying a performance criterion to a universe of trading rules, and a desired p-value is obtained from comparing the performance of the best rule to approximations to the asymptotic distribution of the performance criterion. In this way, the procedure is supposed to take account of dependencies across all trading rules tested.

Sullivan et al. (2003) produce a universe of 17,298 trading rules for the period of 1897-1998, and find that the best trading rule is a 2-day-on-balance volume rule generating an annual mean return of 17.1% on the Dow Jones Industrial Average index with a Bootstrap reality Check p-value of zero and outperforms a buy-and-hold strategy of an annual mean return of 4.8%. Qi and Wu (2002) also apply White's (2000) methodology to seven foreign exchange rates during the 1973-1998 period and find that technical trading rules generate substantial profits of 7.2% to 12.2% per annum in five of the seven markets even after adjustment for transactions costs and systematic risk. However there are problems associated with White's procedure in that the null hypothesis typically consists of multiple inequalities, which lead to a composite null hypothesis that has complications in testing. For further discussion, please refer to Hansen (2003, 2004).

3.4.5 *Chart pattern studies*

This category studies the visual chart pattern widely used by technical analysts in financial markets. The names of chart pattern usually derive from the shapes in bar chart such as triangles, saucers, head-and-shoulders and supports-and-resistances and so forth (The standard texts for chart patterns are Edward and Magee, 2001; Schwager, 1996; Murphy, 1999; Pring, 2002).

Chang and Osler (1999) evaluate the performance of head-and-shoulders pattern using daily spot rates of six currencies during a floating rate period of 1973-1994. They formulate an algorithm for the chart identification and then establish a strategy for entering and exiting positions, such as entering when current price breaks the neckline, while the timing of exit is signaled by stop-loss, bounce possibility, or particular holding periods. They find that the pattern generates statistically significant returns for some exchange rates and they are also significantly greater than those derived from 10,000 simulated random walk bootstrap samples and remain substantial even after adjustment for transactions costs of 0.05% per round-trip, interest differential, and risk. However, the performance of the head-and-shoulders rules appears to be easily overshadowed by the performance of moving average and momentum rules in terms of total accumulated profits and risk measured by sharpe ratio for all six currencies.

Lo et al. (2000) evaluate the usefulness of 10 chart patterns on the daily data of individual New York Stock Exchange and America Stock Exchange and NASDAQ stocks during the 1962-1996 periods. The results for the goodness-of-fit and Kolmogorov-Smirnov tests show that all 10 patterns for the NASDAQ stocks and three patterns for the big boards have significantly different relative frequencies on the conditional returns from those on the unconditional returns. Thus, the patterns may provide incremental information or else the conditional and unconditional returns should be similar. Volume trends appears to provide little incremental information overall.

However, as Dawson and Steely (2003) show, informative does not necessarily translate in to profits by applying Lo et al.'s methodology to UK data as the average market adjusted returns are negative across all the patterns, even though conditional and unconditional returns distributions are significantly different. Dempster and Jones (2002) initiated the study of channel pattern and did not find encouraging results, but their study (1999) on head-and-shoulders patterns was somewhat more successful.

In general, other chart pattern studies provide different results depending on patterns, markets and periods tested and they generally ignore the data snooping problems. They are Caginalp and Laurent (1998), Leigh, Paz and Purvis (2002), Leigh et al. (2002), Curcio et al. (1997), Guillaume (2000), and Lucke (2003).

3.4.6 *Nonlinear studies*

As the name implies, this category incorporates nonlinear techniques such as the feedforward network, which is the most common class of artificial neural networks (ANNs) or the nearest neighbor regressions into a trading rule. There is virtually no theoretical foundation behind ANNs, but their popularity is due to their ability to fit any functional relationship in the data to an arbitrary degree of accuracy. ANNs have a set of inputs linked to one or more outputs via one or more hidden or intermediate layers. A feedforward network with no hidden layers is just another standard linear regression model. An excellent introduction and a description of the issues surrounding neural network model estimation and analysis is given in Mills (1999), and Franses and Dijk (2000).

Nonlinear studies typically incorporate lagged returns or past trading signals from a simple technical trading rule in to a nonlinear model. A single layer feedforward network regression model with d hidden layer units and with lagged returns is typically given as below:

$$y_t = F\left[\alpha_0 + \sum_{j=1}^{d} \beta_j G\left[\alpha_j + \sum_{i=1}^{p} \gamma_{ij} r_{t-i}\right] + \varepsilon_t\right], \quad \varepsilon_t \sim ID\left(0, \sigma_t^2\right).$$

where y_t is an indicator variable which takes either a value of 1 (for a long position) or -1 (for a short position) and $r_{t-i} = \log(p_{t-i} / p_{t-i-1})$ is the return at time $t-i$. Sometimes, the lagged returns are replaced with trading signals generated by a simple technical trading rule such as a moving average rule. Each hidden layer unit receives the weighted sum of all inputs and a bias term and generates an output signal through the hidden transfer function (G), where γ_{ij} is the weight of its connection from the ith input unit to jth hidden layer unit. Similarly, the output unit receives the weighted sum of the output signals of the hidden layer and generates a signal through the output transfer function (F), where β_j is the weight of the connection from the jth hidden layer unit.

Gencay's (1998, 1999) out-of-sample results in terms of correct sign predictions and the mean square prediction error, indicate that both the feedforward network model and the nearest neighbor model in general bring substantial forecast improvement and outperform the random walk model or GARCH (1,1) model in both stock and foreign exchange markets. In addition, those models that incorporate past buy and sell signals of the simple moving average rules provide more accurate predictions than those based on past returns. Better results are derived by incorporating a 10 days volume average indicator in to a feedforward network model as an additional regressor (Gencay and Stengos, 1998). Fernandez-Rodriguez et al. (2000, 2003) studied the Madrid Stock index and European currencies respectively, and Jasic and Wood (2004) studied the S&P500, DAX, TOPIX and FTSE, while Sosvilla-Rivero et al. (2002) studied the mark and yen. In general, technical trading rules incorporate nonlinear models appear to have either predictability or profitability in both the stock and foreign exchange markets. It is interesting to note that the study of neural network application to speculative markets was initiated much earlier in the technical analysts community, as evidenced by publications in some technical analysts' magazines.

3.4.7 Combined studies

This category makes use of technical trading rules available and combines them in variety of ways. Pruitt and White (1988) and Pruitt, et al. (1992) use a combination of cumulative volume, relative strength, and moving average called CRISMA and found that it outperform the buy-and-hold. But a recent study by Goodacre et al. (1999) in the UK equity market found that the results were consistent with weak form efficiency.

3.4.8 Others

This includes all studies that do not belong to any categories described above:

3.4.8.1 Support and resistance levels

Osler (2000) investigates whether or not published support and resistance levels are able to identify points of likely trend interruptions as claimed by technical analysts. She finds that exchange rates bounced more frequently after hitting published support and resistance levels than they would have by chance. The central or null hypothesis is that the published levels have no special ability to identify such points. This is an important study in that support and resistance levels are arguably one of the most frequently quoted technical analysis tools along with the moving averages.

3.4.8.2 Technical analysis with buy-and-hold

Markellos (2004) uses a mixed active and passive strategy by combining simple technical trading systems with a buy-and-hold strategy and finds that it usually perform better in terms of risk-adjusted returns (before transaction costs) than any strategy alone.

3.4.8.3 Technical analysis with time series models

Fang and Xu (2003) combine technical trading rules in the form of moving averages and conventional time series such as GARCH. While both techniques exploit predictable components as a function of past prices or returns; they capture different aspects of market predictability: the former tends to identify periods to be in the market when returns are positive and the later is capable of identifying periods to be out when returns are negative. Applied to 100 years of Dow Jones Industrial Average index data, the combined strategy outperforms both technical and time series alone.

3.4.8.4 Fuzzy logic

Zhou and Dong (2004) attempt to use a fuzzy logic approach to measure the degree of effectiveness of technical patterns.

3.5 Current research themes

3.5.1 Volume studies

Practitioners have long recognized that trading volume provides valuable information about future price movements; and the old market adage that, "volume precedes price" is still very much observed by those more sophisticated financial traders in the markets. Of late, a large body of academic finance literature has shown that there is a negative relationship between trading volume and expected returns in general (for examples, Amihud and Mendelson, 1986; Conrad et al., 1994; Datar et al., 1998; Brenan et al., 1998), although there is little agreement on how the relationship should be interpreted.

Amihud and Mendelson (1986), Campbell et al. (1993) and Brennan et al. (1998) attribute the volume and return relationship to market microstructure effects, whereas others suggest that this relationship is consistent with the behavioral finance theories such as the works of Barberis et al. (1998), Hong and Stein, (1999), Baker and Stein, (2002).

Although prices and volumes are jointly determined by the same market dynamics; the informational role of the interaction between past prices and trading volume in the prediction of future price movements has not been well understood. An interesting recent study by Lee and Swaminathan (2000) provide evidence on the role of interaction between intermediate horizon return predictability and trading volume in the U.S. markets. They document that: (a) High (low) volume stocks earn lower (higher) returns; (b) Momentum strategies are more profitable for high volume stocks than for low volume stocks; (c) Past trading volume predicts both the magnitude and the persistence of future price momentum over longer horizon. Interesting as it is, the findings however, do not appear to fit into any existing theoretical framework.

3.5.2 Momentum studies

There is a growing literature on the predictability of stock returns based on momentum strategy. At very short horizons such as a week or a month, returns are shown to have negative serial correlation (reversal), while at 3 to 12 month horizons, they exhibit positive serial correlation (momentum). During longer horizons such as 3 to 5 years, stock returns again exhibit reversals. The momentum of individual stocks is extensively examined by Jegadeesh and Titman (1993, 2001). They show that one can obtain superior returns by holding a zero-cost portfolio that consists of long positions in stocks that have outperformed in the past (winners), and short positions in stocks that have underperformed during the same period (losers).

To date, no measure of risk has been found that completely explain momentum returns (Grundy and Martin, 2001; Lee and Swaminathan, 2000). Momentum has also shown to be robust across international financial markets (Rouwenhorst, 1998; Chui et al., 2000; Griffin et al., 2002). This unexplained persistence of intermediate-term momentum returns throughout the last several decades is seen as one of the most serious challenges to the asset pricing theory.

3.6 Rationale behind technical trading rules' profits

The foregoing empirical studies suggest that technical trading rules can generate profits in some speculative markets, in particular, the foreign exchange and futures markets. There are various proposed explanations for technical trading rules' profits. Broadly, they can be grouped into two categories, namely theoretical and empirical.

3.6.1 Theoretical explanations

Several theoretical models postulate that price adjusts sluggishly to new information due to noise in the market, traders' sentiments or herding behavior. For examples, the noisy rational expectations equilibrium models of Brown and Jennings (1989), and Blume et al. (1994); the feedback models of De Long et al. (1990, 1991); and the herding models of Froot et al. (1992) and Schmidt (2002).

Clyde and Osler (1997) provide additional theoretical foundation for technical analysis as a method for nonlinear prediction on a high dimension or chaotic system. Thus, there may be profitable opportunities that are not being explored. For example, Brown and Jenning's (1989) noisy rational expectations equilibrium model assume that the current price does not fully reveal private information because of noise in the current equilibrium price, so that historical prices such as those used by technical analysis together with current price help traders make more precise inferences about past and present signals than the current price alone.

3.6.2 Empirical explanations

Several empirical factors have been proposed as the source of technical trading profit:

(a) Central bank interventions. Those empirical works support this explanation are Lebaron (1999); Neely and Weller (2001); Neely (2002); Saacke (2002); Sapp (2004).

(b) Clustering of order flows. Osler (2003); Kavajecz and Odders-White (2004).

(c) Temporary market inefficiency. Schwert (2003); Kidd and Brorsen (2004).

(d) Time varying risk premia. Kho (1996); Sapp (2004).

(e) Market microstructure deficiencies. Bessembinder and Chan (1998); day and Wang (2002).

(f) Data snooping biases. Lo and MacKinlay (1990); Sullivan et al. (2003); Cooper and Gulen (2004).

(g) Statistical fluke due to poor statistical inference and methodology.

3.7 Practice

3.7.1 The US$ 3 trillions a day's market

The study of technical trading rules is further justified by their wide-spread usage in the world's largest financial market in terms of turnover - the foreign exchange market.

According to estimates by Bank for International Settlements (BIS) and McKinsey, as quoted by The Economist (1999), the average turnover of foreign exchange worldwide is a staggering figure of US$2.0 trillion daily and it has grown fifty folds from 1980 to 1998. This daily turnover was much more than the total non-gold reserve of all industrial nations. The latest survey by BIS in 2004 indicates that trade in foreign-exchange derivatives was $1.2 trillion and that turnover in "traditional" foreign-exchange instruments such as spot transactions or swaps, surged to a headline-grabbing $1.9 trillion a day, making a total of $3.1 trillion a day (The Economist, 2004).

3.7.2 Survey studies

Survey studies attempt to directly investigate market participants' behavior and experiences, and also document their view on how a market works. These features can not be easily observed in a typical data set. As a financial trader, it may be important to understand how other market participants behave. The survey of Stewart (1949) provides some interesting insights. His results indicated that traders in general were unsuccessful in their grain futures trading, regardless of their scale and knowledge of the commodity traded. Amateur speculators were more likely to be long than short in the futures markets. Long positions generally were taken on days of price declines, while short positions were initiated on days of price rises. However, a representative successful speculator showed a tendency to buy on reversals in price movement during upward price swing and sell on upswing that followed declines in prices. This may suggest that successful speculators followed market trends. Other surveys also carried by Smidt (1965); Group of Thirty (1985); Brorsen and Irwin (1987); Strong (1988); and Frankel and Froot (1990).

In recent years, Taylor and Allen (1992) survey more than 200 traders on the London foreign exchange market and find that at time horizons from intraday to one week, approximately 90 percent of respondents reported using some chartist input when forming their exchange rate expectations, with 60 percent judging charts to be at least as important as fundamentals. It is believed that the use of technical analysis is also wide spread in other financial markets. Oberlechner (2001) survesy foreign exchange traders in Frankurt, London, Vienna, and Zurich. He compared with the previous results of Taylor and Allen (1992) and found that the importance of technical analysis appeared to increase across all trading horizon. Other similar surveys in the foreign exchange markets were carried out by Menkhoff (1997) in Germany; Lui and Mole (1998) in Hong Kong; Chueng and Wong (2000) in Hong Kong, Tokyo, and Singapore; Chueng et al. (2000) for the UK based dealers; Chueng and Chinn (2001) for the US based traders.

Overall, survey studies indicate that technical analysis has been widely used by practitioners in the futures and foreign exchange markets, and regarded as an important factor in determining price movements at shorter time horizons.

3.7.3 Systematic or discretionary

Edmund (1998) reports that the number of systematic traders using some sort of technical trading rules in the futures industry outnumbers their discretionary counterparts by a ratio of two to one and the gap is even bigger in the larger markets of foreign exchange, interest rates and stock index futures. He also notes that the vast majority of commodity trading programs that have existed for more than one to two decades are systematic traders and it is very unusual to find consistently successful discretionary traders over longer periods of ten or twenty years.

3.8 Data generating process

3.8.1. Stochastic processes

In order to investigate the probability distribution of realized returns from a particular technical trading rules, Acar (1993) suggests that one has to explicitly specify the nature of technical trading rule, the underlying stochastic process for asset returns, and the particular return concept involved.

The most important part in the above framework is the assumption about the stochastic process that generates asset returns. This process should be able to account for the empirical characteristics already found in financial time series: asymmetry and fat tails.

In the literature of financial economics and mathematical finance, many stochastic processes have been proposed to explain the two empirical properties of financial time series. Tucker (1992) categorizes these processes into two types:

(1) The time-independent process
(2) The time-dependent process

Many time-independent processes have been applied to account for the asymmetry and fat tails, for examples, the stable Paretian process (Mandelbrot, 1963; Fama, 1965), the symmetric student process (Blattberg and Gonedes, 1974), the mixed diffusion-jump process (Merton, 1976), the lognormal-normal subordinated process (Clark, 1973), the mixed normal process (Kon, 1984) and the asymetric stable paretian process (Tucker, 1992).

As for the time-dependent process, there is a long history of research on financial time series and we make no attempt to survey this vast literature. Some references of these processes with numerous applied examples include Mills (1999), and ARCH and GARCH is covered in a series of articles in Engle (1995) to name but two.

In a recent interesting study by Chen (2003), genetic algorithms are applied to several simulated data series to study the predicting power of technical trading rules (genetic algorithms simulate how the best rule is uncovered by financial traders over time). He finds that predictability is especially strong for data with moving average and nonlinear structures, and suggests that technical trading rules are exploiting high order nonlinearity in the data that can not be modeled with linear projection frameworks.

We shall discuss the stylized facts, and the temporal and distributional properties of returns in the chapter of data.

3.8.2 High frequency (tick-by-tick) data

The study of high frequency data has the appeals of: (a) less likelihood of instability such as regime shifts, or structural breaks, and thus making more robust estimates and a better quality of statistical inference; (b) revealing some stylized facts about price behavior that do not appear at lower frequency data; (c) facilitating the investigation of market microstructures. However, there are two major differences in analyzing high frequency data. Firstly, collecting, storing, cleaning, and handling such a size of raw observations (approximate 300,000 per day is the number of foreign exchange spot rates made by the inter-bank Reuters network) can be a costly affair. Secondly, statistical techniques would have to adapt to heterogeneous time sequence.

The major findings in a literature review by Dacorogna et al. (2001) of high frequency data which focus mainly in the foreign exchange spot market are as follows:

(a) The returns distributional property is a fat non-Gaussian tails.
(b) Scaling properties indicate fractal behavior of foreign exchange prices.
(c) A significant negative autocorrelation within 4 minutes of trading is found (Goodhart and Figlioli, 1991).
(d) Returns have day seasonal patterns correlated to the changing presence of main market places of the worldwide foreign exchange market. That is lowest on weekends and during the lunch hour in Japan that coincides with night in America and Europe. Dacorogna et al. (2001) recommend for deseasonalization to uncover stylized facts.
(e) Volatility autocorrelations decay at a hyperbolic rather than exponential rate. This indicates the presence of a "heat wave effect". Volatility also leaves a memory effect.

(f) The impact of news on prices (first studied by Goodhart, 1989) is mixed. Economic news announcements generally known instantly to all traders, seems to have an impact that is not coherent with market efficiency. Instead of generating a quick adjustment of prices toward the post news rational price vector, they increase volatility. In addition, large price movements are unrelated to the news.

3.9 Concluding observations

There appears to be more studies that find profitability based on a comprehensive review pertaining to the profitability of technical analysis carried out by Park and Irwin (2004). The review includes theoretical, empirical and survey studies. However, there are quite a number of drawbacks in the methodology of those studies, especially the earlier studies (prior to 1988). Broadly, they are: (a) Only a few technical trading rules or systems are studied. (b) Risks are not taken in to consideration. (c) No statistical test of significance. (d) No parameters optimization and then out-of-sample verification. (e) The issue of data snooping was not considered. After 1988, most studies attempt to rectify the above weaknesses but interpretation of results is again subjected to the type of technical trading rules, financial markets and period studied.

Overall, technical trading rules' performance appears to: (a) Do better in futures and foreign exchange markets than stocks markets in general. (b) Indices appear to be more predictable than individual stocks. (c) A sign of declining performance over time, in particular, those much published technical trading rules. The profitability would largely disappear after transaction costs and risk factors are taken in to consideration.

In terms of methodology, more nonlinear and bootstrap techniques are involved. The study of technical patterns has also taken more seriously by leading academics with mediocre results. Surveys also indicate the increasing application of technical trading rules in the foreign exchange markets across major financial capitals over time.

Timmermann and Granger (2004) provide a guide to the key issues that future studies of the profitability of technical trading rules must address:

(a) The set of forecasting models available at any given point in time, including estimation methods.

(b) The search technology used to select the best (or a combination of best) forecasting model(s).

(c) The available "real time' information set, including public versus private information and ideally the cost of acquiring such information.

(d) An economic model for the risk premium reflecting economic agents' trade-off between current and future payoffs.

(e) The size of transaction costs and the available trading technologies and any restrictions on holding of the asset in question.

3.10 A discussion on the academic literature of technical trading rules

3.10.1 Methodologies

3.10.1.1 Is buy-and-hold a suitable benchmark?

In Park and Irwin's (2004) review of the profitability of technical analysis, out of 81 studies that use a benchmark for comparing with the returns of technical trading rules; 50 of them use buy-and–hold. At first sight, the benchmark appears to be intuitive and simple. However, on closer study, the problem of comparing returns on a downtrend market surfaces; as technical trading rules are still capable of capturing the time series whereas, the buy-and-hold will just have to sit tight and contented with negative returns. The continue use of the buy-and-hold strategy is rather surprising; especially this issue had been expounded by Praetz (1976) and Sweeney (1986) in the Journal of Finance which is one of the leading journal in the field of finance.

3.10.1.2 Some proposed alternatives:

(a) Actual to potential ratio: Comparing the actual captured profits to that of the potential profits possible in every up and down opportunity presented in the time series.

(b) *Naïve trading rule*: Use a randomly generated buy, hold, and sell signals and applying them to the time series. Repeat the process say 500 times and then work out the mean returns and distributional properties.

(c) *Skill score*: This is used by meteorologists to determine if their weather forecasting is due to luck or skill. The formula is as follows:

$$\text{Skill Score} = \frac{\text{Skilled correct-No skill correct}}{\text{Total decisions- No skill correct}}$$

If the skill score is zero or negative, the decision did not involve any skill, only luck. On the other hand, if the score is positive, some skill may be involved (Sherry, 1992).

(d) *Cointegration cumulative profit test*: Markellos and Mills (1997) provide an interesting evaluation technique on the performance of a trading system.. This test is based on the premise that for a trading system to have a significant performance:

(i) It must produce cumulative returns that are I (1), with a positive trend.

(ii) In addition, these cumulative returns must not be cointegrated with the cumulative returns from the market.

The rationale behind (i) statement above is that, if the cumulative returns are I (0), then the system randomly out and under-performs the market and it has no upwards bias towards profits. As for (ii), even if the cumulative trading system returns are I (1) with a positive drift, it is possible that these returns are due to chance. This will happen if the cumulative returns are cointegrated with the cumulative market returns which means that the trading system's returns is tied to the market returns. In other words, it does not outperform the market in the long-run since it must revert through error-correction to the buy-and-hold strategy performance. More specifically, if the cumulative performance of a trading system is cointegrated with the market, then the residuals from their regression will be I (0), so the performance of the trading system will differ from that of the market only in a random manner.

3.10.1.3 Data snooping: issue, motivation and justification

From a market participant's perspective, data mining is very often the first step in working out the predictability. Whether it is applicable in the future is another question altogether, as one still has to assess the likelihood of the same environment to prevail during the forecasting period.

For financial economists, there are the statistical issues yet to be resolved (Hansen, 2003, 2004), and as pointed out by Lebaron (2000), "..., no test for data mining is perfect, as it depends on simulating the snooping process that might have been occurring. No formal test can be performed to answer this question..." Technical trading rules are, by nature, eclectic, combinational and the variety are subject only to one's imagination and creativity. This should further compound the dimensionality of tackling the problem in hand. This problem is also highlighted by some leading researchers in data snooping such as Sullivan et al. (1999): "It is important that the span of the set of trading rules included in our universe is sufficiently large, because the data-snooping adjustment only accounts for snooping within the space spanned by the included rules."

Even if a universe of technical trading rules do not work does not necessarily implies that there are no technical trading rules profits. By the same token, if a black swam has never been seen before, does not necessarily mean that there is no black swam in this world. Whether the study of data snooping will turn in to another debate much like the efficient market hypothesis; only time will tell (such as the weak, semi-strong and strong form of data snooping?). More importantly, does it serve much purpose in forecasting?

To avoid ambiguity, placing qualifications on the interpretation of results may help. For example, the results are subject to that particular period under study, for that particular market, for that particular frequency, and for that particular or those groups of technical trading rule(s), and so forth. A claim on technical trading rules as a whole or without some of the above qualifications may not be justified.

3.10.1.4 Test window: The dilemma of power and stability

Most studies do not make any justification on the size or length of test window. Taylor (1986) makes a point to justify the size of an optimal set of data so that it may have more power. He states that if possible, at least eight years of data should be analyzed. We, on the other hand, argue that the data should encompass two complete full cycles or two peaks and troughs. However, the question of stability (for instance, time invariant data generating process and stationarity) still remains unsolved. In particular, if the parameters are not adaptive and so forth. The size of test window is still an important issue need to be resolved, and indeed warrant more attention, or else the comparability and significant of studies are much weaker or stronger than what they are make out to be.

3.10.1.5 Using the rearview mirror to drive and a possible alternative

To mitigate the problem of driving using the rearview mirror, scenarios forecasting and risk management could be incorporated to make forecasting more effective and practical:

Application= Predictability + Scenarios Forecasting + Risk management

The second component is intuitive as what happened in the past does not necessarily going to repeat in the future. In practice, financial traders have to manage their capital prudently so that they are able to cushion any surprise (market crash) and in the event of trading rules generating wrong signals resulting in a consecutive of losses that may wipe out their capital base, rendering them out of business and become ex-traders. Thus, risk management or the so called "money management" in the technical analysts' community is another important component in the application of technical trading rules. One way of defining risk management is the identifying and managing of risks (for instance, to assume, reduce, transfer, control, and diversify); and then prepare for all eventualities.

For financial traders in the US, the rule of thumb for risk management is not to commit more than 2% of capital in any one trade so as to avoid the chance of ruin, whereas, our calculation indicate that one can go much higher in other speculative markets, and can go as high as 10% in the case of Kula Lumpur Stock Exchange (please refer to the authors for the calculation). The working of these figures is based on the concept of optimal *f* as proposed by John L. Kelly, and therefore also known as the Kelly's formula (Vince, 1990).

3.10.2 Future research

3.10.2.1 Inter-markets dynamics

Dempster and Jones (2002) recommended inter-markets analysis for further work such as those shown in Murphy (1999), who discusses the ripple effect that flows from the dollar to commodities, to bonds, and then to stocks. According to Murphy (1999), there are global linkages. What happen in Asian, Europe, and Latin America has an impact on US markets and vice versa. Inter-market analysis also sheds light on sector rotation within the stock market. For example, relative strength analysis is helpful for seeking out asset classes, market sectors, or individual stocks that are likely to outperform the general market. Some useful ideas also can be obtained in Moore (1990). He shows how the interaction between commodity prices, bond prices, and stock prices follows a sequential pattern that tracks the business cycle.

3.10.2.2 Technical trading rules + time series models and others?

Based on the results of Fang and Xu (2004), there appears to be potential in combining technical trading rules with other rules, strategy, and models. There are also many other potential technical trading rules which are yet to be studied in greater detail such as the candlestick.

3.10.2.3 Risk: performance measures based on downside risk

Beside the sharpe ratio as a measure of risk, there are a few alternatives such as those of Sortino et al. (1999a,b), and Burke (1994) which warrant attention, and their applications to the studies of technical trading rules may yield different risk-adjusted results for previous studies. For example, the Sterling and Burke ratios are widely used by commodity trading advisors because these ratios illustrate what they believe they do best:

namely, let their profits ride and stringently cap their losses. The Sterling ratio incorporates the drawdowns (losses) to measure the risk:

$$Sterling = \frac{r_p - r_f}{d}$$

where d is the maximum drawdown during the observation period. r_p and r_f are returns on portfolio and risk free rate of returns respectively. Burke (1994) on the other hand, proposed using the square root of the sum of the square of each drawdown, in order to penalize deep extended drawdowns as opposed to numerous mild ones:

$$Burke = \frac{r_p - r_f}{\sqrt{\sum_{i=1}^{n}(d_i^2)}}$$

For the Sortino ratio, it is defined as the net rate of return over the minimum acceptable rate of return (MAR) as this rate of return can be quite different for different categories of investors and traders:

$$Sortino = \frac{r_p - r_f}{MAR}$$

3.10.2.4. Prospect theory

Apparently, there are no studies on applying the prospect theory to explain the rationale behind the design of technical trading rules. For example, the basis for the support and resistant levels to work in technical analysis is that traders would often hold on to losers and take quick profit to winners; and this type of behavior is well explained by the prospect theory.

3.10.2.5 High frequency data, and survey

Brooks (1996a) argues that there is a distinct advantage in using high frequency data in empirical testing because of the issues of stationarity and data points availability. There are a number of reasons for the advocacy: (a) Strict stationarity (non-integrated) of data is much more likely to hold over short intervals of calendar time, and therefore allowing the use of constant parameters for comparison purposes. (b) A large number of observations can be collected in a relatively short period of time, and thus satisfy the data requirements. (c) We also hasten to add that most of the users apply technical trading rules on a short term basis as evidenced by those reported in the surveys.

More surveys should be carried out in other speculative markets other than the foreign exchange market as recommended by Park and Irwin (2004).

Chapter 4

Stylized facts and nonparametric analyses

In this chapter, we shall analysis the temporal and distributional properties of returns. In addition, we shall also employ several nonparametric techniques developed to study how the nervous system processes information. These techniques were developed by Sherry (1992) and published in a number of refereed scientific journals such as Brain Research, International Journal of Neuroscience, Brain Research Bulletin, etc.

Given the time and resource constraints, we shall skip general tests such as BDS test and bispectrum test, and specific tests such as the GARCH models on nonlinearity, but concentrate on those nonparametric techniques developed by Sherry (1992). These particular sets of techniques also have intuitive appeal and less studied (as far as we know, there is only one financial economist, Los (1999), in the academic community that used the same techniques so far). In addition, the techniques provide a different perspective from all other dependency tests that we have come across. Thus, in terms of contribution to the general knowledge of our study; the techniques appear to be a natural choice

There is a subtle difference between nonparametric and nonlinear. For instance, nonparametric implies no parameter at all, whereas, nonlinear implies no linear parameter only.

4.1 The importance of stationarity and dependency(ies)

The study of stationarity is important in technical analysis. For example, if a time series is not stationary, the underlying rules that generate the time series change from time to time, usually without warning or external sign. Most pattern detection techniques, even those relatively simple ones like moving averages, and statistical techniques like serial or auto-correlations, assume that the underlying time series is stationary. Violation of this assumption will generally yield results that are meaningless. Further, it means that any patterns that one happens to detect are spurious. On the other hand, if the time series is stationary, then one can use any appropriate pattern detection technical analysis or statistical technique to find some aspects of the behavior of the time series as a technical trading signal. This signal should then be valid over time until it becomes nonstationary.

Independence is another important concept in applying technical trading rules. For example, if the time series is independent, then any pattern that one happens to detect is probably spurious and may not work in the long run. On the other hand, if the time series is dependent, then one should be able to determine the duration of the temporal window during which the time series shows serial dependency or autocorrelation. Thus, if one works within the confines of this temporal window, then one can use a variety of techniques such as technical analysis and statistical techniques to detect pattern, dependency and make profitable financial trading. The forgoing two points are emphasized by Sherry (1992).

4.2 Data

4.2.1 Rationale and limitation of Dow Jones Industrial Average Index (DJIAI)

The main reason why we use the DJIAI is because most major and important works done on technical trading rules to date use the index. For instances, Brock et al (1992), Sullivan et al (1999) and LeBaron (2000). This can allow some cross checking and comparisons; and thus, making interpretation more meaningful. In addition, the DJIA has a much longer history than the S&P500. Although the DJIAI is a price-weighted index, the selection of its component stocks produces almost the same results as an index based on weighting by market value. This is because its component stocks are those of very large companies. As a consequence, movements of DJIAI are almost the same as the movements of an index on weighting by market value such as the S & P 500. For examples, the means and variances of returns of almost similar periods for the DJIAI and S&P 500 are very similar as calculated by Wilcox (1999) and Taylor (2000). Hence, the disadvantages levied on the DJIAI appear to be a bit over emphasized.

The real limitation arises when a price weighted index is adjusted for stock split or bonus issue. The following table illustrates the bias of price weighted method.

Table 4.1 Bias of price weighting method

Component Stocks	Period 1	Period 2	Period 3	Period 4
	------------------	Stock split of $1 to 50 cents	Result of the stock split	----------------
A stock price B stock price C stock price	20 10 6	50 10 6	25 10 6	10 10 6
Average	12	22	22	13.95
Divisor	3	3	1.8636	1.8636

The price of stock A increases from $20 in period 1 to $50 in period 2 while the prices of stocks B and C remain unchanged throughout the 4 periods. The average, therefore, increases from 12 to 22. Assuming there is a stock split of $1 to 50 cents or a bonus of 1 for 1 between period 2 and 3. Assuming no change in the sentiment of stock A, its price should be $25 in period 3 and the average should still be 22. Therefore, the divisor is now reduced from 3 to 1.8636 that is (25+10+6)/22. Suppose, subsequently, the price of stock A declines to $10 in period 4. This is equivalent to the price of $20 in period 1. Therefore, the average in period 4 should be 12. However, with a divisor of 1.8636 used from period 3 onwards, the average in period 4 is calculated to be (10+10+6)/1.8636 = 13.95.

4.2.2 *Sources and characteristics*

The data series used here is the Dow Jones Industrial Average Index (DJIAI) - comprised of 30 actively traded New York Stock Exchange listed issues - from 1988 to 1999 with a total of more than 10 years of daily data.

Each daily price data consist of volume, open, close, high and low of the day. This is necessary for the transformation of original open, close, high and low data into some patterns for the application of certain technical trading rules such as the Candlestick and the use of open or close for buy and sell signals. For our purpose, we only use a relatively shorter period of data as the application of technical trading rules are mostly short-term in nature according to the survey of Taylor and Allen (1992). On the other hand, the issue of stability is also a major concern.

The data is purchased through Key Quote Ltd and verified with similar data produced by Reuter. The 1987 data is excluded to avoid the one day extreme fall of more than 20 percent in October of 1987 and then another extreme raise of 9 percent a few days later.

Table 4.2 contains the summary statistics for the entire series which is characterized by the stylized facts of a skewed and excessively kurtotic distribution. In our view, the negative skewness may be a reflection of "panic" behaviour by investors in a down-turn market. The higher minimum return than maximum return provides some support for this argument. The minimum and maximum returns for the two subperiods bear surprising resemblance, and we speculate that they are what the New York Stock Exchange could accommodate given the then infrastructural systems and supports. The width and depth of the stock exchange system, so to speak.

Table 4.2 Daily Log returns distributions of Dow Jones Industrial Average Index, 1988-1999.			
	1988-1999	**1988-1993**	**1994-1999**
Sample size	2661	1350	1311
Mean	0.058	0.044	0.072
Standard deviation	0.881	0.823	0.941
Range	12.164	11.622	12.315
Minimum	-7.455	-7.156	-7.455
Maximum	4.861	4.467	4.861
Skewness	-0.478	-0.495	-0.657
Kurtosis	6.310	6.317	6.886

All stocks in the DJIA series are actively traded and problems associated with nonsynchronous trading should not be a concern. In addition to the full sample, results are presented for two sub-samples: 1988 to 1993, and 1994 to 1999.

The reasons for the choosing this sub-periods are that there seems to be a distinct difference in the mean returns (please refer to Table 4.2) and the trend for the two sub-periods (please refer to figures 4.1, 4.2 and 4.3). Both subperiods also constitute approximately the same number of observations. The first log differencing of the Dow Jones Industrial Average Index are shown in figures 4.4 and 4.5 for the subperiods 1 and 2 which appear to be stationary; while the returns distributions are presented in figures 4.6 and 4.7 which indicate a non-normal distributional characteristics.

4.2.3 Stylized facts

Many economic time series display one or more of the following five features: a trend, seasonality, atypical observations, clusters of outliers and nonlinearity (see, for example, Franes, 1998).

A survey by Mills (1996), together with his extensive empirical research indicates that the daily FTSE returns are not normally distributed, but are characterized by fat-tails, peakedness and negative skewness. These stylized facts are also present in the data set being used here.

There are several reasons as to why non-normality is observed in equity market returns. Firstly, the presence of limited liability in all equity investments may induce option-like asymmetrics in returns (Black, 1976; Christie, 1982; Nelson, 1991). Secondly, the agency problem may induce asymmetries in index returns (Brennan, et al., 1998). For example, a manager has a call option with respect to the outcome of the firm's investment decision, may prefer high positive skewness. Thirdly, conditional heteroskedasticity may induce fat tails (Bekaert et al, 1998). Fourthly, regime shifts may induce both skewness and kurtosis (Bekaert and Harvey, 1995). Finally, thinly traded securities' returns may appear non-normal.

The departures from normality are important to portfolio managers in two respects. Firstly, the usual mean-variance framework is no longer adequate to characterize investment decisions. The second implication is that the higher moments such as skewness and kurtosis are time-varying. For example, Mills (1996) shows that tails are not stable but are exponentially declining, being consistent with a finite variance. Thus, dynamic models for these higher moments are necessary.

Emerging market returns tend to have more positive skewness than developed market returns, with a coefficient of skewness greater than zero in most cases and they also present more kurtosis than the world benchmark (Bekaert, et al, 1998).

Franses and Dijk (2000) show that in most financial time series: (1) Large returns (in absolute terms) occur more frequently than one might expect under the assumption that the data are normally distributed, (2) Such large absolute returns tends to appear in cluster (indicating the possible presence of time varying risk or volatility), (3) Large negative returns appear more often than large positive ones in stock markets, while it may be the other way around for exchange rates, and (4) Volatile periods are often preceded by large negative returns.

4.2.3 *Temporal relationships: Autocorrelations*

Autocorrelation or serial correlation is the correlation between a time series variable and its lagged value. The j th autocorrelation is the correlation between y_t and y_{t-j}. While it is impossible to obtain a complete description of a stochastic process, the autocorrelation function will nevertheless provide a very useful partial description of the process, such as the correlation between lags and thus to a certain extent, the interdependency. The sample autocorrelation function or coefficient is usually estimated by the following formulae:

$$p_k = \frac{\sum_{t=1}^{T-k}(y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2}$$

This formula should be altered for futures series, and it assumes constant expected returns. The autocorrelation functions p_k have been calculated for all lags k between 1 and 30 trading days inclusive. Table 4.3 summarizes the signs, lags and magnitudes of the coefficients of returns which are significant at the 5% level for the whole and subperiods 1 and 2, while tables 4.4, 4.5 and 4.6 report the autocorrelations of log returns and their transformed returns for the whole and subperiod 1 and 2 respectively. Figure 4.8, 4.9 and 4.10 show the changes of coefficient graphically over time.

As in most autocorrelation studies of stock financial time series, their coefficients are all close to zero and both subperiods first lag are positives. For the subperiod 1, only 7 percent (two) autocorrelations are significant at the 5% level while there are 17 percent (five) autocorrelations significant at the 5% level for subperiod 2. We calculate the total absolute (i.e. without signs) autocorrelations for the first 30 lags of both subperiods, and find that again, subperiod 2 is higher at 0.85 than the 0.63 for subperiod 1. Meanwhile, 60 percent of autocorrelations for subperiod 1 are negatives compared to only 50 percent for subperiod 2 which correspond to a higher net total negative autocorrelation of -0.18 for subperiod 1 compared to a -0.12 for subperiod 2. Overall, absolute and squared returns have substantially higher autocorrelations than there is between the returns themselves.

On the whole, based on the forgoing statistical evidence, subperiod 2 appears to be more dependent than subperiod 1 in terms of autocorrelations. This also coincides with a predominately steeper uptrend; and a slightly higher average directional predictability for subperiod 2 (44.70% as compared to 42.65%). The overall low autocorrelation suggests that the dependent price generating process, if any, may be nonlinear. This has led us to search for alternative techniques to detect nonlinear dependencies in financial time series.

Table 4.3 Linear autocorrelations significant at the 5% level

Periods	Signs and lags
Entire period 1988-1999	-7, +9, -16, -25
Subperiod 1 1988-1993	-7, -25
Subperiod 2 1994-1999	-3, +9, -11, -16, -25

4.2.3.1 Possible causes of autocorrelation

Not all market returns are auto-correlated; it depends upon the frequency of returns, its time period of measurement, and the market itself. However, daily returns for equity indices often do exhibit some autocorrelations. There are three possible explanations for the existence of autocorrelation:

(a) *Inertia of dependent variable*: Alexander (2001) argues that a possible cause of autocorrelation in equity indices is the news arrival process, where information affects trading in some stocks before others. When daily returns are auto-correlated, it may be caused by news arrival in the market during the afternoon session, which affects only those stocks traded late in the day, and the price of other stocks in the index will not be affected until they are traded on the next or subsequent days. She then concluded that important international news is likely to affect the stock indices of different countries in the same way, and thus, common autocorrelation is a possible co-feature in the international equity markets.

(b) *Overreactions*: Financial markets occasionally overreact to good and to bad news. This is particularly pronounced for bad news in time of a bear market and vice-versa. For example, in times of high oil prices, good news on the discovery of new oil or gas reserve for an oil company may lift the shares of that company higher than its intrinsic value, before subsequently falling back to its intrinsic value.

(c) *Market microstructures*: For example, the settlement system for shares transactions may be say fixed on the third day after the transaction date (i.e. T+3). This type of arrangement very often resulted in falling prices on the day of T+3, when there have been raising prices and high volume on the day of T.

4.2.5 Unit root tests

Since most financial time series are invariably nonstationary, we will only make a brief attempt to test the stationarity of the series concerned. Based on the graphical view of index movements; and using EView (version 3.1), the unit root tests results in table 4.9 are well within expectation. The results for returns (i.e. after logarithmic transformation and first differencing) on both tests are less than the critical values and thus the null hypothesis of a unit root is rejected. On the other hand, results for the price level (i.e. raw data) are larger than the critical values and thus the null hypothesis of a unit root is not rejected. Both the ADF (augmented Dicky-Fuller) and PP (Phillips-Perron) unit root test statistics suggest that the series is $I\,(1)$ and thus not stationary.

Table 4.9 Unit root tests for the DJIA index from 6th September 1988 to 24th March 1999 (entire period)

Unit root tests	Levels	First differences	MacKinnon critical value @ 1%
ADF	1.416366	-24.18016	-3.4359
PP	1.406502	-50.62664	-3.4359

4.3 Stationarity and dependence: a nonparametric approach

Driven by the lack of strong evidence for dependencies and the need for such existence so that technical trading rules may be profitable; we conducted several nonparametric tests for stationarity and dependence, in addition to the usual linear autocorrelation test. The non-parametric methodologies we employ were originally developed by Sherry (1992) and his colleagues during the 1970s and 1980s, published in several scientific journals, for the study of information processing in nervous systems (please refer to table 4.10). The motivation behind the study of these methodologies are that they are superior to the conventional parametric tests, since they are very intuitive and do not require the assumption of normality, or any other parametric assumption for the underlying price generating process. The only distribution tests used are Chi-square based, which simply compare observed values with theoretically expected values. All computations were executed in EXCEL spreadsheets. We shall carry out the following tests on stationarity and independence, except Differential spectra because it only detect whether price changes are independent and do not identify the type of serial dependence that may be present.

Table 4.10 Nonparametric methodologies	
1. *Stationarity*	2. *Independence*
(a) Cumulative distributions	(a) Differential spectra
(b) Percentile graphs	(b) Relative price change transition arrays
	(c) Length of temporal trading window
	(d) Category price change transition arrays (CPCT)
	(e) Markov analysis of CPCT arrays

4.3.1 *Types of nonlinear and nonparametric models*

There are an infinite number of different types of nonlinear and nonparametric models. According to Brooks (2002), only a small number of nonlinear models have been found to be useful for modeling financial data. The most popular nonlinear financial models are the ARCH or GARCH models used for modeling and forecasting volatility, and switching models which allow the behavior of a series to follow different processes at different points in time. Broadly, there are two types of nonlinear tests available to detect nonlinear patterns in time series: general tests and specific tests.

General tests, also referred to as portmanteau tests, are usually designed to detect many departures from randomness in data. Such tests will detect a variety of nonlinear structures in the data, but unlikely to detect the specific type of nonlinearity present. Two of the popular tests are known as Ramsey's RESET test and BDS test. Most of the tests suggest there is nonlinear dependence in financial returns time series, but that the dependence is best characterized by a GARCH type process (see for examples, Hinich and Patterson, 1985; Baillie and Bollerslev, 1989; Hsieh, 1989; Brooks, 1996b; and Mills, 1999). Specific tests, on the other hand, are usually designed to have power to find specific types of nonlinear structure. Those tests designed by Sherry (1992) in which we are going to test are both general and specific. The specific tests are for the temporal dependent relationships.

4.3.2 *The drawbacks of some traditional tests*

It is noteworthy to mention that the following tests generally assume stationarity of the underlying time series, and violation of this assumption will render spurious results. For instance, any pattern that one happens to detect may be is by chance or random, and may not last. In addition, the following tests have their own peculiar shortcomings according to Sherry (1992).

4.3.2.1 Serial or auto-correlation tests

In general, they test only for linear forms of dependence such as sequentialness, periodicity and rhythmicity. In addition, they have to assume the continuity or discreteness of the pricing processes. As pointed out by Sherry (1992), "... if the correlation coefficient is low, this does not mean that the time series does not contain significant serial dependencies; it merely means that the time series does not contain the type of serial dependencies that the correlation test for." On the other hand, tests based on power spectral analysis fall in the same linear category as they are essentially Fourier transforms of the correlation tests which are too specific.

4.3.2.2 Runs and persistence tests

They can be confusing, since it is unclear as to what exactly is tested: whether they test for divergence from randomness or independence. In addition, the often hard to check normality assumptions are introduced ad hoc, for instance, to test Besson's coefficient of persistence.

4.3.2.3 Averaging windows

They are heavily dependent on subjective preferences for the length or duration of the averaging windows. In contrast, we test for the time series and then attempt to determine the durations of data.

4.3.2.4 Pattern detection tests

Tests by densitograms, periodograms based on Fourier transforms, triggered categorized price histograms, and temporal correlograms; introduce again, largely subjective judgments or restrictive parameters. These pattern detection techniques would only make sense after the original tests for stationarity and independence have been applied.

4.4 Stationarity test

4.4.1 Definition and assumption of stationarity

A stationary time series is a series whose statistical properties are time invariant. Thus the regime and its price generating processes are constant over time. Stock and Watson (2003) define stationairty as when the joint distribution of a time series variable and its lagged values does not change over time. Broadly speaking, a stationary series has a constant mean and variance, and the correlation between values y_t and y_{t-j} depends only on the time difference j. A stationary time series tends to return often to its mean value. More specifically, a process is "weakly" or "covariance" stationary if:

$$E\ y_t = \mu$$

$$\mathrm{var}(y_t) = \sigma^2$$

$$\mathrm{cov}(y_t, y_{t-j}) = \gamma_j$$

where all the right hand side population moments are independent of time t, and have finite values. In addition, if y_t is normally distributed, then it is strongly stationary. Stationarity is used to mean "weak" or "covariance" stationarity. A white noise error term ε_t is a very specific type of stationary series where the mean and covariance are zero.

The standard hypothesis tests in statistics are based on the assumption that the variables used in constructing the tests are stationary. Thus, for a non-stationary series, the distribution of standard test statistics may not be meaningful. The statistical properties of tests on non-stationary series generally involve substantial changes to the standard tests such as the tables of critical values.

Pattern detection techniques such as moving averages, trend line, serial correlation, will only work if the underlying time series is stationary; otherwise any pattern detected is spurious or by chance, and may not hold over time.

4.4.2 Causes of nonstationairty and test statistics

Time series can fail to be stationary in various ways, but two are especially relevant in the analysis of financial and economic time series data. Firstly, it is the Trends – a persistent long-term movement of a variable over time. There are two types of trends: deterministic or stochastic trends. The former is a nonrandom function of time. In contrast, the latter is random and varies over time. Trends in time series can be detected by informal and formal methods. The informal methods involve visual inspection of a time series plot, and computing the autocorrelation coefficients. The first autocorrelation coefficient will be near one if the time series has a stochastic trend (at least in large samples), whereas, a small first autocorrelation coefficient combined with a time series plot that has no apparent trend suggests that the time series does not have a trend. For the formal method, one of the most reliable and commonly used tests for stochastic trends is the Dickey-Fuller test (Dickey and Fuller, 1979). A stochastic trend can be eliminated by using first differences of the series.

Secondly, it is the Breaks which can arise from a discrete change in the population regression function. In financial time series, this can occur for a variety of reasons such as the change of monetary policy (for instance, the reverse trend in interest rate policy), changes in the market microstructures such as the addition of a market index futures contract, and so forth. The modified Chow test or Quandt likelihood ratio (QLR) statistics (Quandt, 1960) or the sup-Wald statistic is used to detect breaks.

4.4.3 Nonparametric tests

We use two nonparametric tests, namely the *Cumulative distribution* and *Percentile graphs* methodology developed by Sherry (1992) to test stationarity. The procedures are as follows:

(a) The time series is divided in to two equal halves (the chronologically earlier half will be called half 1, and the successive half as half 2).
(b) The two halves are then separated in to bins of equal interval size.
(c) Cumulative graphs of both halves are constructed, and then compare and assess visually (please refer to figure 4.11).

(d) Insert chart with differential spectra, include data points in both halves corresponding to percentile increments of 10% each, and start plotting the 10%, 20%, 30% ... until 100% for half 2 against half 1. Using a 45% line to indicate equality between the two halves, then test for deviation from the 45% line against both halves (please refer to figure 4.12).

(e) Chi-square tests are then conducted. To do so, the bin intervals for half 1 are obtained for cumulative percentiles of approximately 10%, 20% ... until 100%. These bin intervals are then used as reference bins in half 2 to find the respective percentiles associated with each of these bin references. The difference between each percentile in half 1 is then compared with the half 2 percentile differences using the Chi-square test (please refer to table 4.8).

4.5 Independence tests

The independent test attempts to determine if price changes are independent of one another or to determine the temporal relationship of price changes between two different intervals. If the price changes are found to be serially dependent, then one may use it for forecasting. We shall only present the final chi-square test for the Markov CPCT matrices as in table 4.8 (please refer to the author for other test results).

4.5.1 Relative price change transition arrays (RPCTA)

The RPCTA test allows one to determine the type of serial dependence and the duration of the temporal window during which the dependency exists. The following test procedure is used to form relative price change transition arrays to test for independence, with the theoretical relative frequencies or probability of occurrence as in tables 4.11, 4.12, and 4.13.

Table 4.11 *Theoretical probabilities of digrams*	
Digrams	Probabilities
11 or 22	2/6
12 or 21	1/6

Table 4.12 *Theoretical probability of trigrams*	
Trigrams	Probabilities
111 or 222	1/24
221, 211, 122 or 112	3/24
121 or 212	5/24

Table 4.13 *Theoretical probability of tetragrams*	
Tetragrams	Probabilities
1111 or 2222	1/120
1112, 1222, 2111 or 2221	4/120
1121, 1211, 2122 or 2212	9/120
1122 or 2211	6/120
1212 or 2121	16/120
1221 or 2112	11/120

(a) The price changes are translated in to a series of arbitrary symbols such as a sequential increase in the price change is classified as 2; while a sequential decrease in the price change is classified as 1. For example, if a string of price changes is 3,5,4,7, the translated symbols would be 2, 1 and 2. When sequential price changes are the same, a random generator is used to decide whether it is 1 or 2.

(b) The string of symbols of 1 and 2 are then transformed into transition matrices.

(c) The digram series are counted to obtain the relative frequencies of the digrams which are the observed frequencies for the Chi-square test. The theoretical frequency of occurrence of each digram is given in table 4.11, and this probability is multiplied with the total number of actual price changes to obtain the expected frequency for digram. For example, the digram 21 has the following expected frequency:

Expected frequency = (theoretical probability of digram 21) x (total number of price changes)

(d) If the obtained Chi-square value is statistically significant, we proceed to generate the trigram transition array and so forth until the test result is insignificant.

4.5.2 Length of temporal trading windows

Instead of just looking at the immediate sequential price changes, the relative price change transition (RPCT) arrays can also be used to determine the duration of a temporal window for serial dependencies. The procedure is as follows:

(a) A lag n window is generated by pairing the first symbol (for instance, either 1 or 2) with the n-th, the second with the (n+1)th and so forth.

(b) A lag n temporal window is determined by tabulating the frequency associated with each transition matrix; and these frequencies are then used as the observed values.

(c) The observed values are then compared to the theoretical independent probabilities as in tables 4.11, 4.12 and 4.13. If the Chi-square test is significant, the series is not independence, and higher order temporal windows will be tested until it is insignificant.

4.5.3 Category price change transition arrays (CPCT)

This test can provide more detail than the previous two tests. It determines if relatively large or small price changes deviate from independence, by categorizing the time series according to a set of predetermined criteria. In this way, one can have as many categories as one desires, and therefore, when one category is tested to be independence does not necessarily imply that the time series is independent as other categories may provide different results. Thus, CPCT is theoretically, an interesting technique given the affordability of computing power and availability of data. We employ the following criteria, and the steps involved are as follows:

(a) The cumulative frequency distribution of price changes as in the previous section of testing stationarity is divided into three parts: the lowest 10% of the series, the next 80%, and the highest 10%.

(b) Determine in which three categories of the price changes belongs to. We use the symbols 1, 2, and 3 to represent the three different categories i, j, and k respectively.

(c) The digram category price transition (CPT) matrix is generated by specifying how often a 1, 2 or 3 is followed by 1, 2 or 3. The frequency of occurrence of a symbol i is the number of price changes in i categories.

(d) As in previous section, the theoretical probability of occurrence of each component in the digram is computed and the result is multiplied with the total number of price changes to obtain the expected frequency for that digram. In contrast to the RPCT array, the determination of the probability of occurrence of each digram follows the multiplication rule of classical probability theory for assumed independent occurrence. For example, a 13 digram has the following expected frequency;

    Expected frequency = (theoretical probability of 1) x (theoretical probability of 3) x (total number of price changes)

(e) If the Chi-square test is significant; it only implies that the series is not digram independent under the particular categorization (10%, 80% and 10%), and one can then proceed with the trigram and tetragram transition arrays as in the previous section. It should be emphasized that the categorization is arbitrary, and one can choose any other pattern such as 20%, 30% and 50%, or any other combination, and construct the digram matrices, followed by the trigram, tetragram and so forth.

4.5.4 Markov analysis of category price change transition arrays.

Markov analysis allows one to specify the levels of serial dependencies. While in the preceding section, we looked at the digram transition matrices at zero-order Markov process, in this section, we examine higher order Markov processes. Informally, a Markov process is a stochastic process which assumes that in a series of random events, the probability of an occurrence of each event depends only on the immediately preceding outcome (Parker, 1994). Thus, an r th-order Markov process means that the probability of occurrence of a specific price change depends upon the immediate preceding r price change. The steps for Sherry's (1992) Markov analysis of the CPCT matrices are as follows:

(a) The previous section of CPCT is a zero-order Markov process. If the Chi-square test is significant, then proceed to an order-1 Markov process. The degree of freedom for a zero order Markov process is $(\text{C-1})^2$, where c is the number of states. For instance, digram have C = 2 states so that the degrees of freedom is $(\text{C-}1)^2 = 1$.

(b) For an order-1 Markov process, the Chi-square test statistic is calculated as follows:

$$\chi^2 = \sum_{ijk} \frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}}$$

where O_{ijk} is the observed number of occurrences of trigram ijk. E_{ijk} is the expected number of occurrences of the trigram ijk, defined as follows:

$$E_{ijk} = \frac{O_{.jk} O_{ij.}}{O_{.j.}}$$

In the case of $O_{.jk}$ the trigram will begin with any symbol (that is 1, 2 or 3), but will end with a specific digram jk. In the case of $O_{ij.}$ the trigram begins with a specific digram ij, but end with any symbol. Finally, in the case of $O_{.j.}$ the trigram begins and end with any symbol, but has a specific symbol in the middle. The degree of freedom for this order-1 Markov process test for trigram is $C(C-1)^2 = 3(3-1)^2 = 12$. If the calculated Chi-square value is still significant, we perform an order-2 Markov analysis.

(c) For an order-2 Markov process, the Chi-square test statistics is calculated as follows:

$$\chi^2 = \sum_{ijkl} \frac{(O_{ijkl} - E_{ijkl})^2}{E_{ijkl}}$$

where E_{ijkl}, is the expected number of occurrences of the tetragram $ijkl$ and is defined as:

$$E_{ijkl} = \frac{O_{.jkl} O_{ijk.}}{O_{.jk.}}$$

The degree of freedom for this order-2 Markov process Chi-square test on trigrams is $C^2(C-1)^2 = 36$. If the Chi-square test is statistically significant, then an order-3 Markov process would be performed and so forth.

Table 4.14 Chi-Square tests for stationarity and independence for the Dow Jones Industrial Average Index

1. Stationarity (use price changes and not percentage price changes)
(a) Visual inspection: nonstationary
(b) 0.10212 $\chi^2 = 18.48$ at the 1% significant level
2. Independence (use percentage price changes)
(a) Relative percentage price change transition arrays: Digrams 336.714 $\chi^2 = 11.34$ at the 1% significant level Trigrams 1258.796 $\chi^2 = 18.48$ at the 1 % significant level
(b) Digram temporal trading windows: Lag 3 367.67 Lag 4 308.03 Lag 5 360.30 $\chi^2 = 11.34$ at the 1% significant level
(c) Category percentage price change transition matrices: Digrams 26.35 $\chi^2 = 20.09$ at the 1% significant level Trigrams 84.86 $\chi^2 = 45.64$ at the 1% significant level
(d) Markov category percentage price change transition matrices: First-order (trigrams) 21.95 $\chi^2 = 26.22$ at the 1% significant level $\chi^2 = 21.03$ at the 5% significant level Second-order (tetragrams) 67.26 $\chi^2 = 58.62$ at the 1% significant level

Notes:

(1) Stationarity: The results for both tests are conflicting. This could be due to the fact that visual inspection is invariably subjective and depending upon the level of stationarity that one is referring to. Thus, in the absence of a precise yardstick, it may make a different. In any case, the Chi-square test statistics point to a stationary series as expected.

(2) Independence: We use percentage price change rather than the price change (i.e. the first price minus the second price and the second minus the third and so forth)

as used by Sherry (1992). The first two tests on independence (a) and (b) should have no different whether price change or percentage price change is used; because they both employ "up" or "down" as a differentiator, and as such, no magnitude is involved. Whereas, for tests (c) and (d), the price differences are used, and these differences will get bigger as time proceeds. Indeed, the price change results for test (c) are 223.87 instead of percentage price change of 26.35 for diagrams; and 788.92 instead of percentage price change of 84.86 for trigrams. Whereas, test (d) for Markov first-order is 172.96 in the case of price change, and only 21.95 for percentage price change.

4.6 Concluding observations

4.6.1 Some alternatives

We explore several nonparametric analyses to detect dependencies for the Dow Jones Industrial Average Index. By employing the nonparametric techniques designed by Sherry (1992) and his colleagues for neural research; our exploratory and preliminary investigation detected possibly other forms of dependencies or temporal relationships much more significant than the traditional linear autocorrelation.

4.6.2 Dependence, but not stationary

The overall results indicate a nonstationary and dependent time series for the Dow Jones Industrial Average Index. The dependent result is encouraging, and definitely a cheer by the technical analysts; as it implies that it is possible for technical trading rules to be employed to capitalize the dependency in the data. Although the price generating process does not appear to be stationary; it is not to be expected given the long time period of 10 years daily data under the test. A shorter period of data should be investigated for stationarity.

4.6.3 Potential of category price change transition arrays (CPCT)

In theory, there can be an infinite number of CPCT, and thus making it a potentially interesting technique to detect various forms of dependencies. As computing power and software application are increasingly affordable, and necessary in the real world of trading; this could be an interesting project for further investigation. Indeed, the second-order Markov CPCT shows different results from first-order Markov CPCT in that the second-order is highly significant at the 1% level, whereas the first-order is significant at the edge of the 5% level. Therefore, does it indicate different types of dependencies here? For this, we would like to reserve our comment for the time being until more investigations are carried out.

4.6.4 Random but dependence?

It is noteworthy that all of the time series (such as the S&P 500 Stock Index, IBM, Microsoft, Ford, General Motor, Currencies and Commodities Futures etc.) tested by Sherry (1994) appear to be random; but many contain significant serial dependencies. He and his colleagues found essentially the same empirical evidence when they analyzed data from the nervous system. They found it odd and difficult to reconcile. How can a time series be random and still contain significant serial dependencies? Their brief and informal non-mathematical explanation is that independence-dependence refers to sequential relationships between a numbers of data points, while randomness refers to the selection of a single data point.

In short, Los (1999), who applies the nonparametric tests of Sherry (1992), puts up an interesting argument against randomness test:

> "... A random event is one whose outcome is determined purely by chance. For example, like flipping a fair coin (which is an abstraction!) ...

As Sherry states: Therefore, it seems likely that once a particular price change has been determined, this determination limits the size of the frequency histogram of potential future price changes (Sherry, 1992, P. 202). The types of finite constraints placed on the frequency histogram of price changes by this selection of a specific price change is not clear at this point and require considerable future work. Via a different route, using prime numbers, the mathematical system theorist Kalman comes to a similar conclusion that the finiteness of the real world eliminates the possibility of actually observing true randomness (Kalman, 1994, 1995a and 1995b). Thus it does not make much sense to test for pure randomness, when true randomness is impossible to observe. The abstraction of the true randomness can not function even as a null hypothesis. The observation of particular dependent price changes conditions and limits the observable distribution, which may be random only within the constraints of the new frequency histogram. The observable distribution can only be conditionally and not unconditionally random."

Table 4.4 : Autocorrelations for the DJIAI for returns, squared returns and absolute returns
6th September 1988 to 24th March 1999
(Entire Period)

Autocorrelations for ln R entire period			***Autocorrelations for sq ln R entire period***			***Autocorrelations for l ln R l entire period***		
Lag	Autocorr	StErr	Lag	Autocorr	StErr	Lag	Autocorr	StErr
1	0.0185	0.0194	1	**0.2039**	0.0194	1	**0.1385**	0.0194
2	-0.0251	0.0194	2	**0.1165**	0.0194	2	**0.1109**	0.0194
3	-0.0384	0.0194	3	**0.0526**	0.0194	3	**0.1033**	0.0194
4	-0.0094	0.0194	4	**0.0784**	0.0194	4	**0.1285**	0.0194
5	-0.0038	0.0194	5	**0.1391**	0.0194	5	**0.1456**	0.0194
6	-0.0167	0.0194	6	**0.0478**	0.0194	6	**0.1004**	0.0194
7	**-0.0449**	0.0194	7	**0.1080**	0.0194	7	**0.1196**	0.0194
8	-0.0225	0.0194	8	**0.0458**	0.0194	8	**0.0827**	0.0194
9	**0.0486**	0.0194	9	**0.0715**	0.0194	9	**0.1237**	0.0194
10	0.0176	0.0194	10	0.0358	0.0194	10	**0.0934**	0.0194
11	-0.0213	0.0194	11	**0.0596**	0.0194	11	**0.1062**	0.0194
12	0.0257	0.0194	12	**0.0605**	0.0194	12	**0.0756**	0.0194
13	0.0098	0.0194	13	0.0173	0.0194	13	**0.0728**	0.0194
14	0.0107	0.0194	14	**0.0553**	0.0194	14	**0.1123**	0.0194
15	-0.0169	0.0194	15	**0.0394**	0.0194	15	**0.0830**	0.0194
16	**-0.0506**	0.0194	16	**0.0689**	0.0194	16	**0.0834**	0.0194
17	-0.0100	0.0194	17	**0.0474**	0.0194	17	**0.0860**	0.0194
18	-0.0024	0.0194	18	0.0315	0.0194	18	**0.0838**	0.0194
19	0.0319	0.0194	19	**0.0613**	0.0194	19	**0.1056**	0.0194
20	-0.0144	0.0194	20	0.0361	0.0194	20	**0.0798**	0.0194
21	-0.0009	0.0194	21	**0.0582**	0.0194	21	**0.1058**	0.0194
22	0.0021	0.0194	22	0.0233	0.0194	22	0.0342	0.0194
23	0.0086	0.0194	23	**0.0454**	0.0194	23	**0.0925**	0.0194
24	-0.0085	0.0194	24	**0.0652**	0.0194	24	**0.1059**	0.0194
25	**-0.0626**	0.0194	25	0.0302	0.0194	25	**0.0740**	0.0194
26	0.0163	0.0194	26	0.0279	0.0194	26	**0.0702**	0.0194
27	0.0010	0.0194	27	**0.0480**	0.0194	27	**0.0821**	0.0194
28	0.0175	0.0194	28	0.0230	0.0194	28	**0.0642**	0.0194
29	-0.0052	0.0194	29	0.0260	0.0194	29	**0.0768**	0.0194
30	0.0055	0.0194	30	0.0190	0.0194	30	**0.0655**	0.0194

Table 4.5 : Autocorrelations for the DJIAI for returns, squared returns and absolute returns
6th September 1988 to 31st December 1993
(Subperiod 1)

Autocorrelations for ln R sp1			***Autocorrelations for sq ln R sp1***			***Autocorrelations for I ln R I sp1***		
Lag	Autocorr	StErr	Lag	Autocorr	StErr	Lag	Autocorr	StErr
1	0.0142	0.0272	1	**0.1327**	0.0272	1	**0.0905**	0.0272
2	-0.0084	0.0272	2	0.0289	0.0272	2	0.0432	0.0272
3	-0.0077	0.0272	3	0.0198	0.0272	3	**0.0724**	0.0272
4	-0.0306	0.0272	4	0.0310	0.0272	4	**0.0748**	0.0272
5	0.0135	0.0272	5	0.0311	0.0272	5	**0.1049**	0.0272
6	-0.0419	0.0272	6	0.0264	0.0272	6	0.0531	0.0272
7	**-0.0612**	0.0272	7	0.0073	0.0272	7	0.0065	0.0272
8	-0.0257	0.0272	8	0.0517	0.0272	8	**0.0858**	0.0272
9	0.0337	0.0272	9	0.0429	0.0272	9	**0.0774**	0.0272
10	-0.0024	0.0272	10	0.0200	0.0272	10	**0.0759**	0.0272
11	0.0397	0.0272	11	0.0236	0.0272	11	**0.0710**	0.0272
12	0.0241	0.0272	12	0.0156	0.0272	12	0.0028	0.0272
13	0.0080	0.0272	13	0.0259	0.0272	13	**0.0719**	0.0272
14	0.0161	0.0272	14	0.0444	0.0272	14	**0.0904**	0.0272
15	-0.0377	0.0272	15	0.0242	0.0272	15	0.0537	0.0272
16	-0.0088	0.0272	16	0.0298	0.0272	16	0.0434	0.0272
17	-0.0197	0.0272	17	0.0208	0.0272	17	**0.0579**	0.0272
18	-0.0320	0.0272	18	0.0232	0.0272	18	**0.0734**	0.0272
19	0.0038	0.0272	19	0.0264	0.0272	19	**0.0661**	0.0272
20	0.0096	0.0272	20	0.0065	0.0272	20	0.0462	0.0272
21	0.0075	0.0272	21	0.0247	0.0272	21	**0.0637**	0.0272
22	0.0000	0.0272	22	-0.0020	0.0272	22	0.0108	0.0272
23	-0.0061	0.0272	23	0.0152	0.0272	23	**0.0552**	0.0272
24	-0.0027	0.0272	24	0.0248	0.0272	24	**0.0717**	0.0272
25	**-0.0578**	0.0272	25	0.0275	0.0272	25	0.0509	0.0272
26	-0.0184	0.0272	26	0.0067	0.0272	26	0.0449	0.0272
27	-0.0458	0.0272	27	-0.0049	0.0272	27	0.0078	0.0272
28	0.0133	0.0272	28	-0.0088	0.0272	28	0.0179	0.0272
29	-0.0015	0.0272	29	0.0119	0.0272	29	0.0527	0.0272
30	0.0408	0.0272	30	0.0265	0.0272	30	0.0501	0.0272

Table 4.6 : Autocorrelations for the DJIAI for returns, squared returns and absolute returns
1st January 1994 to 24th March 1999
(Subperiod 2)

Autocorrelations for ln R sp2			*Autocorrelations for sq ln R sp2*			*Autocorrelations for l ln R l sp2*		
Lag	Autocorr	StErr	Lag	Autocorr	StErr	Lag	Autocorr	StErr
1	0.0214	0.0276	1	**0.2419**	0.0276	1	**0.1695**	0.0276
2	-0.0383	0.0276	2	**0.1635**	0.0276	2	**0.1566**	0.0276
3	**-0.0626**	0.0276	3	**0.0681**	0.0276	3	**0.1197**	0.0276
4	0.0071	0.0276	4	**0.1023**	0.0276	4	**0.1632**	0.0276
5	-0.0176	0.0276	5	**0.1980**	0.0276	5	**0.1717**	0.0276
6	0.0031	0.0276	6	**0.0567**	0.0276	6	**0.1291**	0.0276
7	-0.0325	0.0276	7	**0.1623**	0.0276	7	**0.1995**	0.0276
8	-0.0206	0.0276	8	0.0391	0.0276	8	**0.0738**	0.0276
9	**0.0594**	0.0276	9	**0.0846**	0.0276	9	**0.1526**	0.0276
10	0.0325	0.0276	10	0.0412	0.0276	10	**0.0979**	0.0276
11	**-0.0690**	0.0276	11	**0.0768**	0.0276	11	**0.1258**	0.0276
12	0.0262	0.0276	12	**0.0827**	0.0276	12	**0.1241**	0.0276
13	0.0106	0.0276	13	0.0087	0.0276	13	**0.0651**	0.0276
14	0.0067	0.0276	14	**0.0581**	0.0276	14	**0.1208**	0.0276
15	-0.0002	0.0276	15	0.0445	0.0276	15	**0.0976**	0.0276
16	**-0.0844**	0.0276	16	**0.0877**	0.0276	16	**0.1058**	0.0276
17	-0.0034	0.0276	17	**0.0590**	0.0276	17	**0.0986**	0.0276
18	0.0216	0.0276	18	0.0325	0.0276	18	**0.0830**	0.0276
19	0.0539	0.0276	19	**0.0775**	0.0276	19	**0.1267**	0.0276
20	-0.0348	0.0276	20	0.0493	0.0276	20	**0.0968**	0.0276
21	-0.0072	0.0276	21	**0.0736**	0.0276	21	**0.1297**	0.0276
22	0.0036	0.0276	22	0.0337	0.0276	22	0.0431	0.0276
23	0.0193	0.0276	23	**0.0588**	0.0276	23	**0.1122**	0.0276
24	-0.0143	0.0276	24	**0.0850**	0.0276	24	**0.1255**	0.0276
25	**-0.0694**	0.0276	25	0.0281	0.0276	25	**0.0828**	0.0276
26	0.0434	0.0276	26	0.0364	0.0276	26	**0.0812**	0.0276
27	0.0380	0.0276	27	**0.0747**	0.0276	27	**0.1323**	0.0276
28	0.0202	0.0276	28	0.0376	0.0276	28	**0.0929**	0.0276
29	-0.0075	0.0276	29	0.0300	0.0276	29	**0.0844**	0.0276
30	-0.0240	0.0276	30	0.0110	0.0276	30	**0.0691**	0.0276

Table 4.7 Regression of Half 2 on Half 1 for stationarity test

Half 1	Percentile	Delta-1	Half 2	Percentile	Delta-1
	9.86	-26.0		10.01	-62.0
	19.64	-15.5		19.94	-31.0
	30.47	-7.5		30.1	-14.5
	40.41	-2.5		40.3	-4.0
	49.66	1.5		49.74	4.0
	60.2	6.0		59.89	13.5
	69.75	11.0		69.9	24.5
	79.91	17.5		79.98	42.0
	90.14	27.5		89.92	76.0
	100	115.0		100	381.0

x^2 test

Observed	Expected	O-E	$(O-E)^2$	$(O-E)^2/E$	
9.78	9.93	-0.15	0.0225	0.002266	
10.83	10.16	0.67	0.4489	0.044183	
9.94	10.2	-0.26	0.0676	0.006627	
9.25	9.44	-0.19	0.0361	0.003824	
10.54	10.15	0.39	0.1521	0.014985	
9.55	10.01	-0.46	0.2116	0.021139	
10.16	10.08	0.08	0.0064	0.000635	
10.23	9.94	0.29	0.0841	0.008461	
				0.10212	df=8-1=7 x^2 test=18.48 at 1% sig level

Table 4.8 Percentage difference 1-order Markov Analysis of DJIA from 6 Sept 1988 to 24 Mar 1999

Trigrams	Observed	Expected	O-E	$(O-E)^2$	$(O-E)^2/E$
111	9	6.29588	2.70412	7.312264	1.161436
112	22	28.71536	-6.71536	45.096	1.570449
113	10	5.988764	4.011236	16.09001	2.6867
121	25	18.45134	6.54866	42.88495	2.324219
122	135	150.6714	-15.6714	245.5918	1.629983
123	26	16.87729	9.122708	83.2238	4.931111
131	4	2.199248	1.800752	3.242707	1.474462
132	28	31.81579	-3.81579	14.56025	0.457642
133	7	4.984962	2.015038	4.060377	0.814525
211	29	32.40075	-3.40075	11.56509	0.356939
212	155	147.779	7.220974	52.14246	0.352841
213	27	30.82022	-3.82022	14.59412	0.473524
221	162	171.0221	-9.0221	81.39823	0.475952
222	1412	1396.545	15.45463	238.8456	0.171026
223	150	156.4325	-6.43253	41.37749	0.264507
231	10	10.88346	-0.88346	0.780499	0.071714
232	159	157.4474	1.552632	2.410665	0.015311
233	24	24.66917	-0.66917	0.447792	0.018152
311	3	2.303371	0.696629	0.485292	0.210688
312	10	10.50562	-0.50562	0.25565	0.024335
313	2	2.191011	-0.19101	0.036485	0.016652
321	24	21.52656	2.473437	6.117889	0.284202
322	176	175.7833	0.216737	0.046975	0.000267
323	17	19.69017	-2.69017	7.237036	0.367546
331	1	1.917293	-0.91729	0.841427	0.438862
332	30	27.73684	2.263158	5.121884	0.18466
333	3	4.345865	-1.34586	1.811352	0.416799
	2660				21.1945

$df=C(C-1)^2$
$=3(3-1)^2$
$=12$
$x^2=26.22$ at 1% sig level

Figure 4.1: Daily Dow Jones Industrial Average Index
6th September 1988 to 24th March 1999
(Entire Period)

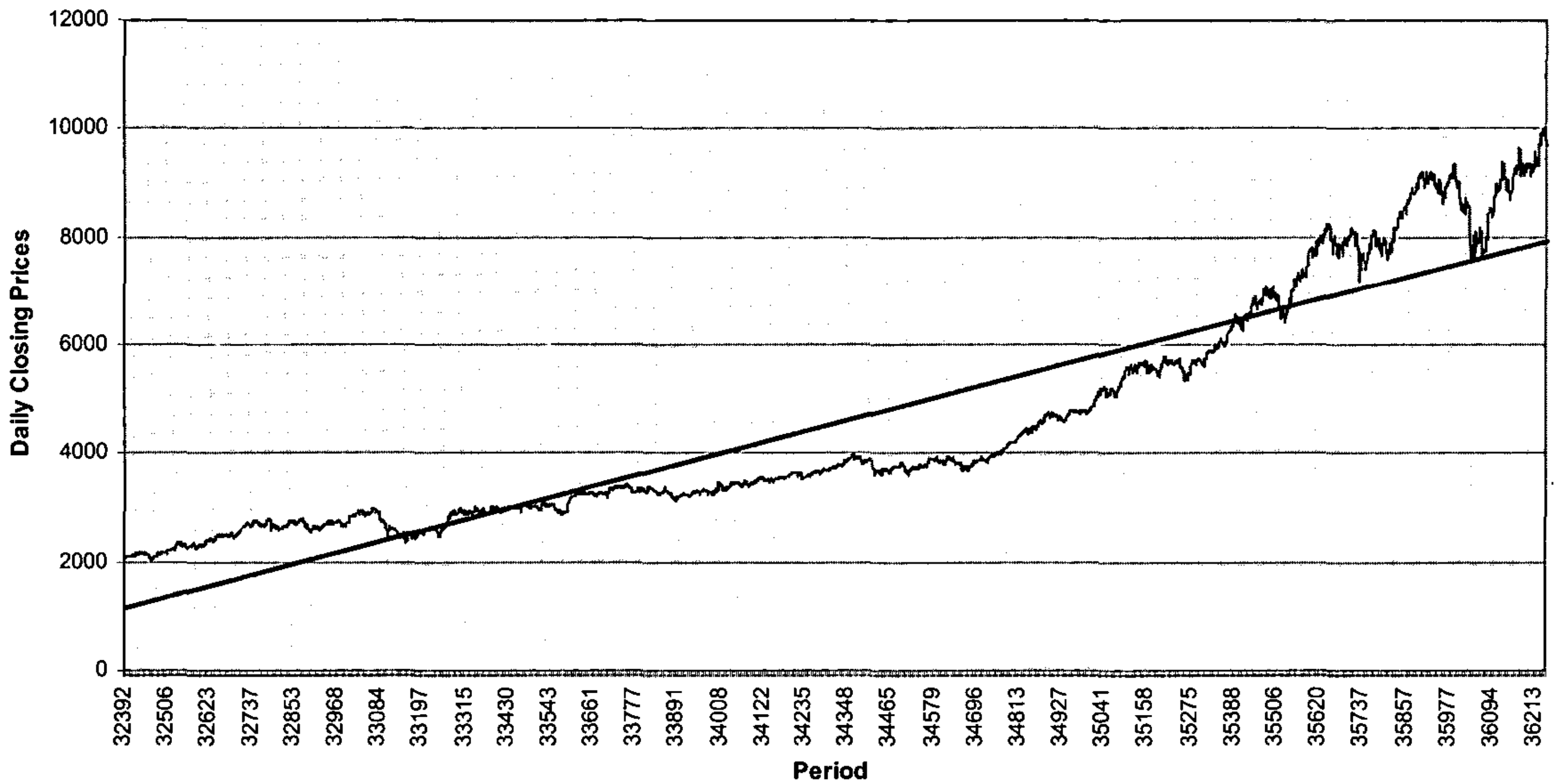
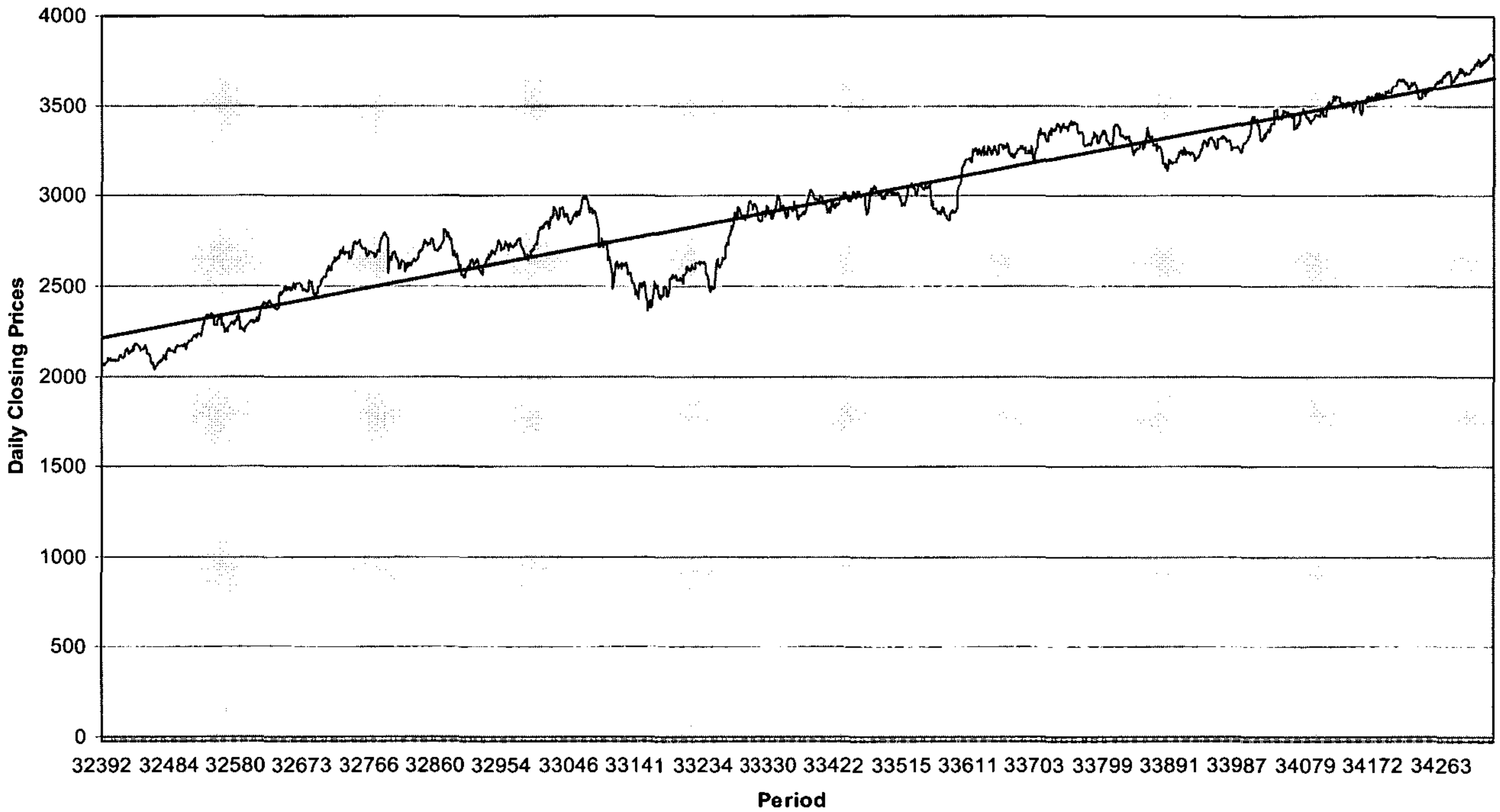


Figure 4.2: Daily Dow Jones Industrial Average Index
6th September 1988 to 31st December 1993
(Subperiod 1)



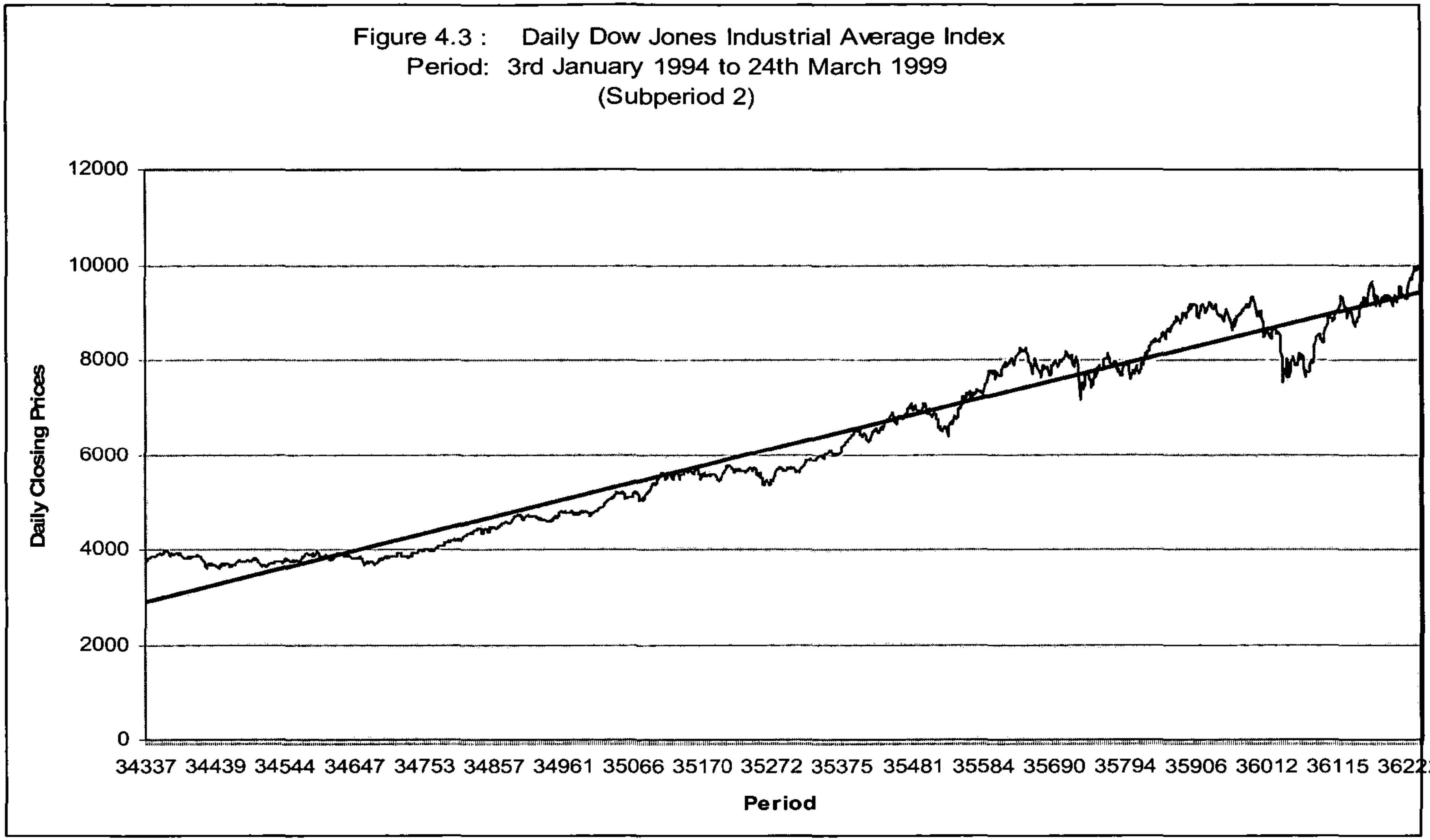


Figure 4.3 : Daily Dow Jones Industrial Average Index
Period: 3rd January 1994 to 24th March 1999
(Subperiod 2)
12000
10000
8000
6000
4000
2000
0
Daily Closing Prices
34337 34439 34544 34647 34753 34857 34961 35066 35170 35272 35375 35481 35584 35690 35794 35906 36012 36115
Period

Figure 4.4: First Log differencing of Dow Jones Industrial Average Index

6th September 1988 to 31st December 1993

Subperiod 1

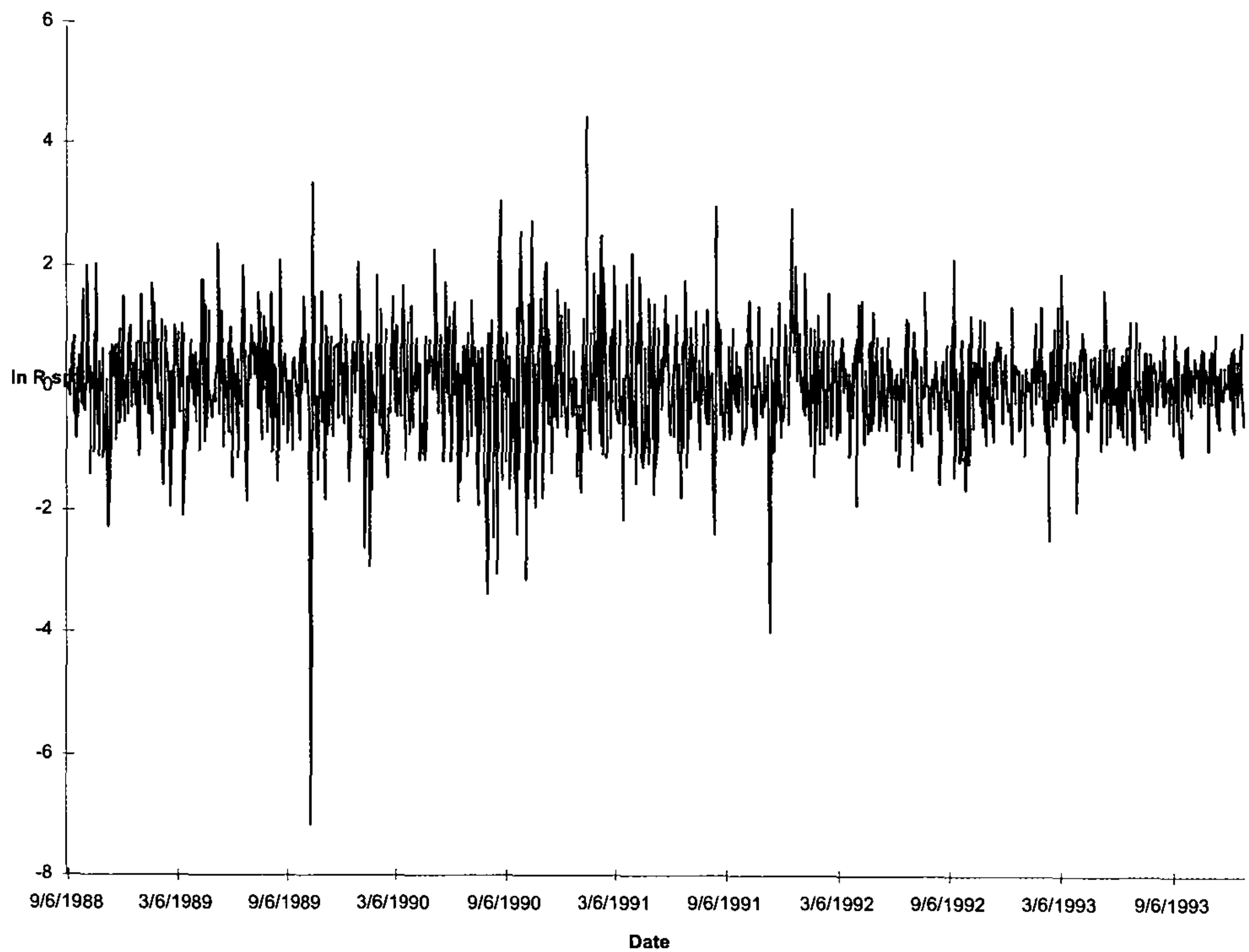
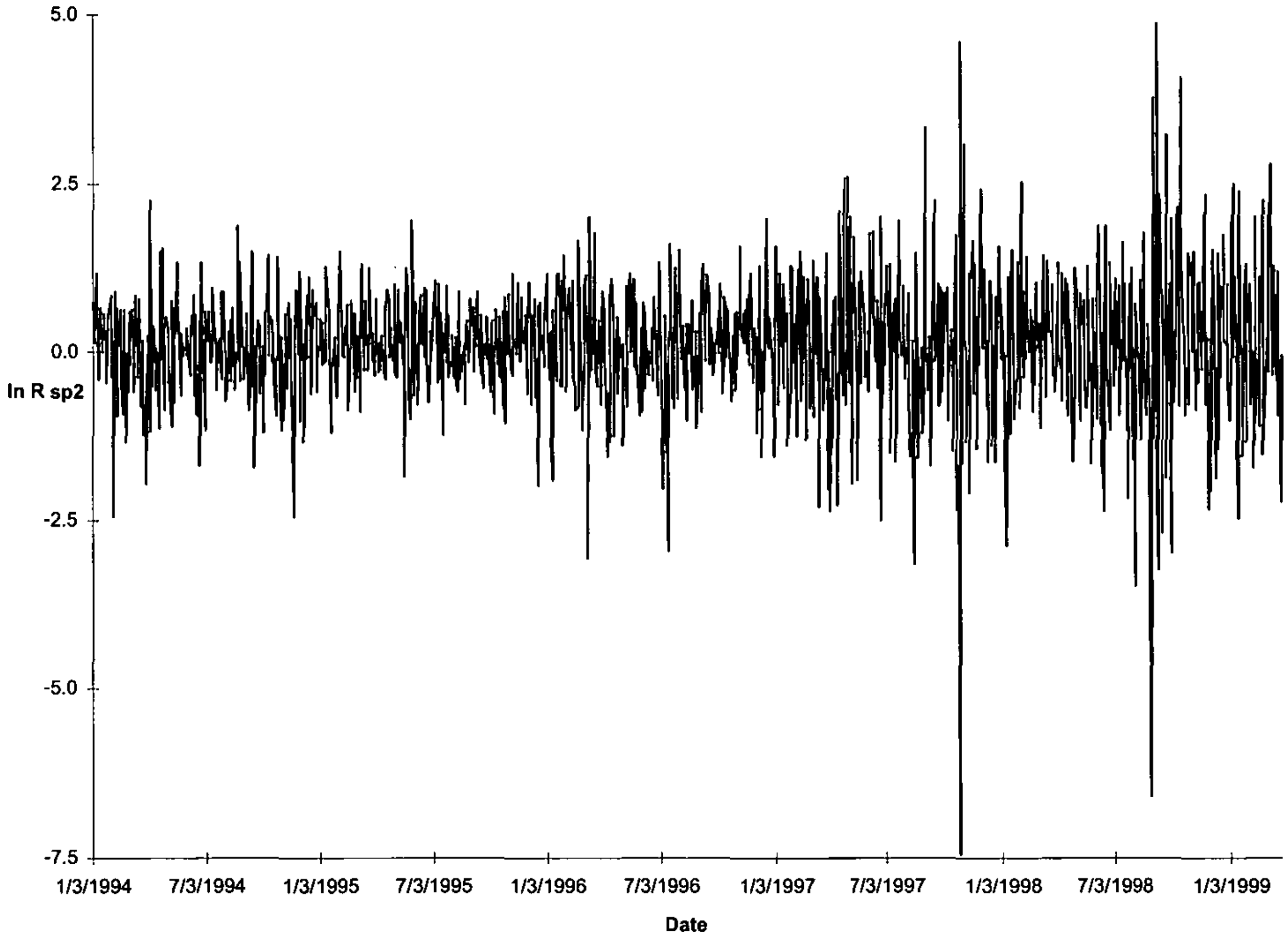


Figure 4.5: First Log differencing of Dow Jones Industrial Index

3rd January 1994 to 24th March 1999

Subperiod 2



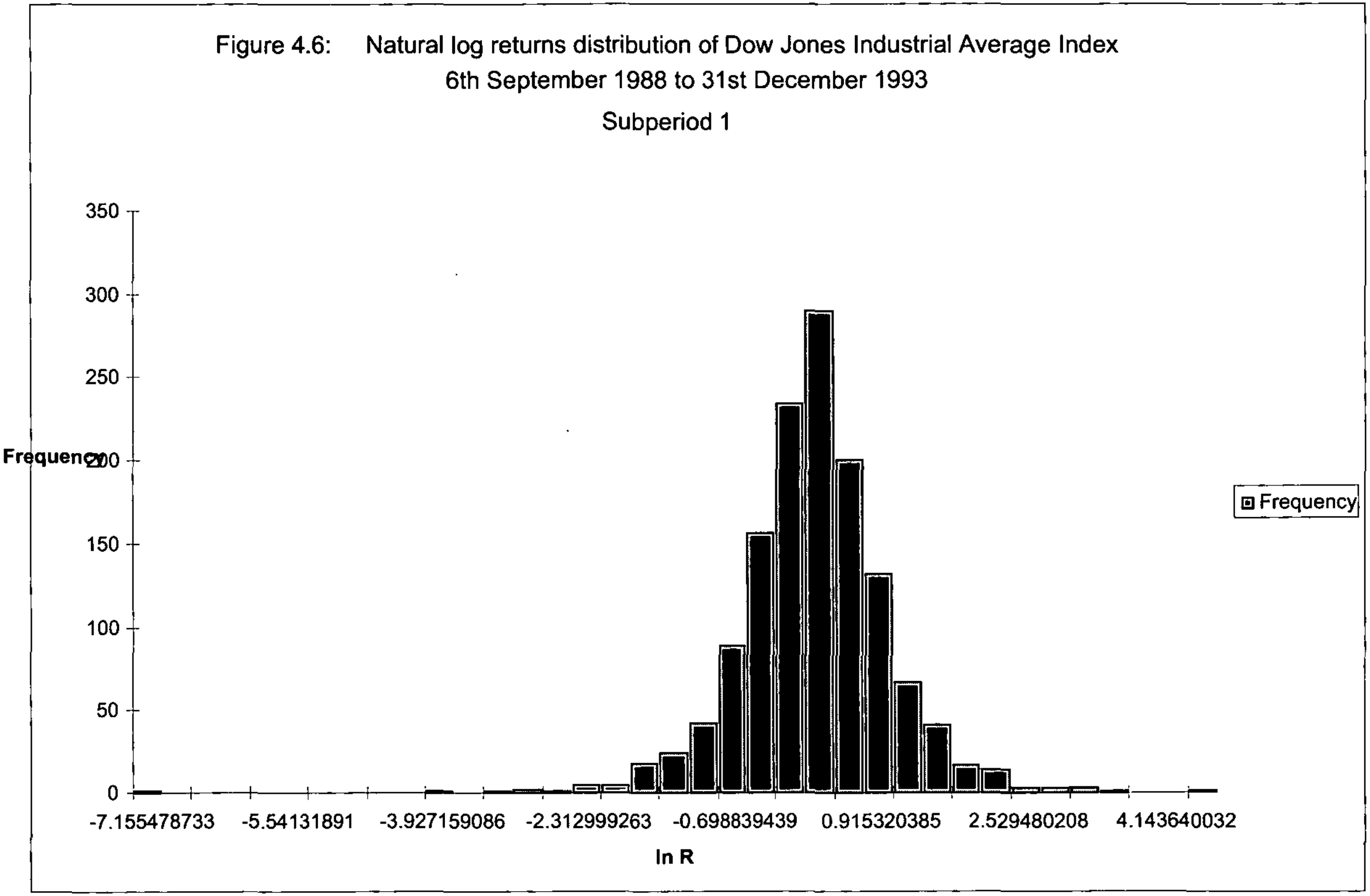
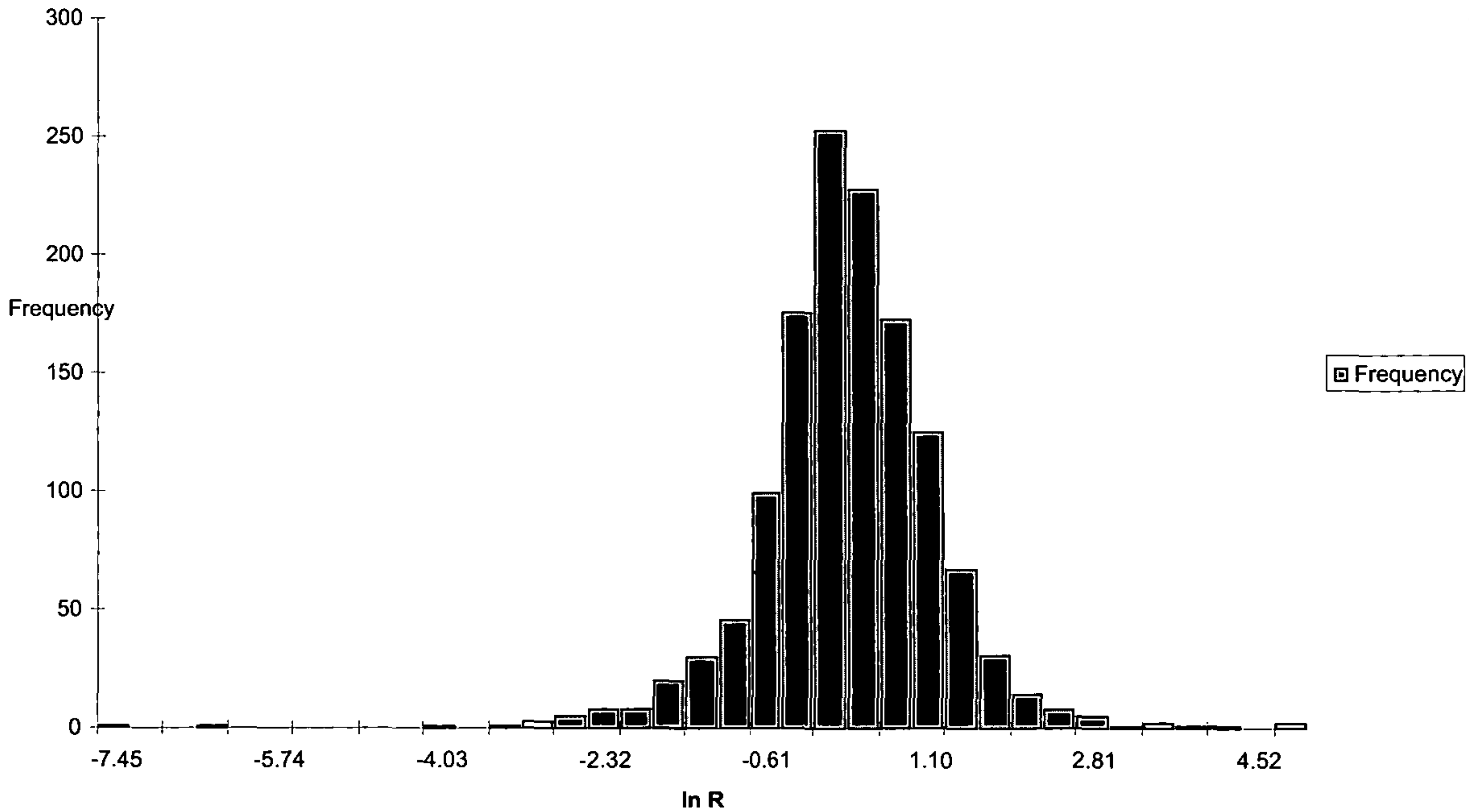


Figure 4.6: Natural log returns distribution of Dow Jones Industrial Average Index
6th September 1988 to 31st December 1993
Subperiod 1
Frequency
350
300
250
200
150
100
50
0
-7.155478733
-5.54131891
-3.927159086
-2.312999263
-0.698839439
0.915320385
2.529480208
4.143640032
ln R
Frequency

Figure 4.7: Natural log returns distribution of Dow Jones Industrial Average Index

3rd January 1994 to 24th March 1999

Subperiod 2



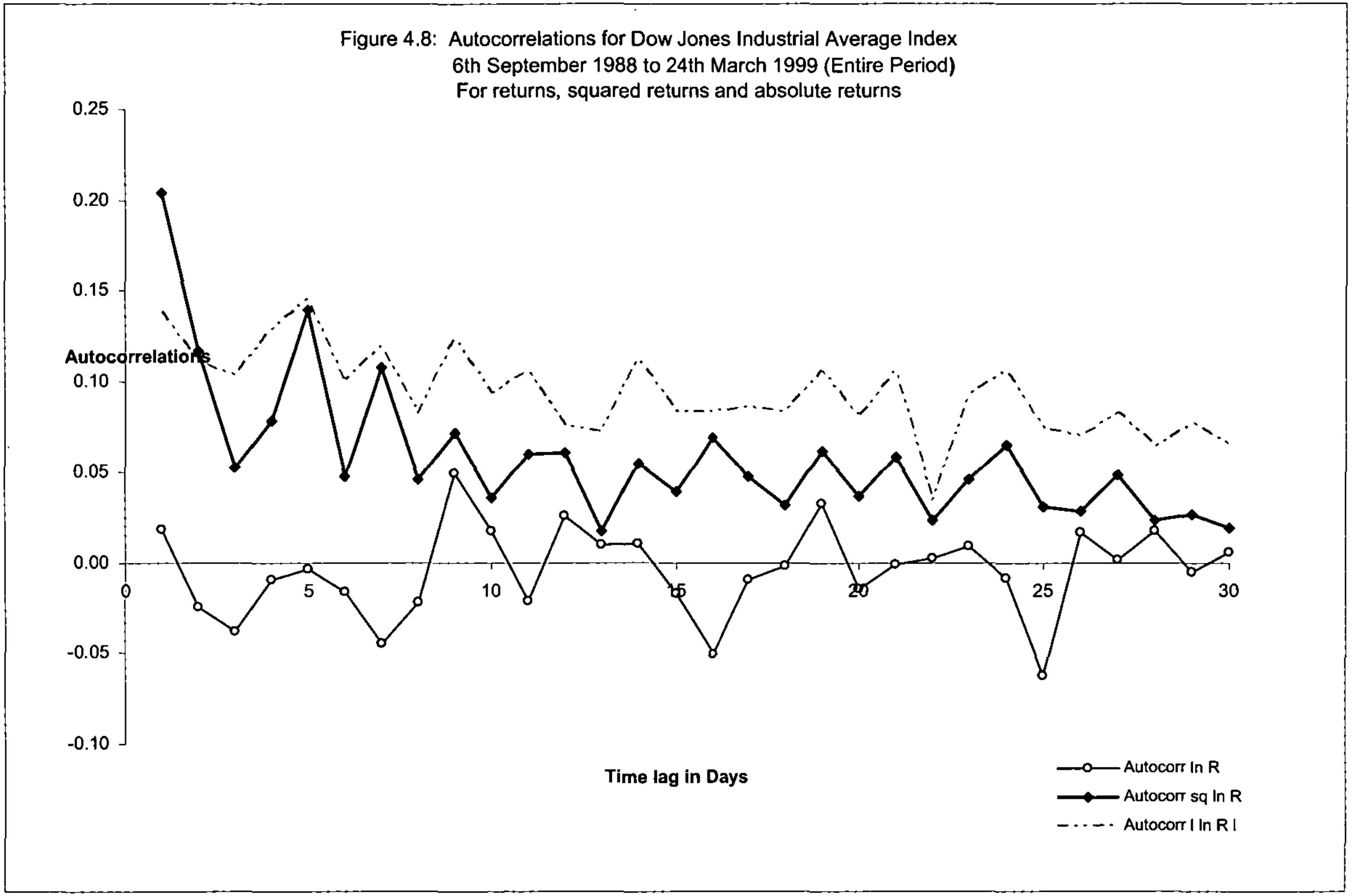


Figure 4.8: Autocorrelations for Dow Jones Industrial Average Index
6th September 1988 to 24th March 1999 (Entire Period)
For returns, squared returns and absolute returns
0.25
0.20
0.15
Autocorrelations
0.10
0.05
0.00
-0.05
-0.10
0
5
10
15
20
25
30
Time lag in Days
Autocorr ln R
Autocorr sq ln R
Autocorr I ln R I

Figure 4.9: Autocorrelations for Dow Jones Industrial Average Index
6th September 1988 to 31st December 1993 (Subperiod 1)
For returns, squared returns and absolute returns

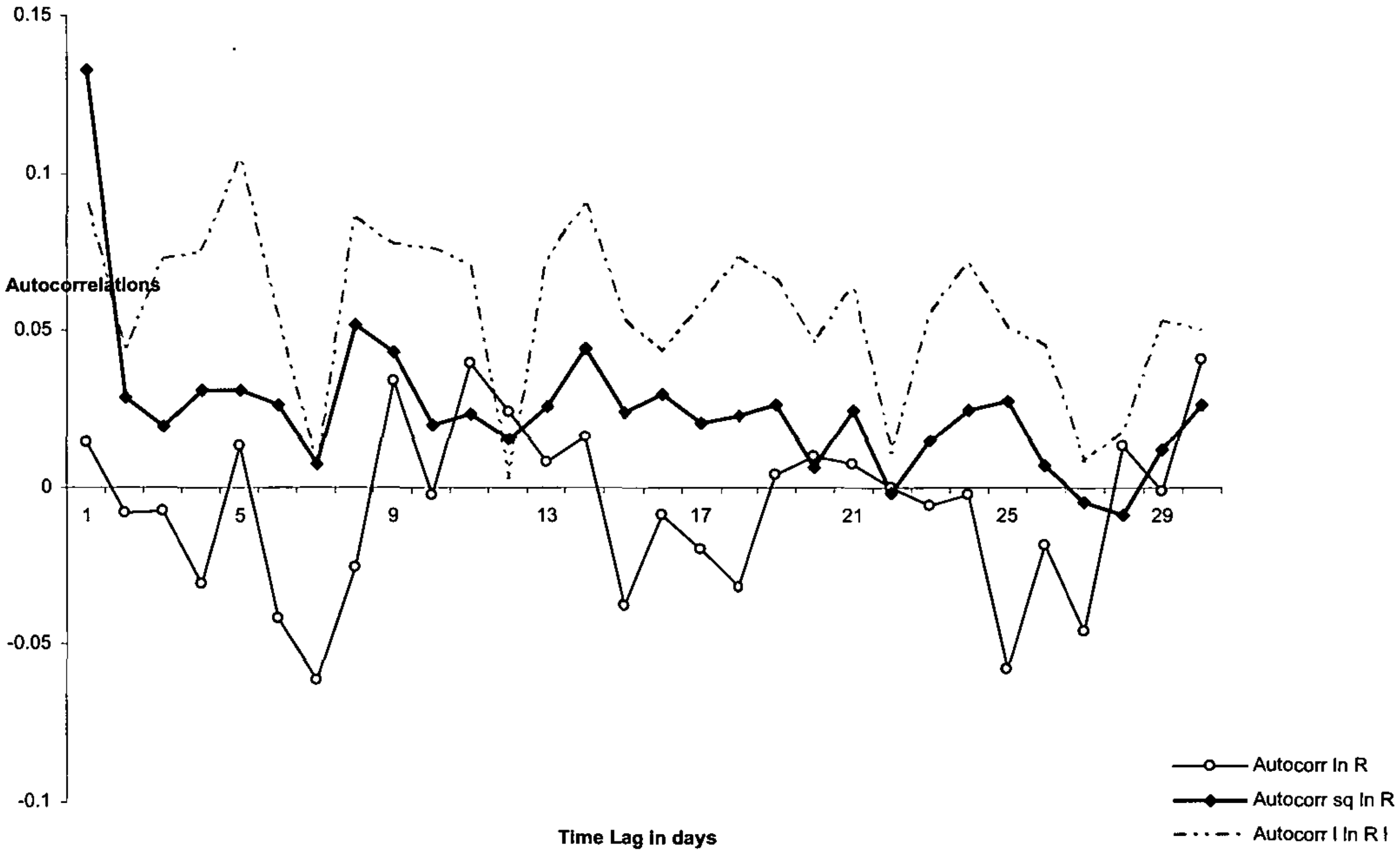


Figure 4.10: Autocorrelations for Dow Jones Industrial Average Index
3rd January 1994 to 24th March 1999 (Subperiod 2)
For returns, squared returns and absolute returns

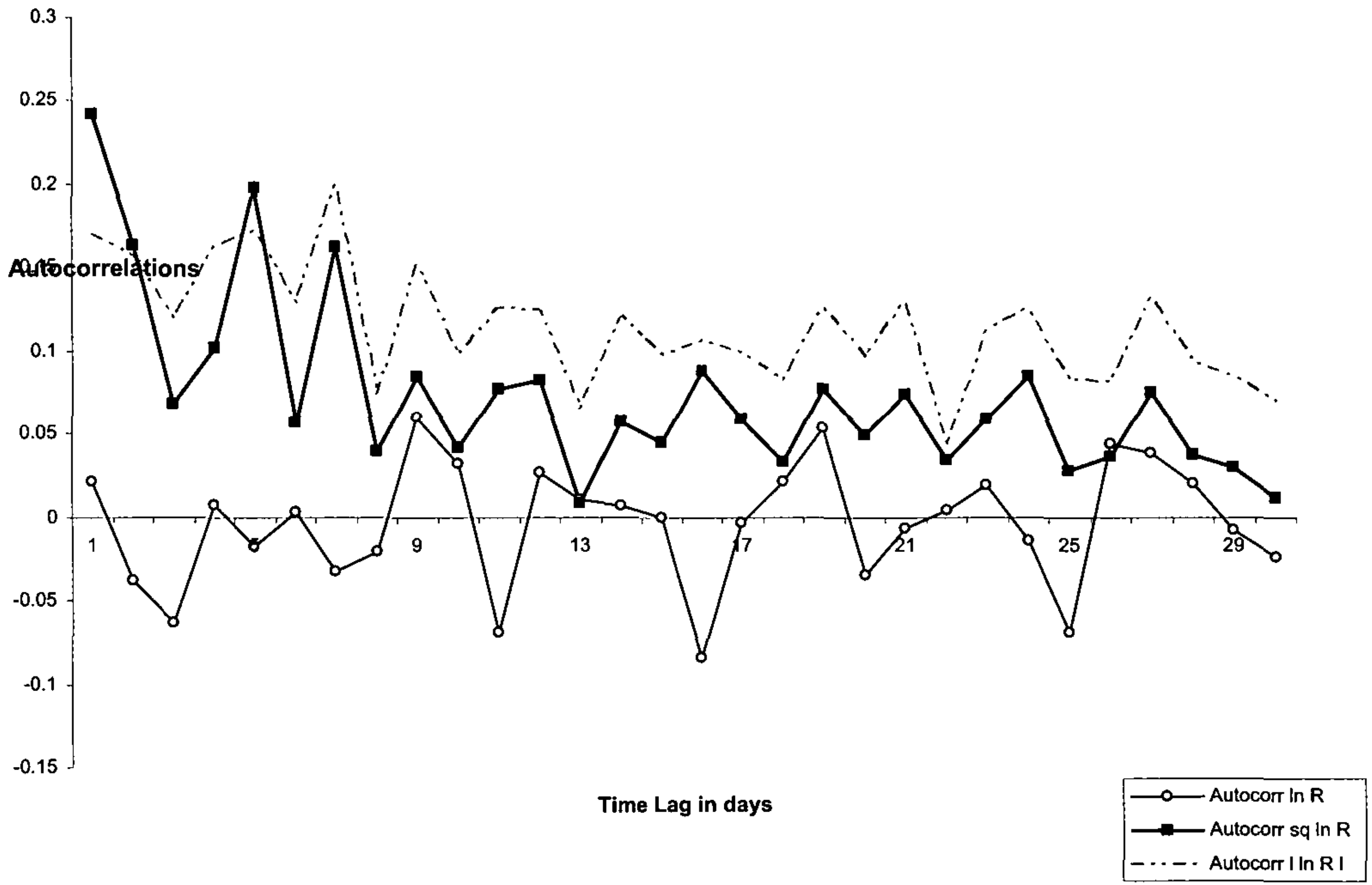


Figure 4.11 Cummulative distribution of Half 1 and Half 2
DJIAI Entire period 1998-1999

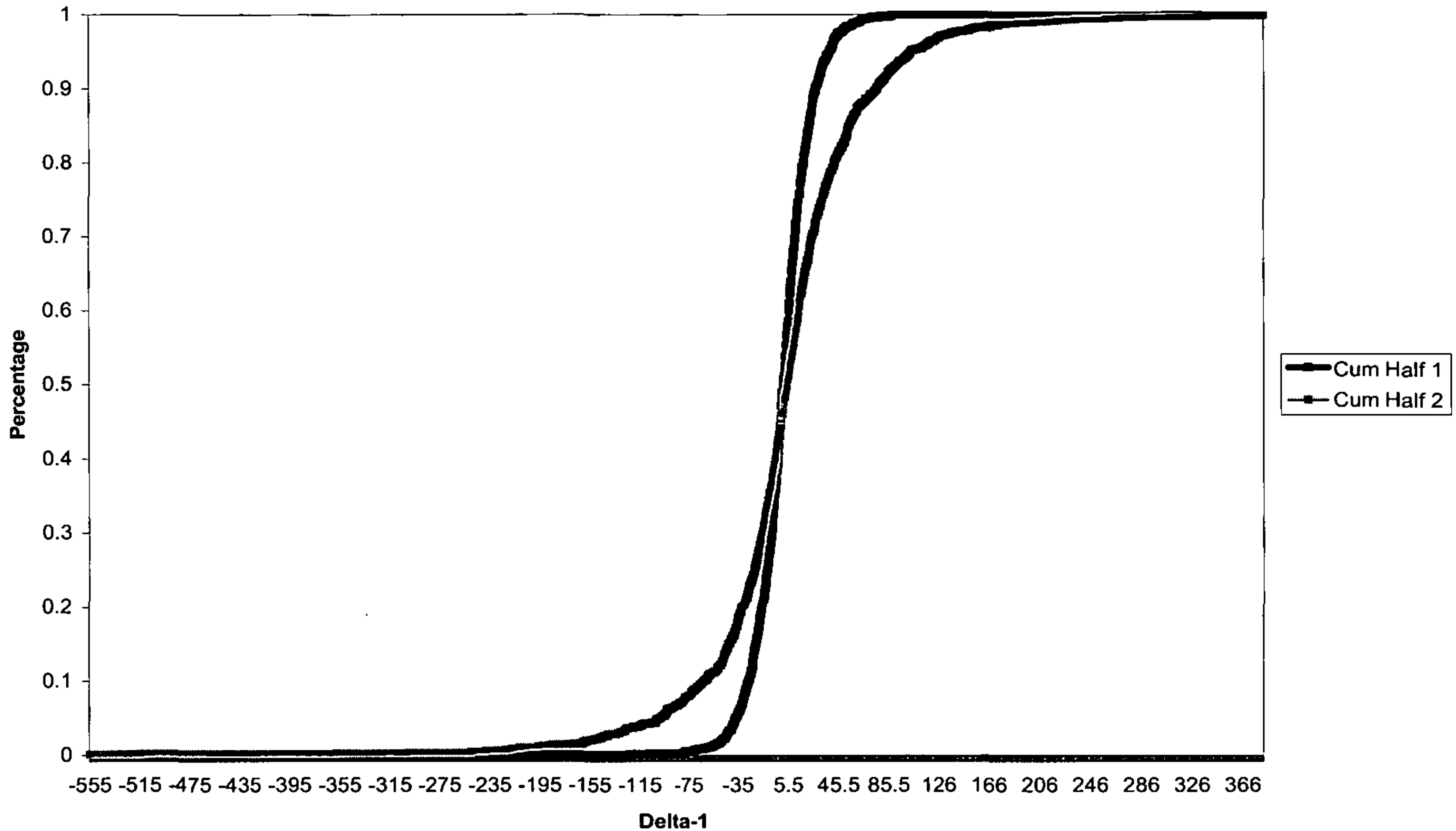
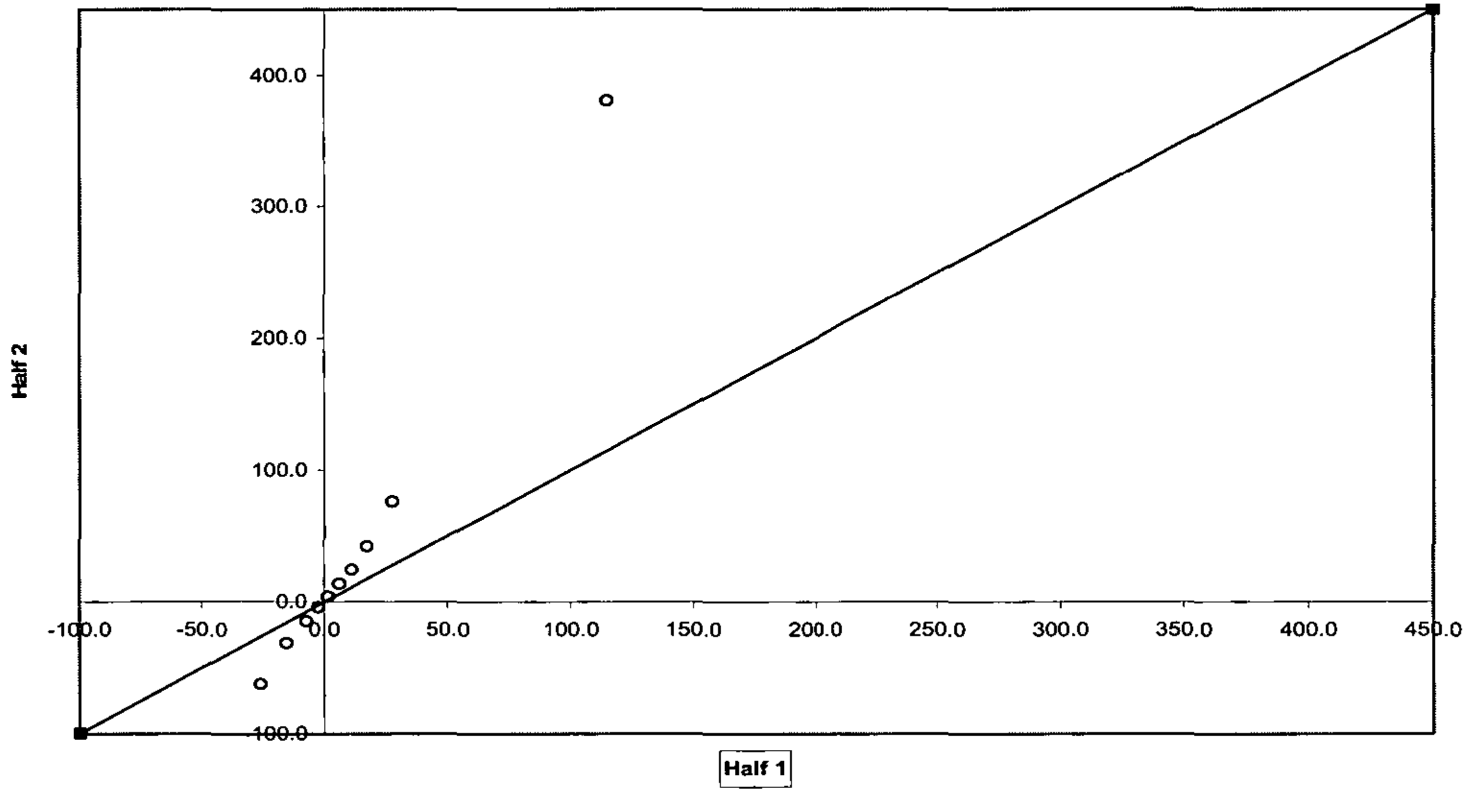


Figure 4.12 Regression of Half 2 on Half 1 of DJIA Index 1998-1999 Entire peroid



Chapter 5

Methodology and issues in empirical testing

5.1 Expected values

We report the average performance of the first four statistical moments namely the mean, variance, skewness and kurtosis, of the entire 200 technical trading rules, conditional upon buy only, sell only and total buy and sell signals. This is the expected performance of a technical trading rule randomly selected from the population.

A distributional study of this size (200 technical trading rules) may provide more information. This is even more so when the underlying process of the time series is unknown and where nonstationarities in one form or another could be present. Other advantages are:

(a) That the combined evidence from different trading signals best mirrors the decision process used by the human traders (Wong and Koh, 1994). This approach is consistent with the findings of Pruitt and White (1988) and Pruitt et al. (1992), who report that technical traders usually do not make decisions based on a single technical indicator.

(b) That the portfolio of technical trading rules' returns exhibits a more normal distribution than single rule returns (Lukac and Brorsen, 1989), although in this case, we only study directional predictability rather than the rules' returns.

Note 1 illustrates the procedure to work out the interval estimate of the population mean. To assess whether the distributions of variables conform to a normal distribution, a normality test can be applied and if the result is significant, then traditional transformation and outlier trimming techniques can be employed such as:

(a) Removing the top and bottom 1 or 2 percent of the observations and removing data that are three standard deviations away from the mean.

(b) Transforming the raw data using square root and logarithmic transformation.

The choice of technique will depend upon the prevailing circumstances then pertaining.

5.2 Efficient Sample Size

To carry out a meaningful distributional study, one of the issues is to choose the number of technical trading rules to investigate. To approach this issue, we propose the concept of an efficient sample size, which is a trade-off between the cost of sampling and the level of standard error thought acceptable.

For our purpose, we are comfortable with a sample size of 200 as the standard error is 7.07 percent $(1/\sqrt{n}\, x100 = 1/\sqrt{200}\, x100)$ which lies between the 10 and 5 percent levels and after outlier reduction may still lies, within the 10 percent standard error, whilst an increase of another 100 in our sample size would only result in a reduction of 1.30 percent in standard error. $(1/\sqrt{300}\, x100 = 5.77\text{percent})$. Figure 5.1 illustrates this concept through the diminishing marginal standard error for every unit of increase in sample size. Notice that the curve flattens at about 500 which are similar to the choice of 500 replications used by Brock et al. (1992) for bootstrapping.

Note 2 demonstrates a procedure called sequential sampling to decide the appropriate sample size based on the required confidence level and range of error.

5.3 Post-Publication Testing (data snooping)

The 200 published technical trading rules collected randomly from various publications are used to test the data with a period that cover before and after the dates of publications (please refer to figure 5.2).

The advantages of using a "spread" (over a time period) of published technical trading rules are to avoid data-snooping when used for time series after the publication dates and the "spread" also avoids the heavy weighting on a particular period of a time series and thus allowing a "spread" of out-of-sample testing.

As Markowitz and Xu (1994) underline, the problem with out-of-sample simulations is that they are routinely "data-mined"; if a method that did well in the in-sample period does poorly in the out-of-sample, the researchers do not abandon the project. Rather he or she tries another method that did well in the in-sample period until one is found that also does well in the out-of-sample period. Such a procedure will eventually produce a successful method even if all methods are equally good.

However, no test for data mining is perfect, as it depends on simulating the snooping process that might have been occurring (LeBaron 2000). Also as pointed out by Sullivan et al. (1999), "It is important that the span of the set of trading rules included in our universe is sufficiently large because the data-snooping adjustment only accounts for snooping within the space spanned by the included rules."

Our larger portfolio of technical trading rules and the spread of them mostly before the test window with less of them during the test window is an attempt to tackle the issue.

5.4 Size of Test Window

The test window is that particular period of data to be used for testing. The following are our criteria used for selecting the test window.

5.4.1 Business cycle

The size of data or test window to be selected is based on the empirical evidence (Mills, 2000) that the average length of a business cycle in industrial nations is about 3.65 years. In light of this finding, we assume that the average stock market cycle is about 4 years and thus a period of more than 8 years would encompass two major peaks and troughs in a typical stock market time series. Our choice also partly based on the empirical evidence of Taylor (1986) as discussed below. On the other hand, the DJIA index's component stocks are those of very large companies and they tend to move with the general economic cycles in the economy as a whole.

5.4.2 *Empirical evidence*

Taylor (1986) shows that test power will increase as the number of observations increases and his results show that it is highly desirable to study time series containing at least 2000 returns. Assuming a 5 day trading week, this is almost the same number for the 8 year period of daily data of 2088 recommended above!

Based on the findings of Brock et al. (1992) and Hudson et al. (1996), the latter suggest that a long period (at least 15 to 20 years plus, depending on the index) may be needed before the examined technical trading rules can be shown to have significant predictive content. However, one also needs to consider whether market structures, be they legal, institutional and operational technicalities such as opening and closing arrangements, order or quote driven, specialist or competing market makers, settlement systems and so on remain relevant over such a long period.

On the other hand, Cochrane (1999) demonstrates that one needs 25 years of data to even start to measure average annual returns: "The standard formula $\sigma/\sqrt{T}$ for the standard error of the mean ... with σ = 16 percent, (typical of the index), even T=25 years means that one standard error is 16/5 = 3 percent per year, and a two-standard error confidence interval run plus or minus 6 percentage points! This is not much smaller than the average returns we are trying to measure. In addition, all of these facts are highly influenced by the small probability of rare events, which make measuring average returns statistically even harder."

Overall, we conclude by making the remark that it all depends upon what type of technical trading rules one is testing. For example, to capture a trend in daily data which may occur, say, three times a year, would only provide a limited number of 24 observations over an eight years period, whereas a short term moving average which gives buy and sell (or vice versa) signals of every fifteen trading days would provide a large number of 136 observations over an eight year period (assuming an average of 250 trading days per annum would provide 17 observations per annum and over an eight years period would provide 136 observations).

But then, if one is testing an individual stock which has a market component to it, then the observations may not be independent.

5.4.3 Investment horizon

The length of a testing period is partly a function of the investors and/or traders' holding period and we use a period of 10 years based on the assumption made and empirical evidence found in 5.4.1 and 5.4.2 respectively. Furthermore, the practical value of a particular technical trading rule would be in doubt if it cannot indicate the level of required economic significance within a 10 year period.

5.4.4 Regime

The most recent period is chosen based on the assumption that the economic and financial structures do change and evolve over time (i.e. the institutional and regulatory frameworks of a financial market) and, hence, the more recent the data, the more relevant it is for forecasting, save for changes of regime such as a total foreign exchange control and changes of futures contract, for a particular commodity.

Researchers should be cautious about estimating models over long time series for financial data, since the implicit assumption of parameter constancy is most unlikely to be valid. Hsieh (1991) uses a Monte Carlo study to demonstrate that simple models which are iid, but with different means or different variances for part of the sample, lead to virtually 100 percent rejections of iid using the BDS test.

Brook et al.(1999) conjecture that many recent papers which have rejected the null hypothesis may simply be doing so as a consequences of a few large structural changes or regime shifts in the (extremely long) series under consideration, rather than some inherent nonlinearity in the data generating process.

5.4.5 Number of Trades

The size of test window should preferably be able to generate more than 30 trades for the particular technical trading rule to be tested. The more trades, the better.

5.5 Market crash

It is almost a conventional wisdom nowadays, to exclude the period of market crash in studying the returns and/or modeling of financial time series; and there is no exception here. We follow this convention so that our results can be compared with other similar studies.

However, the effect of a market crash is invariably critical to the survival of financial traders and/or investors; turning many (even star) traders and/or investors into ex-traders and/or ex-investors. As such, the event of a market crash should be of interest, and indeed warrant our inclusion in the series under investigation. Whether the inclusion will add difficulties and/or inconveniences in the modeling process, does not alter the justification of most investigations.

5.6 Test of significance: t-test or bootstrap?

The standard test of significance between two variables or distributions is usually performed using the standard Student's t-test or t-test calculated as:

$$t = \frac{\mu_t - \mu_{t-1}}{\left(\frac{\sigma^2}{N_t} + \frac{\sigma^2}{N_{t-1}}\right)^{1/2}}$$

where u_t is the conditional mean of directional predictability of the sample of 200 technical trading rules in period t and u_{t-1} is the conditional mean directional predictability of the same sample of technical trading rules in period $t-1$. N_t and N_{t-1} are the total number of buys and sells signals generated in their respective periods. σ^2 is the estimated variance for the entire sample.

It could be argued that the Student's t-test is of little value because it assumes a normal, stationary and time independent distribution. There are several well known deviations from the normal distribution such as leptokurtosis, conditional heteroskedasticity and changing conditional means. Thus, the Student's t-test may be biased and an alternative is the bootstrap approach which assumes nothing about the distribution generating function.

Testing procedures based on bootstrap methodology to assess the significance of technical trading rules in financial markets are not new and have been implemented by dozens of authors such as those of Brock et al. (1992), Levich and Thomas (1993), Mills (1997), Taylor (2000), and LeBaron (2000); to name just a few.

However, critical thresholds from the nonparametric bootstrap tests are found to be extremely close to the ones issued from the parametric Student's t-tests according to Acar and Lequeux (1995). Curcio et al. (1997) also observe that the results in Brock et al. (1992) are not qualitatively altered by using bootstrapped standard errors and therefore they focus on the traditional t-statistics to provide statistical inference. This observation appears to occur in other similar studies such as Mills (1997) and Taylor (2000).

So, it appears that as far as technical trading rule returns are concerned, criticism levied on Student's t-test on financial time series is still premature.

5.7 Why directional predictability and not profitability first?

There are several reasons why we prefer to study directional predictability first rather than profitability. Firstly, it is our objective to first find out which market is comparatively more tradable amount a dozen of highly liquid markets, and thus, a productive way of finding out is to test the directional predictability rather than profitability as the latter will entail complications and an enormous time and resources to achieve. In addition, in order to have more power in our test, we employed a universe of 200 different technical trading rules.

It is also argued that directional predictability is a sufficient, but not a necessary condition to indicate the viability of a trading rule, simply because profit would have to depend upon the accuracy of the closing trade, which is dependent upon the entering trade of directional predictability. For with out a correct directional predictability; there would not be profitability to start with, no matter how accurate the closing trade is. On the other hand, assuming the directional predictability is correct, but the closing trade exits too early or too late, resulting in lower profit than what it could have or just completely miss out a profit taking opportunity. In addition, a large portion of the profit could be due to just a single or a few trades. Thus, knowing the directional predictability may be more informative in general and more relevant in our case. Some of the issues that one needs to consider in calculating profitability of technical trading rules are as follows:

(a) There are different trading cost structures in different countries.

(b) Even within the same country, the cost structures are different between markets. For instance, there is a huge disparity between the transaction costs of trading futures and stocks.

(c) In the case of futures, what is the margin requirement (amount of trader's equity in the trade) and the cost of margin (borrowing).

(d) In the case of currency trading, the interest paid on currencies brought at a spot market, and then deposited in the banking system, also vary between traders.

(e) In addition, the costs are not only the brokerage commission, stamp duty, and stock exchange clearing fees, but also income or corporate or capital gain tax which vary between traders and countries.

(f) If one takes risks in to consideration, then there are various ways of calculating risks. For instance, (1) the volatility, (2) the upside or downside volatility, (3) the largest drawdown (loss) or the average drawdown, and so forth.

(g) Different traders and investors have different risks tolerant. For example, if a pension institution's requirement of return is below the mean return of the trading rule, then it is not risky to the institution; as compared to a hedged fund with a required return much higher than the mean return.

(h) There is also the bid-ask spreads (also known as the slippage costs, execution costs, and liquidity costs) depending upon the liquidity of the particular stock and market.

(i) The cost of acquiring and interpreting information to a typical institution is quite different to a typical individual trader.

(j) The returns of technical trading rules are often not adjusted for inflation.

(k) The transaction costs are also a function of the size of each trade.

(l) The services (such as research and real time market information) and execution provided may also vary according to traders.

(m) For individual stocks, the difficulties of calculating not only dividends, but also incorporate right issues, bonus shares (split), warrants, and the effect of conversion by convertible loans/bonds from time to time and upon expiration.

(n) The issue of what should be the rate of interest on cash during the neutral period when no trading signals are given from the trading rule after closing trades.

(o) What should be the amount on each trade? The cumulative amount or a fixed amount on each trade, or a fixed percentage of the remaining capital? All these shall have a profound effect on profitability.

5.8 Technical Trading Rules

We randomly collected 200 technical trading rules which are defined as trading rules that use past and present prices and volumes for the decision of generating buy (long) or sell (short) signals. Out of the 200 technical trading rules' computing codes in "Easy Language," 121 of them are either written or based on others' published computing codes by Samuel and Raffalovich (1995) of G. Morris Corporation. Another 63 of the codes were programmed directly in to the "Trade Station" software by the authors based on published codes (with three proprietary "Turtle Trading Systems" from our colleague), and the remaining 16 are those already incorporated in to the "Trade Station" software upon our purchase. The sources of the 200 technical trading rules are as per references part II.

Prices include open, close, high and low and prices of another time series (i.e., inter-markets) beside the one that is being used for prediction.

Within the sample, the technical trading rules range from a simple moving average to a sophisticated one that is generated by Genetic Algorithm.

This sample of technical trading rules is much larger and heterogeneous than those used in previous studies with the exception of Sullivan et al. (1999); hereinafter referred to as Sullivan. However, this sample differs from Sullivan in respect of heterogeneity as it includes those categories of technical trading rules such as candlestick, volume, volatility, inter-markets and genetic algorithm etc. which are not in Sullivan's universe of technical trading rules. Sullivan uses 5 basic concepts and by changing the parameters and their combinations; giving raise to 7,846 technical trading rules. However, some of the rules here also include those designed for the commodities futures and bond markets.

The branch of technical analysis that uses astrology to predict is not included here; neither are those charting techniques that involve subjective judgment.

Most of the technical trading rules are taken from various books and magazines. There are as many technical trading rules as one can imagine. The sample here can further be expanded into thousands by changing their parameters and combining the rules in various ways. For example, Sullivan use the concept of a moving average and expand it into a universe of 2,049 technical trading rules by changing the parameters and their combinations.

As far as we are aware of, this portfolio of technical trading rules is the largest to date in terms of heterogeneity and also in terms of directional predictability since Sullivan do not publish all their directional predictability results.

5.9 Issues on empirical testing

In view of the increasing complexity and sophistication in empirical testing of financial time series; it is important to discuss and highlight some of the general findings and concepts in this area which are not already mentioned and discussed in previous sections before we conclude this chapter.

This section is useful and indeed *often ignored* in quantitative works, as it is imperative to review the dynamics between our initial objectives, the pros and cons of the methodology used, and the results generated – to arrive at a meaningful interpretation, and a better perspective. The following discussions are written with special reference to the study of technical trading rules, and are by no means exhaustive. We divide the discussions in to three sections, namely statistical interpretation, non-statistical interpretation and real- world application.

5.9.1 Statistical interpretation

5.9.1.1 Repeatability

As in most social sciences, to repeat the same experiment for the same results may not be easy to come by as compared to most of the physical and life sciences, where the conditions of experiment can be controlled to a large extent than in social sciences' experiments. Thus, the differences of results between the two sub-periods under study here are of no surprise; and so the application of technical trading rules in the real-world based on our findings here should be treated with cautions

5.9.1.2 Statistical and economic significance

A statistical significance may not always translate into an economic significance and vice-versa. In this case, although economic significance is an obvious overriding factor, the statistical significance should also not be ignored; at least in the long run – if the same trading environment prevails.

5.9.1.3 Catastrophe and level of significance

In the event of a market crash, however small is the probability of such an occurrence, it still can be highly significance for a financial trader, for it can wipe out his entire invested capital, or even more (if certain derivatives are involved) in just a single event resulting in financial ruin. As such, the usual standard 5 and 1 percent significant level has to be viewed in light of acceptability or affordability to a financial trader.

Certain risk management techniques (i.e., minimize, control, diversify, transfer and option etc.) can alleviate the acceptable significant level – often at a cost - depending upon the constraints and objectives of the financial trader concerned.

5.9.1.4 Long run and relevant

Most statistical techniques are based on the law of large number and therefore, tend to stretch the validity – to the extent of in the long run.

This is where a distinction has to be made in terms of interpretation between social, physical and life (social) sciences. For example, the findings on directional predictability may not be repeatable as a result of the following factors in the long run such as changes in institutional framework; changes in regulatory environment; and changes in liquidity of the global economic system and so forth.

Objectively, the core of the argument is not whether it is long, medium, or short term, but rather whether those conditions or the environment in which the results were generated are still prevailing; and that whether the objectives of empirical testing are still relevant. These should be the prime concerns irrespective of social, physical, or life sciences.

5.9.1.5 Bootstrapping

5.9.1.5.1 Weaknesses

Since the publication of Brock et al.'s (1992) article on technical trading rules, the study of this subject is almost synonymous to bootstrapping. However, one should be aware of the following limitations:

a) Using sampling with replacement can only allow data selection from within the original sample and hence, one can only "see" those events that have occurred in the original sample.

b) More importantly, using a random sampling with replacement approach, the new price patterns may not represent actual market behavior, such as the market psychology and the underlying supply and demand forces at that particular point in time.

c) If there are outliers in the data, the conclusions of the bootstrap may be affected. In particular, the results for a given replication may depend critically on whether the outliers appear and if so, how often in the bootstrapped sample (Brooks, 2002).

d) The bootstrap methodology implicitly assumes that the data are independent of one another. This obviously would not hold for most financial time series. A potential solution to this problem is to use a "moving block bootstrap". Davison and Hinkley (1997), and also Efron (1979; 1982) discuss several issues relating to the theory and practical usage of bootstrap. It is noteworthy that variance reduction techniques are also available under the bootstrap. Gorener et al. (2004) utilize the concept of moving block bootstrap and find that it replicates the features of non-stationary time series, including especially the autocorrelation structure. In this respect, it outperforms the conventional bootstrap considerably and therefore offers a basis for replicating historical time series for various testing purposes.

5.9.1.5.2 Expected return not to be expected

Using bootstrapping procedure on 20 years of return data, Kritzman (2000) illustrates why the expected return is not to be expected. By bootstrapping 10,000 times from the historical returns, he finds that the expected return is greater than the actual final return in the historical returns, and the likelihood that the number of bootstrapped expected returns are at a sum at least equal to its expected value is less than 50 percent.

Given the above drawbacks, bootstrapping is still a very useful technique until a better alternative is found.

5.9.1.6 Data transformations

Extreme caution should be taken when using transformed data such as seasonally adjusted data, as the incorrect use of such data may lead to misleading findings. For example, many seasonal correction methods apply sequences of outliers' removal and moving average filtering techniques to discretely measured data. These types of procedures may result in seasonally adjusted time series which have properties quite different from the original unadjusted series. For instance, Ghysels et al. (1996) show that seasonal adjustment may introduce nonlinearity into an otherwise linear process.

On the other hand, seasonal adjustment may actually reduce the relevance of switching regime, leading to a finding of less nonlinearity. This arises as sequences of moving average filters clearly smooth away the effect of structural shifts.

5.9.1.7 Percentage returns and logarithmic returns

Natural log differencing is almost like a wonder drug in the econometrics world of linearity. By taking successive logarithmic differences,

$\Delta x_t = \ln(x_t) - \ln(x_{t-1}) = \ln(x_t / x_{t-1})$; it helps to:

(a) Remove trends (unit roots),

(b) Make the series more stationary,

(c) Reduce heteroskedasticity,

(d) Obtain a more normal distribution, and

(e) Transform the data approximately equal to percentage returns.

Although there are advantages in using logarithmic transformation in the study of returns, it also has its fair share of disadvantages such as the log of a sum is not the same as sum of a log because the operation of taking a log constitutes a non-linear transformation and thus, it is not additive across a portfolio.

Another less noticed drawback is that, beyond 10 to 15 percentage returns, the natural log or log e or ln transformations would translate into a larger disparity as the percentage returns increase. For example, a 20 percent price level return would transform into a 18 percent ln return, resulting in a 2 percent difference in return between the two (which is 10 percent of the original 20 percent). Likewise, a 30 percent price level return would transform into a 26 percent ln returns and the difference is a 4 percent return. The disparity would increase further as the percentage returns increase. This type of differences can be substantial for the study of small capitalized or illiquid financial instruments as it is not unusual for them to swing up or down 30 percent (the maximum limit of 30 percent in the case of Kuala Lumpur Stock Exchange) in price within a single trading session. For the two sessions in the same direction within a day could amount to a 69 percent return.

5.9.1.8 Outliers

Nonlinearity may be found, due to a small number of outlying observations, if standard non-robust tests are used. Dijk et al. (1996a,b) propose tests for nonlinearity and ARCH in the presence of outliers. Their tests give less weight to irregular data points (outliers). Extensive Monte Carlo evidence in these two papers show that these type of robust test statistics have good size properties, and suffer little from diminished power. The two figures below illustrate the sensitivities of outliers on the computation of coefficient:

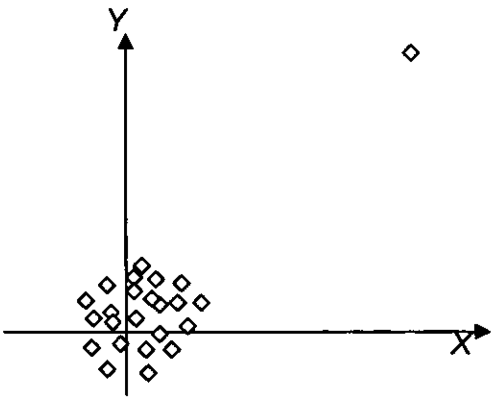


Figure 5.3 An extreme outlier may result in a correlation coefficient close to one

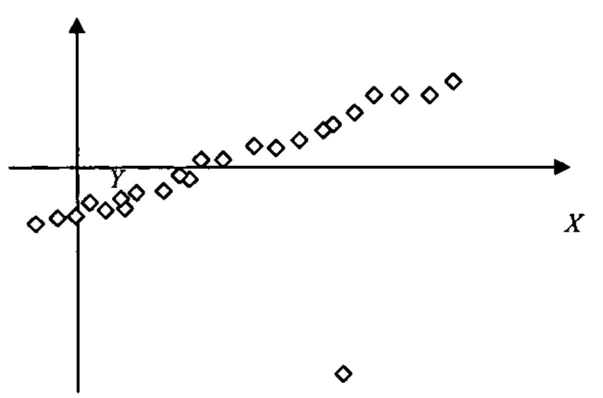


Figure 5.4 An extreme outlier may result in a correlation coefficient close to zero

For financial data, Franses and Dijk (1997) document that one may also often find ARCH because of neglected outliers. They examine 22 weekly and monthly exchange rate series, as well as 13 stock market indices. Their main result is that spurious GARCH is found over 50 percent of the time. Monte Carlo evidence shows that their results are indeed driven by outliers.

There is a clear tradeoff between how many outliers are admitted and the usefulness of models for capturing asymmetries and nonlinearities which may characterize a data series. In particular, allowing too few outliers also has drawbacks, as one may argue that certain so called outliers are precisely those data which are not well treated using linear models, and which one wish to model using nonlinear models.

As for the study of distributional properties, the calculation of skewness and kurtosis statistics are sensitive to outliers because they make use of the third and fourth powers of the data. For the sample of technical trading rules studied here, although we treat those rules with less than 30 trades and those generated with 100% or 0% directional predictabilities as outliers; we are not too sure whether all these outliers should be taken out. However, given the large sample used here, the problem may not be so pronounced as compared to a small sample.

5.9.1.9 Nonlinear model selection

Swanson and Franses (1999), in a review article on nonlinear econometric modeling, summarize their selection process as follows:

> "... When selecting among nonlinear models, it is sensible to first select model selection criteria based on carefully constructed loss functions. Individual end users generally require models which are useful for many different purposes, from forecasting mean to maximizing profits. Second, it is reasonable to assume that any single model selection criteria only shed light on a small "part" of the overall picture. Using a number of model selection criteria may thus be useful when comparing models. Third, there are an infinite variety of model which may be compared. When using nonlinear models, it is perhaps sensible to begin with some basic benchmark linear models, and then consider a small set of alternative nonlinear models which are of particular interest, given economic theory and other considerations."

5.9.1.10 Test of significance: t-test or bootstrap

Most studies in technical trading or trading rules so far provide evidence of same statistical results for both tests in the form of rejecting the null at the standard significance levels such as the 1 and 5 percent. There are two possible explanations here that would basically lead to the same result of rejecting the "null":

(a) Firstly, for the t-test, it could be due to the large sample size in all these studies rendering the standard statistical t-test (or z-test) to reject the null hypothesis.
(b) Secondly, for the bootstrap, unless the models are grossly misspecified or "bad models", it is quite possible that the price dynamic that one is trying to capture would not be there once the time series is scrambled. Thus, resulting in the rejection of the "null".

5.9.1.11 Model risk

Forcardi et al. made a comment about model risk: "With more parameters in the models and more sophisticated econometric techniques, we run the risk of overfitting our models. Distinguishing spurious phenomena as a result of overfitting or data mining can be a difficult task."

5.9.1.12 Cost and accuracy

Due to the affordability of computing power; the dilemma of cost versus accuracy does not appear to be an issue here and thus accuracy is not being compromised.

5.9.1.13 Softwares

The important of properly tested softwares should not be overlooked. The author was given to understand by a professor of mathematics at one of the leading universities in South East Asia that even Microsoft Excel has inherited errors. The renounced journal for forecasting - International Journal of Forecasting - recently awarded the best paper for 2000/2001 to McCoullough (2000) for his article on the accuracy of forecasting softwares is a case in point.

5.9.2 Non-statistical interpretation

The study of technical trading rules on financial time series is a complex subject and that the following conditions (or factors) are important to understand the dynamic relationship.

5.9.2.1 The design of technical trading rules

There are as many rules as one can imagine. For example, one can vary the parameters such as a 10 days moving average to a 20 days moving average and combine the different rules in various ways. Hence, the 200 technical trading rules presented here can be expanded to thousands of rules.

The usefulness of a particular technical trading rule for capturing financial time series is as good as the rule itself. As such, the usefulness of technical trading rules should not be judged by just applying one or two rules on a time series and starts making claims on the results.

5.9.2.2 Period of time series under study

Theoretically speaking, it is necessary to use at least a period of data which encompasses two full cycles of price movement - two peaks, two troughs and two sideway movements.

Based on the authors' observation, a larger full cycle is usually a twelve years cycle with seven years of steady up-ward movements and five years of more volatile and down-ward movements, and some sideway movements in between (the chapter on methodology has a detailed discussion on this issue).

5.9.2.3 Performance of technical trading rules in different phases of the cycle

Each phase of a cycle may have a different impact on the performance of technical trading rules, especially if the performance is judged by comparing to a buy-and-hold strategy. For example, in a down-trend market, the buy-and-hold strategy would produce a negative return, whereas a technical trading rule may still produce a positive return since it can also sell (or short) in a down-trend market.

5.9.2.4 Efficiency of the market under study

As efficiency can be measured in many ways depending upon its definition, it would be more productive to focus on the relative or comparative efficiency concept. It is worthwhile to note that the level of efficiency, however, may not be the same as the level of development. For instance, some developing stock markets employ computer technology to match buy and sell orders rather than an open outcry system even at their earliest stage of development.

5.9.2.5 Collection process and definition of data

For instant, the problems associated with data collection and the definition of data in the foreign exchange markets are more difficult to resolve than say stock markets in general.

5.9.2.6 The type of market

Certain important factors are more dominant and unique to certain markets such as the role of Central Bankers in stabilizing the foreign exchange markets; and the inelasticity of supply in the commodities markets. For examples, empirically, Taylor (1986) found that US stock returns were positively skewed and that metals returns were negatively skewed; and it appeared that metals and agricultural goods had more kurtosis and more extreme outliers than currencies and US stocks. The latter example for commodities, in our view, may be due to the large disequilibrium created by the inelasticity of supply.

5.9.2.7 The uniqueness of each market

Each market tends to has its own characteristics either due to the institutional (for instance, time horizon and risk profiles of market participants); infrastructural (for instance, computerization of transactions; or through an open outcry system or the use of specialists as in the case of New York Stock Exchange and so on); regulatory and cultural (see Fuhrmars and Murgan, 1999 for an interesting comparison of risk attitudes between investors of Hong Kong and Germany) frameworks.

For empirical examples, Mills (1997b) finds evidence of greater autocorrelation in smaller than larger capitalization of stock indices, and Granger and Ding (1994) find long memory in a number of speculative return series. With the globalization of financial services, the differences are expected to be narrowing.

5.9.2.8 The frequency of data

For example, Markellos et al. (1998) along with other studies show that there is less randomness in higher frequency time series than lower frequency time series.

5.9.2.9 Compilation of time series

There are various ways of compiling a financial time series. The typical are either simple average or weighted average calculation for indices. However, the impact of the frequent changes in the components of index is often ignored (for instance, index rebalancing and rebasing) and less published.

In the case of individual stock, dividend, issuance of split or bonus, warrant, convertible loan stock and rights and so forth are often not adjusted for calculation of returns. As dividends are often ignored in the calculation of returns, they will result in preference over growth stocks with larger capital gain than income stocks that pay high dividends.

In the futures markets, the different ways of compiling futures contracts time series are interesting and the effects are not known. Stridsman (2001) provides an interesting chapter 3 on this particular topic. Various methods have been invented to splice several contracts together to form a longer time series. For examples, Stridsman (2001) explained three different methods to splice contracts together. The non-adjustment method, the back-adjustment method, and the perpetual-adjustment method. The back-adjustment method can be further subdivided into point-based adjusted and ratio-adjusted. However, in the foreign exchange market, there is difficulty in getting a standard time series for subsequent comparison.

5.9.2.10 Data and references

To ensure clean data, a visual check on price chart could often provide a quick check on any error. And then a cross check with an alternative source would ensure a clean time series.

5.9.2.11 Motivation

For some of the articles published in journals and reviews, it may pay, occasionally, if in doubt, to find out the motivation and affiliation of the author in order to have an unbiased view of the subject.

5.9.3 Real-world application

5.9.3.1 Future applications and the design of trading rules

What works today may in all probabilities work less efficiently tomorrow. This may not be an unrealistic assumption as financial markets tend to be more efficient as time passes by. The finding of diminishing calendar anomalies by Tan and Wong (1998) and the similar diminishing findings in foreign exchange and other markets on profitability as reviewed earlier are a case in point. Hence, a sound logical basis for the design of technical trading rules is no less important than just to capture the statistics generated by historical data.

5.9.3.2 To capitalize those unprofitable technical trading rules

As long as a rule can provide consistent results, be it profitable or not, can all be capitalized upon. In the case of unprofitable rules, one could do the exact opposite of whatever signals generated by those rules.

5.9.3.3 Risks and uncertainties

Although the risks profile associated with a particular technical trading rule can be assessed through its statistical properties such as consecutive losses, largest drawdown, lowest equity position, returns distribution and so forth; but the key problem of "uncertainty" associated with a particular technical trading rule remains unknown (as risks can be measured by using historical data whereas uncertainty can not).

However, the risks associated with a particular technical trading rule can be reduced through diversification by using:

a) Different frequency of data,
b) Across different uncorrelated markets and,
c) Different technical trading rules which are uncorrelated.

5.9.3.4 Transaction costs, slippages and interest earned

Some results do not take account of the above factors and hence may somewhat presented a best case scenario than otherwise. However, one may also argue that the costs and benefits of slippage may just cancel out each other in the long run given that the overall directional predictability is close to 50% and that transaction costs and interests earned on cash position may somewhat balance out each other depending upon the profitability and frequency of trade generated by that particular technical trading rule involved.

5.9.3.5 Can we implement research on technical trading rules?

Ball, Kothari and Wasley (1995) show that the tendencies to buy at bid, and short at ask in trading rules simulation impart an upward bias to estimated profit.

They conclude that research on trading rule profitability usually simulates trading on historical data. The algorithm to estimate closing price typically takes the last trade (which might be at the closing bid or closing ask, or neither), or the bid-ask average (in the absence of a last trade). A trading rule could not normally be implemented at these prices, for even a small number of shares. We offer two suggestions to explain: (a) lack of liquidity for some stocks and indices. (b) Each trade has an effect on subsequent prices.

5.9.3.6 Stability

In Forcardi and Jonas (1997), they interviewed over 100 persons in the financial forecasting industry and academia. One of the interesting comments in the book is by Paul Refenes of London Business School, who highlighted one of the most critical and yet unresolved problem in financial trading: "Understanding if a series is stable enough to allow for profitable training is a big question." This concern is also often raised by other researchers. For example, Wilcox (1999) states that: "Instability of system structure of all kind is a significant obstacle to quantitative methods." For this, we have derived a methodology to minimize the impact of instability which shall be the subject of another study.

Notes:

1) The interval estimate of the population mean is estimated by the formula:

$$u = \bar{x} \pm \frac{1.96s}{\sqrt{n}}$$

$\bar{x}$ = sample mean
s = sample standard deviation
n = number of observations.

In this case, 95% of the means would be within the range of 44.12% to 48.70%. In the case of before outlier reduction, the range is 45.65% to 50.49%.

2) Based on the results of this sample, we use a procedure called sequential sampling to decide the appropriate sample of our choice. The formula is:

$$n = \left(\frac{ZS}{E}\right)^2$$

Z = standardization value indicating a confidence level
S = sample standard deviation or an estimate of the population standard deviation.
E = acceptable magnitude of error, plus or minus an error factor

In this case, if we wish to have a 95% confidence levels (Z) and a range of error (E) of less than 5 percent. As the sample standard deviation is 16.53%, the appropriate sample size is:

$$n = \left(\frac{(1.96)(16.53)}{5}\right)^2 = 41.99$$

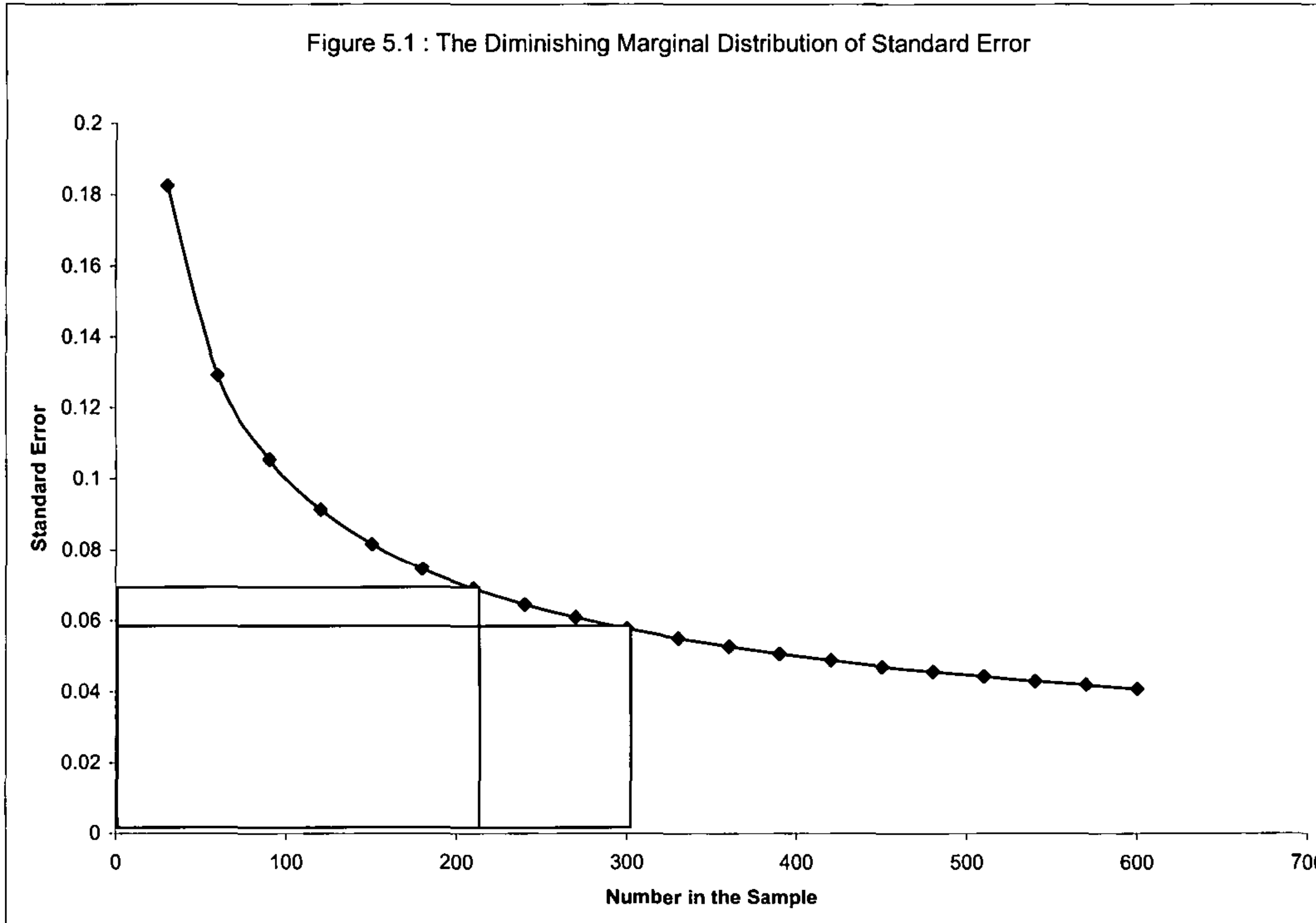
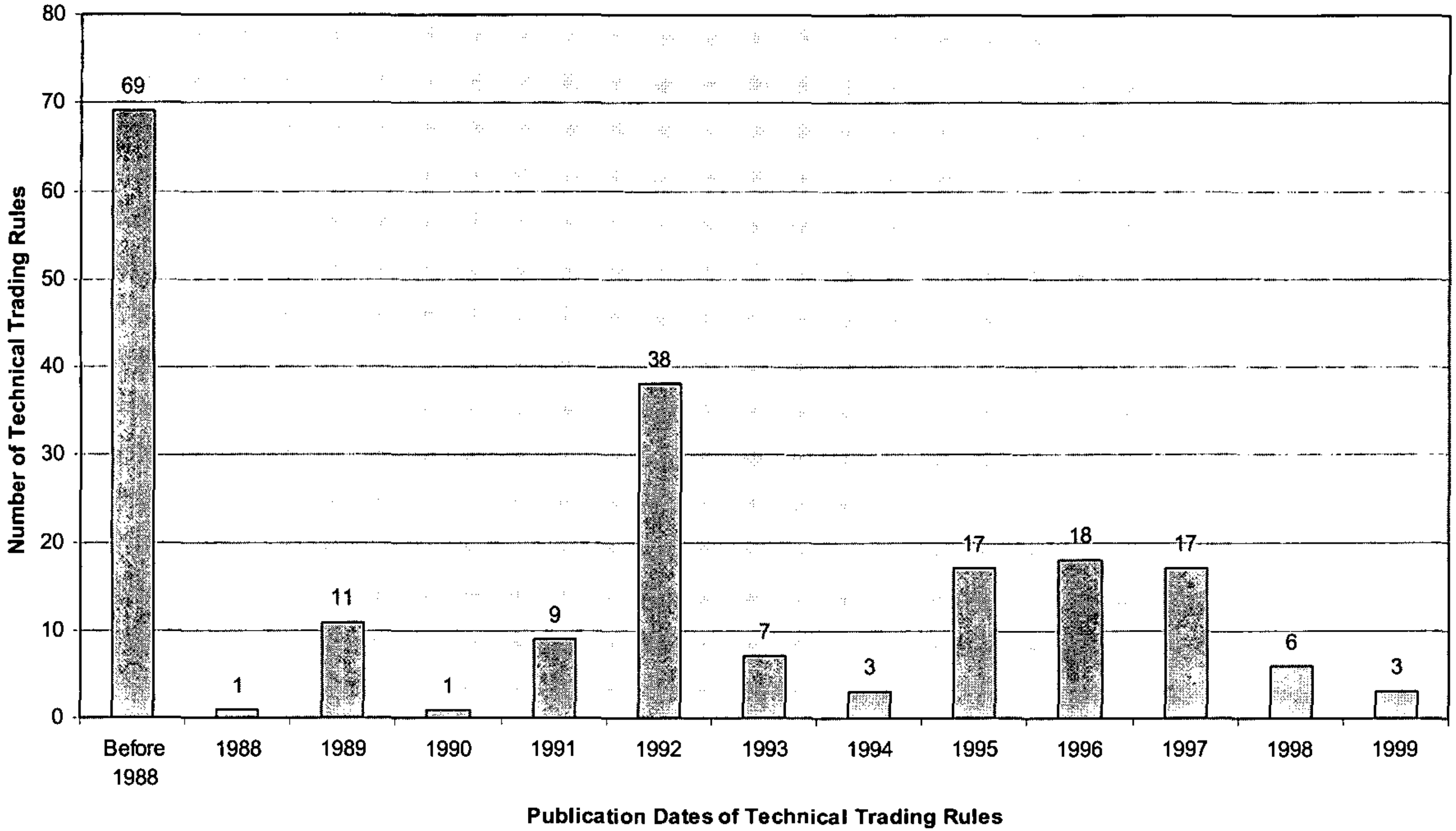


Figure 5.1 : The Diminishing Marginal Distribution of Standard Error
Standard Error
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
100
200
300
400
500
600
700
Number in the Sample

Figure 5.2 : Distribution of Technical Trading Rules' Publication Dates



Chapter 6

To predict or not to: Is that still the question?

6.1 Empirical results and analysis

6.1.1 Outliers

The definition of outliers is those technical trading rules which generate less than a total of 30 trades and generate either a 0% or 100% directional predictability (a trade consists of a buy and a sell or vice versa).

Due to the large number (20 Percent) of outliers in the original sample, the results of both before and after outlier reduction are presented. In addition, the outliers' definition here may be a bit restrictive considering the evidence of Lukas and Brorsen (1989) that larger term parameters and hence less trades to be generated tends to have better risk/return characteristics.

We shall only discuss those results after outlier reduction; bearing in mind that the conditional means tend to be higher before outliers deduction in general.

6.1.2 Conditional means

6.1.2.1 Stability

Table 6.1 presents estimates of conditional mean directional predictabilities during total, buy and sell periods by the 200 published technical trading rules. The results between before and after outlier reduction appear to be similar in almost all aspects. Neither are there many differences between the two sub-periods. However, a t-test performed on each of the total, buy only and sell only as in columns 5, 6 and 7 between the two sub-periods have all rejected the null hypothesis of equality at the 1 percent level of significance (the respective t-test scores are 15.38, 23.81 and 9.13 for the total, buy only and sell only).

The first three column labelled N(total), N(buy) and N(sell) are the total respective number of signals generated. Here, the number of buy only and sell only signals are equally generated for all periods, which is not one would expect from the result of a particular technical trading rule, and this may have to do with the law of large numbers here.

6.1.2.2 Directional predictability

The fifth, sixth and seventh columns report the conditional means of total, buy only, and sell only signals' directional predictabilities. Although the number of buy and sell signals are almost equal, their respective directional predictabilities differ widely with an average ratio of 1.67x in favour of buy signals for the entire period. If technical trading rules do not have any forecasting power, then one should observe that directional predictability on days when the rules emit buy signals do not differ significantly from directional predictability on days when rules emit sell signals.

The high ratio of buy to sell directional predictability is within expectation in a predominantly up-trend time series. By the same token, the ratio for sub-period 2 is expected to be higher than sub-period 1 as it can be seen from figure 4.1 in chapter 4 that the former has a steeper up-trend than the latter.

The large difference in conditional means between buy only and sell only for the entire period is large enough to be relevant. This is confirmed by a t-test score of 120.88 for the difference which is highly significant, and rejecting the null hypothesis of equality with zero.

The fifth column of conditional mean directional predictability of 46% over the entire period is close to an expected population mean of 50% as suggested by the central limit theorem of normal distribution. However, the statistical test reveals a t-test statistics of 31.62, which is highly significant even at the 1 percent level and thus rejecting the null hypothesis of equality to 50%.

6.1.2.3 Is there a message for the technical analysts?

The above statistical test may come as a rude shock to those die-hard technical analysis fans; as it implies a random decision making process may do just as well as the average technical trading rule and likely better in the long-run! However, for some professional technical analysts, the below 50% predictability is of no surprise as they belief most technical trading rules' predictability are within a range of 25% to 50% predictability (for examples, Rotella, 1992 and Smith, 2001).

6.1.2.4 Unconventional: Lower risk but higher return and vice versa

Risk is higher on sell days as measured by the coefficient of variation in table 6.1 than on buy days, whereas the conditional mean directional predictability is higher for buy days than sell days. This observation is consistent with the results of several other studies on the conditional returns of equity indices such as those of Brock et al. (1992) and Mills (1997) to name just two.

6.1.2.5 Against the odd

What is interesting from the results of table 6.2 is the much higher percentage of buy signals that have a more than 50% directional predictability (as in column two) and the ratio of the buy and sell signals (column four) for the entire period is a staggering 4.15x and the ratio is comparatively higher for the steeper up-trend sub-period 2 (6.88x) than sub-period 1 (3.31x).

The conditional mean of a buy signals having a probability of more than 50% predictability is 54 percent compared to only 13 percent of the time for sell signals. This phenomenon of better performance for buy signals is in line with other studies (for instance, Brock et al., 1992 and Mills, 1997) on the profitability of technical trading rules whereby buy signals consistently out-perform sell signals.

Under the null hypothesis that technical trading rules do not produce useful signals, the fractions of conditional mean predictability which are more than 50% should be the same for both buys and sells. We are not going to join the debate on efficient market hypothesis. But for those who are in doubt on the hypothesis, a classic argument against the hypothesis is given by Grossman and Stiglitz (1980) and a more up-to-date work is given by Lo and McKinlay (1999).

6.1.2.6 The 80/20 rule

The results for the top 20 percent and bottom 80 percent of technical trading rules in table 6.3 indicate that the better performing technical trading rules tend to have smaller differences in the performance of buy and sell signals, whereas the worse performing technical trading rules tend to have larger differences as shown by the ratios of 1.42x and 2.12x for the top 20 percent and bottom 80 percent respectively.

These statistics may be due to the better designed technical trading rules for the top 20 percent group which can capture both the up and down directions of the time series quite well, whereas, the worse designed technical trading rules have to rely upon the inherited and predominately up-trend component for their performance.

The major results of each individual technical trading rule for the entire period, sub-period 1 and 2 are as per tables 6.4, 6.5 and 6.6.

6.2 The use and abuse of statistics: Rejection of the null, under the t-test, in the presence of a rise in the N

6.2.1 "Rejection of the null" phenomenon

All the above standard statistical tests are all highly significant at the 1 percent level and rejecting all the null hypotheses. This should not come as a surprise but rather as would be expected; given the large sample of data under our investigation (200 technical trading rules on 10 years of daily data).

Due to the availability of large data set in empirical finance and the affordability of computing power, researchers are facing a new phenomenon when using the standard statistical tests; let us call it the "rejection of the null" phenomenon. For example, if one is to increase the sample size, and therefore the value of t-test (since n is the sub-denominator of a denominator in the t-test formula), one would ultimately reach the point where all null hypotheses would be rejected using the standard significance levels i.e. 5 percent and 1 percent. In other words, when the null hypothesis is not rejected, then it may be that the sample size is not large enough.

According to Granger (1999), "... for a very large data set virtually every precise null hypothesis will be rejected using standard significance levels, unless the hypothesis is exactly correct."

6.2.2 Present and future

The availability of large data set nowadays means that new statistical techniques have to be devised to take advantage of them; as classical techniques were developed for small data sets originated from agricultural and biological experimental situations.

Granger (1999) argues that the assumption of linear relationships and thus also of normality can certainly be dropped and ways of estimating and interpreting conditional distributions will have to be found. He even ventures to prophesy (before he becomes a Nobel Laureate in Economics) that, "Essentially, many of the tools you are currently learning in statistics and econometrics will not be needed in the future, although the foundations and strategies you are being taught should certainly remain helpful." His view is not difficult to share with; after all, normal distribution is at the core of most financial models. For examples, random walk, capital asset pricing, value-at-risk, black-s choles models, and so on.

6.3 Concluding remarks

We do not discount the possibility that there may be many other published and unpublished technical trading rules which have higher directional predictability, but given the top 20 percent of technical trading rules tested here produces a conditional mean of 73% directional predictability; this is enough of an indication of the economic significance and continuous practice of technical trading rules.

One may not need to have high predictability to achieve much. To give a hypothetical example, for a predictability of 51%, if it can be capitalized on a weekly basis, it can turn into a return of 52 percent per annum before risks and transaction costs.

Neither does one need to look very far ahead to make a useful prediction. For example, more than 75% of foreign exchange trading takes place within the day (Taylor and Allen, 1992).

Table 6.1 : Result of Directional Predictability Tests for 200 Technical Trading Rules

Column	1	2	3	4	5	6	7	8	9
Before Outlier Reduction	N(Total)	N(Buy)	N(Sell)	Ratio of N(Buy) to N(Sell)	Total %	Buy %	Sell %	Buy-Sell	Ratio of Buy to Sell
1988-1999 Entire Period	33394	17154	16780	1.02x	48 (36)	60 (37)	31 (69)	29	1.94x
1988-1993 Subperiod 1	16745	8552	8193	1.04x	48 (48)	58 (46)	32 (78)	26	1.81x
1994-1999 Subperiod 2	16216	8188	8027	1.02x	47 (40)	57 (44)	30 (77)	27	1.90x

After Outlier Reduction	N(Total)	N(Buy)	N(Sell)	Ratio of N(Buy) to N(Sell)	Total %	Buy %	Sell %	Buy-Sell	Ratio of Buy to Sell
1988-1999 Entire Period	33374	16772	16565	1.01x	46 (36)	55 (28)	33 (54)	22	1.67x
1988-1993 Subperiod 1	16537	8423	8114	1.04x	43 (39)	51 (31)	34 (45)	17	1.50x
1994-1999 Subperiod 2	15884	7979	7905	1.01x	45 (33)	54 (22)	31 (50)	23	1.74x

N (Total), **N** (Buy) and **N** (Sell) are the number of total, buy only and sell only signals generated by the portfolio of 200 technical trading rules. The Total, Buy and Sell represent the conditional mean predictability obtained during Total, Buy Only and Sell Only periods respectively. Buy -sell are the differences between the conditional means. Figures in the parentheses are the coefficients of variation which measure the volatility of variation about the mean

Table 6.2 : Fraction of Technical Trading Rules with more than 50% Predictability

Before Outlier Reduction	Total>50%	Buy>50%	Sell>50%	Ratio of Buy to Sell
1988-1999 Entire Period	0.40	0.60	0.16	3.75X
1988-1993 Subperiod 1	0.39	0.57	0.17	3.35x
1994-1999 Subperiod 2	0.40	0.59	0.13	4.54x

After Outlier Reduction	Total>50%	Buy>50%	Sell>50%	Ratio of Buy to Sell
1988-1999 Entire Period	0.36	0.54	0.13	4.15x
1988-1993 Subperiod 1	0.35	0.53	0.16	3.31x
1994-1999 Subperiod 2	0.38	0.62	0.09	6.88x

Total>50%, Buy>50% and Sell>50% are the fraction of Total, Buy Only and Sell Only conditional mean predictability greater than 50% respectively.

Table 6.3 : Conditional Mean Predictability for the Top 20 percent and Bottom 80% Groups of Technical Trading Rules				
Before Outlier Reduction	Total	Buy	Sell	Ratio of Buy Only to Sell Only
Top 20 percent Top 40 Rules	74.93	91.89	64.6	1.42x
Bottom 80 percent Bottom 160 Rules	41.35	52.39	22.68	2.31
After Outlier Reduction				
Top 20 percent Top 32 Rules	72.75	83.97	59.25	1.42x
Bottom 80 percent Bottom 129 Rules	39.88	50.57	23.91	2.12x

Note : Of the 200 technical trading rules, there are only 161 rules after outlier reduction.

Table 6.4 Major Results of Technical Trading Rule's Directional Predictability (before outlier reduction)
Entire Period : 09/06/1988 to 3/24/1999
Daily

Rules	Predictability %			No of Trades		
	Total	*Buy*	*Sell*	*Total*	*Buy*	*Sell*
S1	55	65	44	161	81	80
S2	49	49	0	51	51	0
S3	26	36	16	178	92	86
S4	26	35	16	319	160	159
S5	35	40	30	759	380	379
S6	27	45	9	89	44	45
S7	30	33	26	574	287	287
S8	74	74	0	61	61	0
S9	61	61	0	519	519	0
S10	45	60	31	189	94	95
S11	27	45	9	89	44	45
S12	32	46	17	164	82	82
S13	31	44	17	91	45	46
S14	35	50	21	65	32	33
S15	22	39	8	116	54	62
S16	39	50	28	201	101	100
S17	24	35	12	177	88	89
S18	73	81	65	652	326	326
S19	69	69	0	61	61	0
S20	52	83	18	23	12	11
S21	71	71	0	112	112	0
S22	50	78	22	36	18	18
S23	51	51	0	45	45	0
S24	78	100	60	9	4	5
S25	50	100	0	6	3	3
S26	43	75	0	7	4	3
S27	75	100	33	8	5	3
S28	50	0	100	2	1	1
S29	55	55	0	76	76	0
S30	57	57	0	82	82	0
S31	100	100	0	101	101	0
S32	34	48	21	184	92	92
S33	33	38	28	682	341	341
S34	36	44	27	510	255	255
S35	47	57	36	335	167	168
S36	66	76	56	118	59	59

S37	37	49	31	347	121	226
S38	22	80	19	236	10	226
S39	49	100	26	329	103	226
S40	67	76	57	136	68	68
S41	43	62	33	304	108	196
S42	43	61	33	311	115	196
S43	42	59	32	311	115	196
S44	25	0	25	4	0	4
S45	38	46	30	743	372	371
S46	69	89	50	36	18	18
S47	34	46	22	238	119	119
S48	33	40	25	9	5	4
S49	39	62	27	74	26	48
S50	24	63	13	86	19	67
S51	67	91	40	21	11	10
S52	24	65	14	82	17	65
S53	28	63	18	87	19	68
S54	42	69	31	179	54	125
S55	66	76	56	118	59	59
S56	32	47	25	314	101	213
S57	53	65	44	206	84	122
S58	49	67	31	85	43	42
S59	57	73	41	159	80	79
S60	49	67	31	85	43	42
S61	79	79	0	28	28	0
S62	79	0	79	67	0	67
S63	88	88	0	40	40	0
S64	86	0	86	70	0	70
S65	55	55	0	11	11	0
S66	47	0	47	47	0	47
S67	14	0	14	7	0	7
S68	79	79	79	95	28	67
S69	87	90	86	110	40	70
S70	48	55	47	58	11	47
S71	25	100	14	8	1	7
S72	75	67	100	8	6	2
S73	67	50	75	6	2	4
S74	80	100	67	5	2	3
S75	67	73	62	24	11	13
S76	80	86	73	25	14	11
S77	25	33	22	12	3	9
S78	83	77	85	54	13	41

S79	91	94	90	67	18	49
S80	58	60	58	36	5	31
S81	25	100	14	8	1	7
S82	83	78	89	18	9	9
S83	42	25	50	12	4	8
S84	67	0	67	3	0	3
S85	70	100	67	10	1	9
S86	67	100	63	9	1	8
S87	29	100	17	7	1	6
S88	53	69	36	135	68	67
S89	35	44	27	358	179	179
S90	56	78	29	16	9	7
S91	42	49	35	567	284	283
S92	62	81	42	157	79	78
S93	79	82	77	1815	930	885
S94	43	50	35	545	273	272
S95	54	68	39	208	104	104
S96	37	47	27	315	158	157
S97	60	79	39	57	29	28
S98	71	83	58	119	60	59
S99	74	89	57	65	35	30
S100	77	100	52	43	22	21
S101	71	94	47	31	16	15
S102	57	76	37	83	42	41
S103	41	54	28	178	89	89
S104	31	48	15	67	33	34
S105	45	61	35	233	94	139
S106	29	40	18	364	182	182
S107	39	47	32	676	338	338
S108	43	67	34	113	33	80
S109	25	35	16	267	133	134
S110	51	56	45	740	370	370
S111	44	57	30	202	101	101
S112	64	82	44	33	17	16
S113	33	47	19	109	55	54
S114	31	47	14	72	36	36
S115	30	37	22	236	118	118
S116	38	44	31	528	264	264
S117	35	47	23	300	148	152
S118	69	74	63	379	189	190
S119	56	66	46	274	137	137
S120	30	39	22	171	85	86

S121	67	100	33	12	6	6
S122	59	82	36	22	11	11
S123	50	100	0	2	1	1
S124	56	71	42	48	24	24
S125	60	65	56	461	230	231
S126	45	80	10	20	10	10
S127	31	40	22	352	176	176
S128	38	55	20	21	11	10
S129	50	100	0	2	1	1
S130	57	78	35	35	18	17
S131	40	62	19	42	21	21
S132	50	100	0	6	3	3
S133	45	62	28	116	58	58
S134	56	76	35	34	17	17
S135	18	27	10	60	30	30
S136	60	81	38	84	42	42
S137	24	41	7	82	41	41
S138	50	100	0	8	4	4
S139	32	44	21	124	62	62
S140	67	82	51	87	44	43
S141	47	60	34	116	58	58
S142	35	39	24	168	123	45
S143	67	80	53	60	30	30
S144	36	42	30	240	120	120
S145	64	79	49	115	58	57
S146	31	42	20	157	78	79
S147	73	73	0	45	45	0
S148	65	81	49	83	42	41
S149	29	50	12	62	28	34
S150	57	73	42	453	226	227
S151	38	47	30	243	122	121
S152	61	61	0	23	23	0
S153	26	38	14	217	108	109
S154	35	58	13	65	33	32
S155	44	54	34	184	92	92
S156	52	58	47	1088	544	544
S157	60	65	55	110	55	55
S158	52	63	40	424	212	212
S159	40	52	29	89	44	45
S160	34	49	19	145	73	72
S161	52	70	34	88	44	44

S162	57	57	0	14	14	0
S163	35	49	21	221	111	110
S164	36	49	24	113	55	58
S165	33	35	26	104	77	27
S166	36	65	8	74	37	37
S167	35	45	24	142	71	71
S168	37	49	25	160	80	80
S169	26	39	14	236	118	118
S170	32	46	17	163	82	81
S171	42	61	22	36	18	18
S172	41	42	35	145	119	26
S173	43	45	33	141	117	24
S174	28	39	18	263	132	131
S175	41	50	29	115	64	51
S176	49	75	24	49	24	25
S177	35	49	18	63	35	28
S178	72	90	53	39	20	19
S179	66	66	0	148	148	0
S180	43	60	26	109	55	54
S181	40	61	33	90	23	67
S182	34	44	25	204	102	102
S183	33	45	12	48	31	17
S184	33	45	12	48	31	17
S185	36	45	27	536	268	268
S186	53	58	46	213	124	89
S187	35	64	8	23	11	12
S188	44	45	46	72	67	5
S189	69	92	46	52	26	26
S190	38	47	29	341	178	163
S191	49	57	41	616	308	308
S192	32	38	19	56	40	16
S193	33	35	29	72	48	24
S194	30	30	30	64	44	20
S195	70	98	42	118	59	59
S196	31	36	26	804	402	402
S197	61	72	50	59	29	30
S198	35	45	24	353	177	176
S199	26	40	12	101	50	51
S200	30	41	18	283	142	141
Total	***9613***	***12061***	***6212***	***33934***	***17154***	***16780***
Average	***48.065***	***60.305***	***31.06***	***169.67***	***85.77***	***83.900***

Table 6.5 Major Results of Technical Trading Rule's Directional Predictability (before outlier reduction) Subperiod 1: 09/06/1988 - 12/31/1993 (Daily)						
Rules	Predictability %			No of Trades		
	Total	*Buy*	*Sell*	*Total*	*Buy*	*Sell*
S1	60	72	48	85	43	42
S2	36	36	0	22	22	0
S3	28	33	22	86	49	37
S4	25	33	18	160	80	80
S5	33	37	29	387	194	193
S6	24	42	8	49	24	25
S7	26	28	24	296	148	148
S8	78	78	0	32	32	0
S9	60	60	0	260	260	0
S10	39	51	28	94	47	47
S11	24	42	8	49	24	25
S12	26	40	14	87	43	44
S13	29	46	12	49	24	25
S14	33	60	7	30	15	15
S15	20	34	7	59	29	30
S16	50	62	38	84	42	42
S17	24	38	10	97	48	49
S18	74	80	68	382	191	191
S19	67	67	0	33	33	0
S20	45	67	20	11	6	5
S21	70	70	0	61	61	0
S22	50	83	17	24	12	12
S23	50	50	0	16	16	0
S24	60	100	33	5	2	3
S25	67	100	0	3	2	1
S26	50	100	0	4	2	2
S27	60	100	0	5	3	2
S28	0	0	0	0	0	0
S29	51	51	0	37	37	0
S30	56	56	0	43	43	0
S31	100	100	0	25	25	0
S32	32	44	21	96	48	48
S33	33	37	30	329	164	165
S34	36	43	29	262	131	131
S35	44	53	35	170	85	85
S36	74	80	69	70	35	35

S37	46	58	40	166	60	106
S38	23	100	21	109	3	106
S39	58	100	34	167	61	106
S40	69	76	62	74	37	37
S41	47	65	36	151	55	96
S42	46	61	36	155	59	96
S43	46	63	35	155	59	96
S44	0	0	0	0	0	0
S45	36	40	31	361	181	180
S46	75	90	60	20	10	10
S47	27	35	20	121	60	61
S48	67	50	100	3	2	1
S49	52	67	41	29	12	17
S50	24	55	12	37	11	26
S51	67	80	50	9	5	4
S52	26	56	15	35	9	26
S53	29	55	19	38	11	27
S54	56	78	44	75	27	48
S55	74	80	69	70	35	35
S56	37	51	30	148	49	99
S57	58	73	48	110	44	66
S58	47	63	31	53	27	26
S59	59	74	44	83	42	41
S60	47	63	31	53	27	26
S61	100	100	0	9	9	0
S62	85	0	85	20	0	20
S63	92	92	0	12	12	0
S64	86	0	86	21	0	21
S65	75	75	0	4	4	0
S66	43	0	43	14	0	14
S67	0	0	0	1	0	1
S68	90	100	85	29	9	20
S69	88	92	86	33	12	21
S70	50	75	43	18	4	14
S71	100	100	0	1	1	0
S72	100	100	100	3	2	1
S73	67	100	50	3	1	2
S74	100	100	100	4	2	2
S75	86	100	67	7	4	3
S76	75	100	33	8	5	3
S77	33	0	33	3	0	3
S78	100	100	100	13	2	11

S79	88	67	93	17	3	14
S80	44	100	38	9	1	8
S81	50	100	0	2	1	1
S82	80	67	100	5	3	2
S83	50	50	50	4	2	2
S84	100	0	100	1	0	1
S85	75	100	67	4	1	3
S86	75	100	67	4	1	3
S87	67	100	50	3	1	2
S88	54	67	40	71	36	35
S89	32	39	25	167	83	84
S90	44	60	25	9	5	4
S91	43	47	38	289	145	144
S92	67	83	51	83	42	41
S93	78	80	75	899	459	440
S94	43	49	37	267	134	133
S95	51	65	37	103	52	51
S96	42	51	32	151	76	75
S97	55	75	33	31	16	15
S98	75	85	64	67	34	33
S99	82	95	67	38	20	18
S100	86	100	70	21	11	10
S101	69	86	50	13	7	6
S102	55	72	38	49	25	24
S103	31	42	20	87	43	44
S104	31	47	15	39	19	20
S105	51	63	41	114	51	63
S106	28	36	21	181	90	91
S107	38	45	30	354	177	177
S108	46	65	35	48	17	31
S109	26	36	15	133	66	67
S110	48	54	43	369	185	184
S111	42	55	30	99	49	50
S112	54	80	38	13	5	8
S113	29	46	11	56	28	28
S114	28	45	10	40	20	20
S115	27	33	22	117	58	59
S116	40	44	35	288	144	144
S117	34	47	21	165	81	84
S118	70	73	67	197	98	99
S119	56	66	46	139	70	69
S120	25	33	17	93	46	47

S121	75	100	50	8	4	4
S122	67	83	50	12	6	6
S123	0	0	0	0	0	0
S124	0	0	0	0	0	0
S125	63	70	55	200	100	100
S126	38	75	0	8	4	4
S127	31	41	21	181	90	91
S128	44	60	25	9	5	4
S129	0	0	0	1	0	1
S130	62	82	40	21	11	10
S131	25	42	8	24	12	12
S132	0	0	0	1	0	1
S133	40	48	31	58	29	29
S134	56	63	50	16	8	8
S135	15	25	5	39	20	19
S136	62	84	40	50	25	25
S137	20	32	8	50	25	25
S138	50	100	0	6	3	3
S139	30	39	21	66	33	33
S140	72	91	52	46	23	23
S141	47	58	36	66	33	33
S142	37	41	25	90	66	24
S143	80	93	67	30	15	15
S144	0	0	0	0	0	0
S145	68	81	55	63	32	31
S146	27	37	17	93	46	47
S147	79	79	0	24	24	0
S148	73	87	59	45	23	22
S149	29	46	17	31	13	18
S150	53	67	39	199	99	100
S151	40	48	32	120	60	60
S152	75	75	0	8	8	0
S153	20	31	8	117	58	59
S154	35	53	18	34	17	17
S155	49	63	36	93	46	47
S156	49	52	46	531	266	265
S157	43	47	39	76	38	38
S158	49	54	43	243	122	121
S159	44	53	35	39	19	20
S160	35	46	24	74	37	37
S161	59	74	43	46	23	23
S162	50	50	0	6	6	0

S163	36	48	24	99	50	49
S164	26	32	21	57	28	29
S165	24	24	27	49	38	11
S166	39	67	13	31	15	16
S167	36	46	26	78	39	39
S168	37	50	24	84	42	42
S169	21	32	10	119	59	60
S170	27	40	14	86	43	43
S171	35	44	25	17	9	8
S172	27	24	38	63	50	13
S173	29	28	36	58	47	11
S174	23	31	15	135	68	67
S175	43	47	36	58	36	22
S176	52	73	33	23	11	12
S177	37	56	14	30	16	14
S178	74	90	56	19	10	9
S179	65	65	0	78	78	0
S180	39	57	21	56	28	28
S181	34	42	31	47	12	35
S182	27	33	21	78	39	39
S183	26	37	8	31	19	12
S184	26	37	8	31	19	12
S185	36	43	30	258	129	129
S186	53	56	50	116	70	46
S187	44	75	20	9	4	5
S188	43	40	100	37	35	2
S189	77	92	62	26	13	13
S190	36	43	28	128	67	61
S191	48	55	41	312	156	156
S192	28	30	17	29	23	6
S193	29	27	33	35	26	9
S194	22	17	33	32	23	9
S195	73	100	45	62	31	31
S196	28	30	26	390	195	195
S197	64	71	57	14	7	7
S198	36	44	28	173	87	86
S199	21	35	7	53	26	27
S200	27	38	17	154	77	77
Total	***9568***	***11557***	***6369***	***16745***	***8552***	***8193***
Average	***47.840***	***57.785***	***31.845***	***83.725***	***42.760***	***40.965***

Table 6.6 Major Results of Technical Trading Rule's Directional Predictability (before outlier reduction) Subperiod 2: 01/03/1994 to 3/24/1999 (Daily)						
Rules	Predictability %			No of Trades		
	Total	*Buy*	*Sell*	*Total*	*Buy*	*Sell*
S1	50	59	41	74	37	37
S2	59	59	0	27	27	0
S3	25	41	10	89	41	48
S4	26	38	14	153	77	76
S5	38	45	32	349	175	174
S6	28	47	10	39	19	20
S7	34	39	30	264	132	132
S8	70	70	0	27	27	0
S9	61	61	0	248	248	0
S10	52	69	35	91	45	46
S11	28	47	10	39	19	20
S12	38	54	22	73	37	36
S13	33	40	25	40	20	20
S14	36	44	29	33	16	17
S15	27	43	15	56	23	33
S16	32	42	21	114	57	57
S17	25	33	17	81	40	41
S18	72	82	63	262	131	131
S19	71	71	0	28	28	0
S20	64	100	20	11	6	5
S21	72	72	0	47	47	0
S22	55	67	40	11	6	5
S23	52	52	0	29	29	0
S24	100	100	100	4	2	2
S25	50	100	0	2	1	1
S26	33	50	0	3	2	1
S27	75	67	100	4	3	1
S28	50	0	100	2	1	1
S29	61	61	0	36	36	0
S30	61	61	0	38	38	0
S31	100	100	0	70	70	0
S32	36	52	21	85	42	43
S33	34	41	27	334	167	167
S34	36	46	26	238	119	119
S35	49	60	38	160	80	80

S36	57	75	39	47	24	23
S37	29	40	23	175	60	115
S38	28	42	20	144	57	87
S39	41	100	19	157	42	115
S40	66	77	53	61	31	30
S41	40	58	29	148	53	95
S42	41	61	29	151	56	95
S43	38	55	28	151	56	95
S44	25	0	25	4	0	4
S45	40	51	29	369	185	184
S46	67	88	43	15	8	7
S47	43	59	27	111	56	55
S48	20	33	0	5	3	2
S49	32	57	20	44	14	30
S50	24	75	14	45	8	37
S51	73	100	40	11	6	5
S52	23	75	11	43	8	35
S53	24	75	14	45	8	37
S54	32	58	22	98	26	72
S55	57	75	39	47	24	23
S56	27	42	20	161	52	109
S57	46	56	38	92	39	53
S58	56	75	38	32	16	16
S59	54	70	38	74	37	37
S60	56	75	38	32	16	16
S61	73	73	0	22	22	0
S62	75	0	75	44	0	44
S63	88	88	0	26	26	0
S64	85	0	85	46	0	46
S65	43	43	0	7	7	0
S66	43	0	43	30	0	30
S67	25	0	25	4	0	4
S68	74	73	75	66	22	44
S69	88	92	85	72	26	46
S70	43	43	43	37	7	30
S71	25	0	25	4	0	4
S72	75	67	100	4	3	1
S73	67	0	100	3	1	2
S74	0	0	0	1	0	0
S75	56	50	60	16	6	10
S76	81	75	88	16	8	8
S77	22	33	17	9	3	6

S78	76	73	78	38	11	27
S79	91	100	88	47	15	32
S80	58	50	60	24	4	20
S81	25	0	25	4	0	4
S82	85	83	86	13	6	7
S83	38	0	50	8	2	6
S84	50	0	50	2	0	2
S85	86	100	83	7	1	6
S86	60	0	60	5	0	5
S87	0	0	0	4	0	4
S88	52	74	30	61	31	30
S89	39	48	30	182	91	91
S90	71	100	33	7	4	3
S91	40	49	32	272	136	136
S92	56	78	33	73	37	36
S93	81	83	78	904	465	439
S94	44	52	36	264	132	132
S95	56	72	40	100	50	50
S96	35	44	27	155	78	77
S97	73	92	54	26	13	13
S98	69	85	52	51	26	25
S99	69	87	45	26	15	11
S100	67	91	40	21	11	10
S101	76	100	50	17	9	8
S102	61	82	38	33	17	16
S103	49	64	34	88	44	44
S104	28	43	13	29	14	15
S105	40	57	30	113	42	71
S106	30	44	15	175	88	87
S107	42	50	34	309	155	154
S108	43	69	33	61	16	45
S109	26	35	16	125	62	63
S110	53	59	47	360	180	180
S111	45	61	29	98	49	49
S112	65	75	50	20	12	8
S113	37	46	28	51	26	25
S114	33	47	20	30	15	15
S115	31	42	20	113	57	56
S116	35	43	28	233	117	116
S117	35	46	25	130	65	65
S118	67	75	58	171	85	86
S119	57	67	46	122	61	61

S120	36	46	27	74	37	37
S121	50	100	0	4	2	2
S122	56	80	25	9	5	4
S123	67	100	0	3	2	1
S124	57	71	43	47	24	23
S125	59	61	57	255	127	128
S126	55	83	20	11	6	5
S127	31	39	23	165	83	82
S128	33	50	17	12	6	6
S129	0	0	0	0	0	0
S130	67	88	43	15	8	7
S131	56	88	25	16	8	8
S132	50	100	0	4	2	2
S133	48	74	22	54	27	27
S134	63	100	25	16	8	8
S135	23	27	18	22	11	11
S136	62	82	41	34	17	17
S137	25	50	0	32	16	16
S138	50	100	0	2	1	1
S139	32	46	18	56	28	28
S140	62	75	47	39	20	19
S141	52	67	38	48	24	24
S142	34	37	26	77	54	23
S143	60	73	47	30	15	15
S144	0	0	0	0	0	0
S145	62	80	44	50	25	25
S146	38	50	26	61	30	31
S147	70	70	0	20	20	0
S148	59	79	39	37	19	18
S149	30	53	7	30	15	15
S150	61	77	45	250	125	125
S151	36	45	27	120	60	60
S152	47	47	0	15	15	0
S153	32	46	18	97	48	49
S154	32	56	7	31	16	15
S155	44	61	28	113	56	57
S156	48	52	44	418	209	209
S157	43	38	48	42	21	21
S158	45	53	37	172	86	86
S159	37	52	22	46	23	23
S160	33	51	15	69	35	34
S161	47	72	22	36	18	18

S162	57	57	0	7	7	0
S163	33	49	17	117	59	58
S164	43	62	26	53	26	27
S165	40	45	27	53	38	15
S166	34	63	5	38	19	19
S167	31	42	19	62	31	31
S168	35	46	24	74	37	37
S169	32	46	18	111	56	55
S170	38	56	19	72	36	36
S171	0	0	0	0	0	0
S172	52	56	31	79	66	13
S173	54	58	31	80	67	13
S174	35	48	21	123	62	61
S175	39	56	22	54	27	27
S176	44	75	15	25	12	13
S177	34	42	23	32	19	13
S178	75	90	60	20	10	10
S179	68	68	0	68	68	0
S180	43	62	24	51	26	25
S181	37	46	32	41	13	28
S182	39	51	27	126	63	63
S183	41	55	17	17	11	6
S184	41	55	17	17	11	6
S185	35	45	24	266	133	133
S186	53	62	41	93	52	41
S187	23	50	0	13	6	7
S188	48	50	0	33	32	1
S189	67	100	33	24	12	12
S190	40	49	30	207	108	99
S191	49	59	40	294	147	147
S192	40	53	20	25	15	10
S193	36	48	20	36	21	15
S194	38	45	25	32	20	12
S195	69	96	41	54	27	27
S196	35	42	27	396	198	198
S197	62	76	48	42	21	21
S198	33	46	21	174	87	87
S199	30	43	17	46	23	23
S200	31	42	21	127	64	63
Total	***9435***	***11441***	***5961***	***16216***	***8188***	***8027***
Average	***47.175***	***57.205***	***29.805***	***81.08***	***40.94***	***40.135***

Chapter 7

Distributional properties and belief of technical trading rules

There is a certain belief in the financial markets in respect of technical trading rules that is intriguing, but not so well known, and yet is profound and fundamental in the study of technical trading rules. In this chapter, we shall use the empirical results generated so far and see whether our evidence coincide with that of the financial traders' belief.

7.1 Distributional properties of technical trading rules

The distributional properties of directional predictabilities generated here reveal interesting information. Firstly, tables 7.2 and 7.3 and figures 7.1 and 7.2 show positively skewed distributions of directional predictabilities.

Tables 7.2 and 7.3 also show that sell signals' directional predictabilities distribution is positively skewed, and with higher kurtosis than a small negatively skewed buy signals. This suggests that there is a distributional difference between buy signals and sell signals. The implication is that the market is not efficient in the context of technical trading rules in general, since in an efficient market, there should not be a difference between the buy and sell signals.

7.2 Traders' belief

We and several authors, such as Rotella (1992), believe that most successful financial traders (practitioners of technical analysis) have an average technical trading rules' directional predictability in the region of 25% to 50%. Smith (2001) and Conway (1996) have a narrower range of 35% to 40% and 30% to 40% respectively. These ranges roughly coincide with the mode of 35% directional predictability for the total (buy and sell) conditional mean distribution generated here (please refer to table 7.1).

This lower than 50% predictability of rules believed to be used by successful financial traders is an intriguing issue under further investigation, as it implies a net profitability despite a lower than 50% directional predictability! Table 7.1 shows that 60 percent of the rules are within the region of 25% to 50% directional predictability. In other words, 60 percent for a quarter or one-fourth or 25 percent of the range is a relatively high area of concentration.

Table 7.1 Mode and fraction of technical trading rules within the range of 25% to 50% predictability for the entire period (figures in the parentheses are before outlier reduction).

	Total	Buy only	Sell only
Mode	35 (35)	45 (100)	31 (0)
Fraction	0.60 (0.57)	0.43 (0.37)	0.48 (0.43)

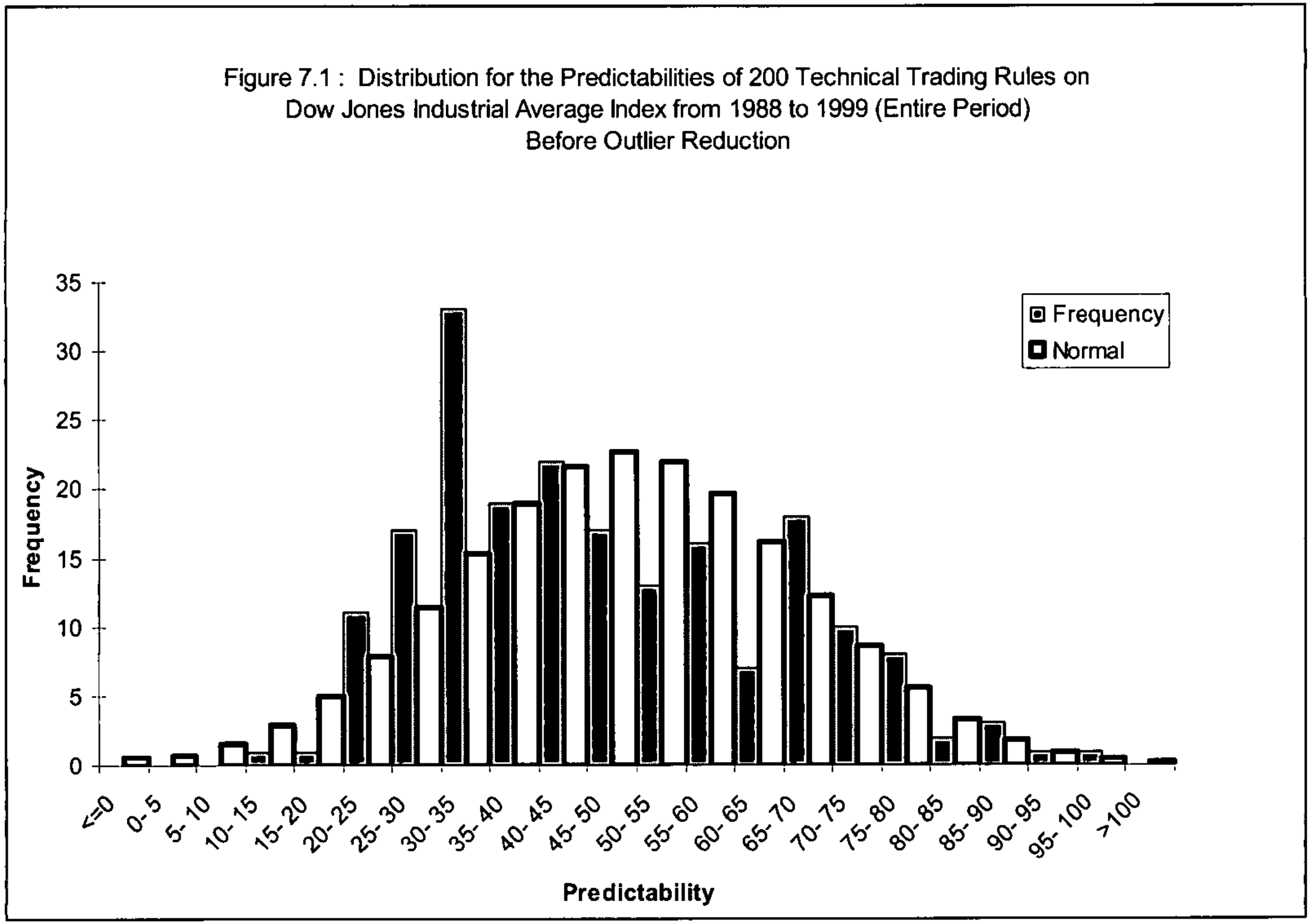


Figure 7.1 : Distribution for the Predictabilities of 200 Technical Trading Rules on
Dow Jones Industrial Average Index from 1988 to 1999 (Entire Period)
Before Outlier Reduction
Frequency
Normal
Frequency
35
30
25
20
15
10
5
0
<=0
0-5
5-10
10-15
15-20
20-25
25-30
30-35
35-40
40-45
45-50
50-55
55-60
60-65
65-70
70-75
75-80
80-85
85-90
90-95
95-100
>100
Predictability

Figure 7.2 : Distribution for the Predictabilities of 200 Technical Trading Rules on Dow Jones Industrial Average Index from 1988 to 1999 (Entire Period) After Outlier Reduction

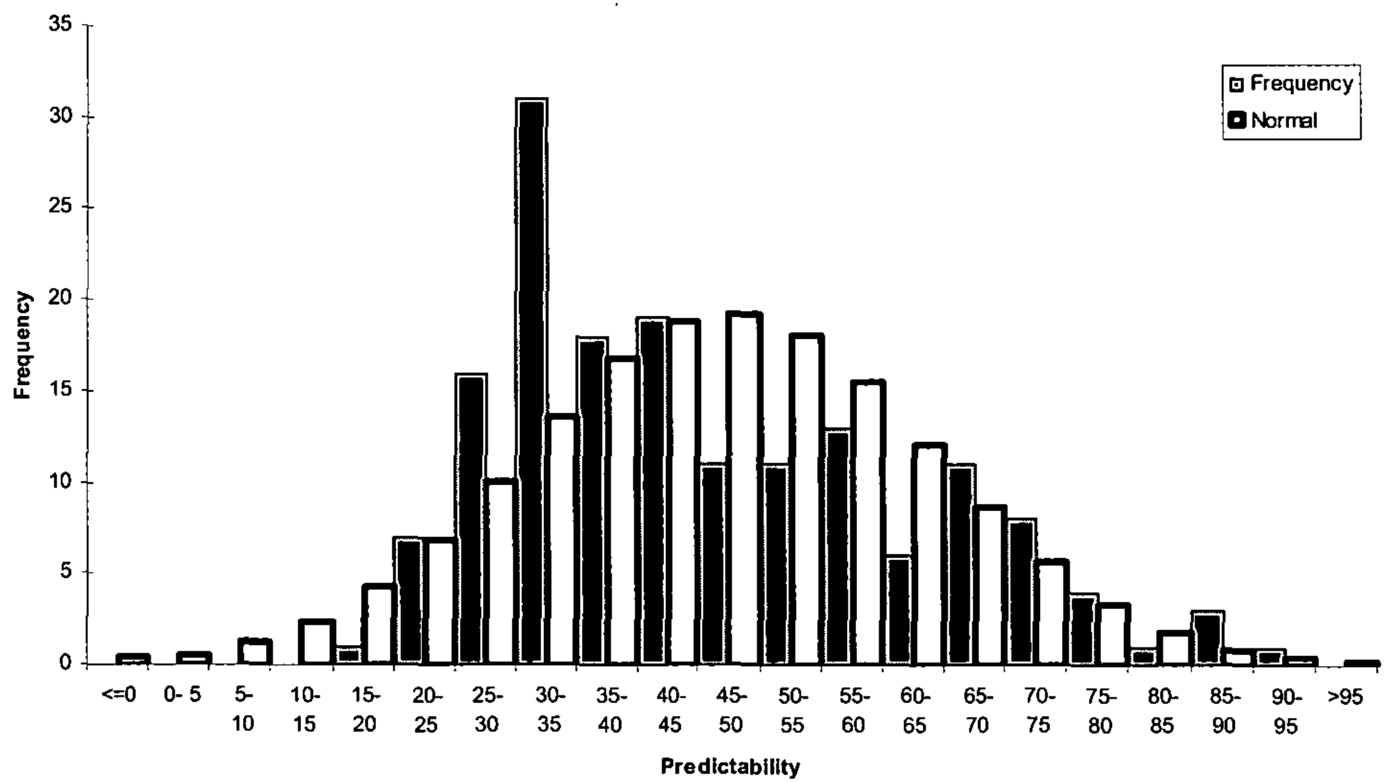


Table 7.2 : Summary Statistics for Predictability of Total, Buy Only and Sell Only Signals Before Outlier Reduction

	Total Entire Period	Total Subperiod 1	Total Subperiod 2	Buy Entire Period	Buy Subperiod 1	Buy Subperiod 2	Sell Entire Period	Sell Subperiod 1	Sell Subperiod 2
Count	200.000	200.000	200.000	200.000	200.000	200.000	200.000	200.000	200.000
Mean	48.065	47.840	47.175	60.305	57.785	57.205	31.060	31.845	29.805
Median	44.500	45.500	43.500	60.000	55.500	56.000	28.000	30.000	26.000
Mode	35.000	50.000	43.000	100.000	100.000	0.000	0.000	0.000	0.000
Standard deviation	17.479	22.758	18.769	22.517	26.767	25.047	21.550	24.911	22.900
Minimum	14.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Range	86.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Variance	305.498	517.934	352.276	507.027	716.451	627.360	464.398	620.564	524.419
First quartile	34.000	29.750	34.000	45.000	40.000	45.000	17.000	14.000	17.000
Third quartile	60.250	65.500	60.250	76.250	78.000	75.000	42.000	43.250	40.000
Interquartile range	26.250	35.750	26.250	31.250	38.000	30.000	25.000	29.250	23.000
Mean absolute deviation	14.660	18.377	15.279	18.004	21.814	19.105	16.441	19.284	16.930
Skewness	0.526	0.291	0.240	-0.205	-0.183	-0.479	0.850	0.849	1.084
Kurtosis	-0.520	-0.264	0.143	0.219	-0.407	0.355	0.734	0.501	1.384

Table 7.3 : Summary Statistics for Predictability of Total, Buy Only and Sell Only Signals After Outlier Reduction

	Total Entire Period	Total Subperiod 1	Total Subperiod 2	Buy Entire Period	Buy Subperiod 1	Buy Subperiod 2	Sell Entire Period	Sell Subperiod 1	Sell Subperiod 2
Count	161.000	132.000	134.000	130.000	90.000	80.000	126.000	83.000	85.000
Mean	46.410	42.650	44.701	54.931	51.933	53.600	33.262	33.988	31.388
Median	43.000	39.000	40.000	49.500	48.500	51.000	30.000	32.000	28.000
Mode	35.000	26.000	32.000	45.000	33.000	61.000	31.000	21.000	27.000
Standard deviation	16.530	16.841	14.854	15.148	16.501	11.771	18.013	15.365	15.600
Minimum	18.000	15.000	23.000	27.000	24.000	33.000	7.000	7.000	10.000
Maximum	91.000	88.000	91.000	98.000	100.000	83.000	90.000	75.000	88.000
Range	73.000	73.000	68.000	71.000	76.000	50..000	83.000	68.000	78.000
Variance	273.256	283.633	220.647	229.460	272.288	138.547	324.451	236.085	243.359
First quartile	33.000	28.000	34.000	44.000	39.25	45.000	21.000	21.500	21.000
Third quartile	57.000	53.250	55.500	65.750	64.500	61.000	42.000	42.000	38.000
Interquartile range	24.000	25.250	21.500	21.750	25.250	16.000	21.000	20.500	17.000
Mean absolute deviation	13.823	13.918	12.132	12.784	13.658	9.675	13.642	12.036	11.143
Skewness	0.664	0.698	0.917	0.613	0.532	0.651	1.179	0.672	1.707
Kurtosis	-0.402	-0.422	0.348	-0.431	-0.388	-0.252	1.334	0.135	3.487

Chapter 8

Downtrend, volatility and predictability

8.1 In the present of a downtrend: surprises is the word

It has been five years since we last performed the empirical tests as presented in this thesis. During the last five years, the Dow Jones Industrial Index has somewhat moved from a predominantly uptrend through out the 1980s and 1990s to a predominantly mixture of downtrend and sideway movement (please refer to figures 8.1, 8.2, and 8.3; and table 8.1). In view of the changes in the trend movement, we seize the opportunity to test empirically once again to see how a downtrend and sideway movements would affect the performance of technical trading rules in general. The major results are reported in tables 8.2 and the details are in 8.5, while the distributional properties of directional predictability are presented in figure 8.4. The distributional properties exhibit the typical positively skewed feature coupled with an upper or right fat tail. Although the stock exchange no longer provides volume data since our last undertaking, we still feel it is a worthwhile exercise given that there are only 13 technical trading rules out of a total 200 that incorporate volume as the sole or one of their inputs in generating trading signals.

The results of directional predictability for before and after outlier reduction are better for subperiod 3. In the case of after outlier reduction, subperiod 3 is 10.69 percent better than subperiod 2. More specifically, they are 49.48% after outliers' reduction, and 50% before outlier reduction. This is not quite within our expectation as theoretically, and based on our observations, volatility tends to be more pronounced in a downtrend market and as such, technical trading may not be able to predict that well as compared to in an uptrend market which is usually less volatile. In other words, the signals to noise ratio should be comparatively lower in a downtrend. Again, our observation is subject to empirical verification. Looking at the standard deviations as presented in the summary statistics of table 8.1, subperiod 3 is 30 percent more than subperiod 2, and subperiod 2 is 14.26 percent more than subperiod 1. These also correspond to the proportionate increase of directional predictability of subperiod 3, which is 10.69 percent more predictable than subperiod 2, and subperiod 2 is 4.67 percent more predictable than subperiod 1. Thus:

(a) Is directional predictability a function of volatility such as variance or standard deviation?

It may not seem intuitive at first glance; but on second thought, it appears to be rational. Imagine: a small movement in either directions may not provide comfort and confirmation for a clear signal to be generated by a technical trading rule as it requires the average of a few data points in the case of a moving average rule. Therefore, the more volatile (in any one direction), the clearer is the signal. This goes back to our earlier argument that volatility provides profit opportunity. Obviously more empirical tests are needed before any conclusion is drawn, and it definitely merits immediate attention!

On the other hand, whether the exclusion of a few (13) rules that incorporate volume for forecasting is the answer to the slightly higher results does not seems to be the case, as there is already evidence between subperiods 1 and 2.

8.2 Dependency: autocorrelation

We also take the opportunity to test out dependency by employing the usual autocorrelation test for subperiod 3, and the results are presented in tables 8.3 and 8.4; and figure 8.5. The log returns autocorrelations for the first 30 lags are different from subperiod 1and 2; although the test windows are almost of the same size in all three subperiods (please refer to table 8.6). The only exception is that, like many other financial time series, the squared and absolute returns are more auto-correlated than the actual returns as in the other two subperiods. It is worth mentioning that the first lag is negatively autocorrelated which also coincide with a predominantly down trend time series of subperiod 3.

In general, the sum of log returns autocorrelation is negative (table 8.7). There are two possible explanations for this phenomenon. (a) The "panic" factor may be more influential than the "greed" factor. For instance, good news may not have a bigger impact than bad news. In other words, market participants are more averse to risks (losses) than to the prospect of gaining (profit). (b) The "cut loss" rule imposed by institutional and professional traders and investors; provide a greater influence for the negative autocorrelation.

Table 8.6 Lags of autocorrelations significant at the 5% level

Subperiods	Signs and lags
1	-7, -25
2	-3, +9, -11, -16, -25
3	-5, +12,

Table 8.7 Sum (total) of first 30 lags autocorrelations

	Log returns (ln R)	ln R without signs	Squared ln R	Absolute ln R
Subperiod 1	-0.1842	0.6325	0.7535	1.6872
Subperiod 2	-0.1191	0.8526	2.2033	3.4311
Subperiod 3	-0.1800	0.7565	2.7966	3.8065

8.3 In support of P.D. Praetz (1976) and R.J. Sweeney (1986)

Our empirical results here support the argument put forwarded by Praetz (1976) and Sweeney (1986) that buy-and-hold strategy is not an appropriate benchmark or yardstick to judge the performance of technical trading rules. That is, although the buy-and-hold strategy will provide a negative return in a downtrend market, technical trading rules will continue to capture the financial time series in the present of a downtrend market.

8.4 Predicaments of expected value in the present of a large *N*

8.4.1 Expected value

Although results are already interesting, and philosophical question discussed; the results also give raise to the questions of:

(a) Whether technical trading rules react indifferently to different trend movements such as up, down and sideway, or

(b) They respond differently to different trend movements; but the effects are diversified away in the presence of a large number? For instance, some rules may perform better in a downtrend, some in an uptrend and some in a sideway movement. Thus, the averaging effects of a portfolio of 200 heterogeneous technical trading rules may just cancel out the effect of each other, or

(c) The subperiod 3 is not a typical severe downtrend, but more like a sideway movement with a down drift.

On closer examination, there appears to be some differences on directional predictability for most of the technical trading rules between subperiods. Based on this, the second theoretical explanation may be more appropriate. This further gives raise to another philosophical question:

(d) Should one undertake a similar exercise of a large portfolio of technical trading rules as what we have done here? Given that the results may invariably end up near to the 50% mark for directional predictability.

If we do, the consequence is, in retrospect, obvious. That is to expect the expected value of close to 50% directional predictability if one is to undertake the same exercise as what we have done here. Therefore, a test on a particular group of technical trading rules and then compare the results with another group of technical trading rules appears to be a fruitful follow up after this project.

In practical terms, one could use different and large number of technical trading rules for diversification (for instance, Markellos, 2004) and stabilization purposes.

Table 8.1 : Summary Statistics of Daily DJIAI, 1988 to 2004 (Subperiod1,2 and 3)

		In R sp1	In R sp2	In R sp3
	Count	1350.000	1311.000	1393.000
	Sum	59.759	94.519	0.981
	Mean	0.044	0.072	0.001
	Median	0.055	0.080	0.011
	Standard deviation	0.823	0.941	1.222
	Minimum	-7.155	-7.455	-7.396
	Maximum	4.466	4.861	6.155
	Range	11.622	12.315	13.551
	Variance	0.678	0.885	1.494
	First quartile	-0.388	-0.381	-0.692
	Third quartile	0.476	0.601	0.677
	Interquartile range	0.864	0.982	1.368
	Mean absolute deviation	0.588	0.666	0.907
	Skewness	-0.495	-0.657	-0.033
	Kurtosis	6.317	6.886	2.751

Table 8.2: Directional predictabilities of 200 technical trading rules

09/06/1988 - 10/15/2004 (Daily)

Subperiods 1,2 and 3

After Outlier Reduction (< 30 trades and 0% and 100%)

Summary measures for Total Signals Only after outlier reduction				
	Period: 1988 to 2004	Total Sub-Period 1	Total Sub-Period 2	Total Sub-Period 3
	Count	133.000	134.000	130.000
	Sum	5680.000	5990.000	6382.000
	Mean	42.707	44.701	49.092
	Median	39.000	40.000	46.000
	Standard deviation	16.790	14.854	17.070
	Minimum	15.000	23.000	17.000
	Maximum	88.000	91.000	98.000
	Range	73.000	68.000	81.000
	Variance	281.891	220.647	291.371
	First quartile	28.000	34.000	37.000
	Third quartile	53.000	55.500	58.000
	Interquartile range	25.000	21.500	21.000
	Mean absolute deviation	13.874	12.132	13.265
	Skewness	0.690	0.917	0.897
	Kurtosis	-0.419	0.348	0.567

Table 8.3 : Autocorrelations from Lag 1 to Lag 30 of DJIAI
From 1999 to 2004 (Subperiod 3)

Autocorrelations for ln R sp3			*Autocorrelations for sq ln R sp3*			*Autocorrelations for I ln R I sp3*		
Lag	Autocorr	StErr	Lag	Autocorr	StErr	Lag	Autocorr	StErr
1	-0.0206	0.0268	1	**0.0833**	0.0268	1	**0.0982**	0.0268
2	-0.0172	0.0268	2	**0.1736**	0.0268	2	**0.2015**	0.0268
3	-0.0040	0.0268	3	**0.2877**	0.0268	3	**0.2071**	0.0268
4	0.0326	0.0268	4	**0.0713**	0.0268	4	**0.1265**	0.0268
5	**-0.0537**	0.0268	5	**0.1697**	0.0268	5	**0.1940**	0.0268
6	-0.0111	0.0268	6	**0.1158**	0.0268	6	**0.1181**	0.0268
7	-0.0243	0.0268	7	**0.1455**	0.0268	7	**0.1938**	0.0268
8	0.0319	0.0268	8	**0.1314**	0.0268	8	**0.1874**	0.0268
9	-0.0173	0.0268	9	**0.0938**	0.0268	9	**0.1380**	0.0268
10	0.0071	0.0268	10	**0.1318**	0.0268	10	**0.1627**	0.0268
11	-0.0506	0.0268	11	**0.1120**	0.0268	11	**0.1723**	0.0268
12	**0.0597**	0.0268	12	**0.1190**	0.0268	12	**0.1580**	0.0268
13	0.0188	0.0268	13	**0.0947**	0.0268	13	**0.1284**	0.0268
14	-0.0070	0.0268	14	**0.0748**	0.0268	14	**0.1148**	0.0268
15	-0.0311	0.0268	15	0.0492	0.0268	15	**0.0942**	0.0268
16	0.0453	0.0268	16	**0.0826**	0.0268	16	**0.1401**	0.0268
17	-0.0016	0.0268	17	0.0479	0.0268	17	**0.0988**	0.0268
18	-0.0181	0.0268	18	**0.1001**	0.0268	18	**0.1194**	0.0268
19	-0.0470	0.0268	19	**0.0564**	0.0268	19	**0.1229**	0.0268
20	-0.0282	0.0268	20	**0.0748**	0.0268	20	**0.1196**	0.0268
21	-0.0118	0.0268	21	**0.0896**	0.0268	21	**0.1057**	0.0268
22	-0.0254	0.0268	22	0.0533	0.0268	22	**0.0826**	0.0268
23	0.0037	0.0268	23	0.0285	0.0268	23	**0.0853**	0.0268
24	0.0123	0.0268	24	0.0128	0.0268	24	0.0516	0.0268
25	-0.0475	0.0268	25	**0.0755**	0.0268	25	**0.1096**	0.0268
26	-0.0309	0.0268	26	0.0459	0.0268	26	**0.0985**	0.0268
27	0.0135	0.0268	27	0.0327	0.0268	27	**0.0735**	0.0268
28	0.0164	0.0268	28	**0.1199**	0.0268	28	**0.1112**	0.0268
29	0.0470	0.0268	29	0.0277	0.0268	29	**0.0756**	0.0268
30	-0.0209	0.0268	30	**0.0953**	0.0268	30	**0.1172**	0.0268

Table 8.4 : Sum of First 30 lags autocorrelations for DJIAI
From 1999 to 2004 (Subperiod 3)

Lag	Autocorr ln R	ln R Absolute value	Autocorr sq ln R	sq ln R Absolute value	Autocorr I ln R I	I ln R I Absolute value
1	-0.020555898	0.020555898	0.083284918	0.083284918	0.098172623	0.098172623
2	-0.017213321	0.017213321	0.173552722	0.173552722	0.201546248	0.201546248
3	-0.003978096	0.003978096	0.287698414	0.287698414	0.207056022	0.207056022
4	0.032590112	0.032590112	0.071262447	0.071262447	0.126510047	0.126510047
5	-0.053739113	0.053739113	0.169716292	0.169716292	0.193962794	0.193962794
6	-0.011060535	0.011060535	0.115849098	0.115849098	0.118114375	0.118114375
7	-0.024271999	0.024271999	0.145484336	0.145484336	0.193780343	0.193780343
8	0.031885572	0.031885572	0.131366559	0.131366559	0.18736092	0.18736092
9	-0.017303015	0.017303015	0.09380065	0.09380065	0.138014893	0.138014893
10	0.007149624	0.007149624	0.131771729	0.131771729	0.162728284	0.162728284
11	-0.050639898	0.050639898	0.111995837	0.111995837	0.172278321	0.172278321
12	0.059702967	0.059702967	0.118958914	0.118958914	0.158008077	0.158008077
13	0.018800307	0.018800307	0.094737819	0.094737819	0.128424825	0.128424825
14	-0.006959628	0.006959628	0.074846308	0.074846308	0.114834767	0.114834767
15	-0.031140139	0.031140139	0.049155199	0.049155199	0.09419832	0.09419832
16	0.045285362	0.045285362	0.08258958	0.08258958	0.140061516	0.140061516
17	-0.001551169	0.001551169	0.047871323	0.047871323	0.098774438	0.098774438
18	-0.018081959	0.018081959	0.100096805	0.100096805	0.119365338	0.119365338
19	-0.047008217	0.047008217	0.056382398	0.056382398	0.1229369	0.1229369
20	-0.028249666	0.028249666	0.074790596	0.074790596	0.11956861	0.11956861
21	-0.011790903	0.011790903	0.089601826	0.089601826	0.10566535	0.10566535
22	-0.025408226	0.025408226	0.053337027	0.053337027	0.08257392	0.08257392
23	0.003679911	0.003679911	0.028535757	0.028535757	0.085290092	0.085290092
24	0.012292489	0.012292489	0.012824195	0.012824195	0.051638174	0.051638174
25	-0.047475409	0.047475409	0.075508467	0.075508467	0.109619774	0.109619774
26	-0.030864564	0.030864564	0.045942827	0.045942827	0.098490719	0.098490719
27	0.013482033	0.013482033	0.03271868	0.03271868	0.073546255	0.073546255
28	0.016371568	0.016371568	0.119861215	0.119861215	0.111183244	0.111183244
29	0.047016117	0.047016117	0.027733587	0.027733587	0.07559745	0.07559745
30	-0.020918921	0.020918921	0.095313132	0.095313132	0.117247181	0.117247181
	-0.179954612	0.756466737	2.796588656	2.796588656	3.806549824	3.806549824

Table 8.5 : Performance Summary on Daily DJIAI 03/25/1999 to 10/15/2004 Sub Period 3, After Outlier Reduction (< 30 trade and 0% and 100%) *(No Volume Rules)*				
No	Systems	% Profitable *Total*	No of Trades *Total*	Profit Factor *Total*
1	123 Reversal	63	90	1.16
2	Adaptive Mov Avg	28	167	1.11
3	AMA	36	391	1.08
4	Aztec Real Oil	38	39	1.04
5	B. Williams 19	49	280	1.62
6	Bottom Fishing	47	36	0.69
7	Buy Mon, 1400 stXMOC	52	269	1.18
8	CCI Avg. Crossover	48	101	1.24
9	Channel Breakout	38	39	1.04
10	Channel Brk IntraBar	48	73	1.34
11	Channel Brk On Close	44	55	0.78
12	Channel Brk Weighted	47	51	0.76
13	Conner 19	27	51	0.93
14	Consecutive Closes	43	89	0.92
15	DeTrend	26	105	0.78
16	Dinapoli 5	71	242	1.15
17	Derivative MA	44	36	0.73
18	Dunnigan ST	51	51	0.63
19	EZ Bonder	45	55	0.90
20	Generation 1197	50	42	1.15
21	Generation 1723	51	43	1.33
22	GM2.% R (20/80)Xover	68	73	1.06
23	GM2.% R(20/80)E/X/Chg	38	213	0.99
24	GM2.% R (20/80) Stop/MA	37	160	1.10
25	GM2.% R (20/80) w/Stops	74	257	1.10
26	GM2.CCI(+/-) CrossOver	60	63	1.12
27	GM2.CCI(+/-) XO/ Exchg	38	173	0.84
28	GM2.CCI(+/-) XO/ ExMAV	36	175	0.85
29	GM2.CCI(+/-) XO/Stops	35	175	0.85
30	GM2.GenOsc/Mov.Avg	35	399	0.96
31	GM2.GenOsc/Thresh/MA	74	35	1.66
32	GM2.Parabol.SAR.Xover	37	111	0.82
33	GM2.ROC/Xover/Stops	40	62	0.85
34	GM2.StocD/Xover/Stop	47	113	0.85
	Page Total	1565	4314	34.61

No	Systems	% Profitable *Total*	No of Trades *Total*	Profit Factor *Total*
35	GM2.Stock Cross Over	68	73	1.06
36	GM2.Stock/XO/Stop/MA	35	197	0.88
37	GM2.Stock/Xover/Stop	52	118	0.97
38	GM2.Trix En/Ex-chng	58	45	1.13
39	GM2.Trix En/Ex-mavg	49	75	0.45
40	GM2.Trix Stops-chng	58	45	1.13
41	GM3.All%D Long	80	51	0.54
42	GM3.All%D Short	88	59	1.40
43	GM3.All CCI Long	92	51	2.30
44	GM3.All CCI Short	87	63	1.00
45	GM3.All MFI Long	98	49	0.00
46	GM3.All with % D	85	110	0.90
47	GM3.All with CCI	89	114	1.55
48	GM3.All with MFI	98	49	0.00
49	GM3.Harami & %D	87	71	0.68
50	GM3.Harami & CCI	91	81	1.54
51	GM4.DirMov. ROC/MA	48	62	0.68
52	GM4.DirectMove ROC	35	176	1.03
53	GM4.GenOSC w/Mavg	35	320	0.79
54	GM4.GenOSC w/thr & MAV	63	72	0.81
55	GM4.GenOSC w/thresh	77	920	0.87
56	GM4.LinearTrend	40	292	0.92
57	GM4.LinTrend W/MAVG	49	95	0.60
58	GM4.LinTrend W/E/X/ch	45	170	0.91
59	GM4.MACD (True)	57	35	0.96
60	GM4.Morris Db1MomOsc	65	52	1.02
61	GM4 Morris Mstr Tradr	61	31	1.28
62	GM4.SKST/MA/Bands	66	41	1.29
63	GM4.SksTd w/MAVg	43	94	1.12
64	GM4.Triple MA in Sync	17	46	0.46
65	GM6.83 - CCI+100/-100	41	123	1.03
66	GM6.83 - CCI ZeroCross	34	175	0.87
67	GM6.83 - SwingLineCross	37	355	1.15
68	GM6.86 - RSI Quanlity	28	141	1.01
69	GM6.87 - EnhancedIndex	49	397	0.99
70	GM6.88 - MACD - MOTrader	42	107	0.88
	Page Total	2147	4955	34.20

No	Systems	% Profitable *Total*	No of Trades *Total*	Profit Factor *Total*
71	GM6.89 - Channel - 8	41	71	0.78
72	GM6.89 - Channel - 12	43	47	0.82
73	GM6.89 - Volatility	32	155	1.01
74	GM7.90 - Shrt Sigs DJI	66	172	0.97
75	GM7.91 - %M and StdDev	54	102	0.87
76	GM7.91 - %M Zero Cross	34	85	0.79
77	GM7.91 - Double Stoc	62	47	1.36
78	GM7.91 - PivotPNt Fast	58	373	1.09
79	GM7.91 - Var.MA Cross	35	164	0.70
80	GM8.92 - DM Trade Model	18	33	0.29
81	GM8.92 - Pring KST XO	45	56	1.55
82	GM8.92 - TRIX MO System	72	43	2.03
83	GM8.92 - TRIX System	35	43	0.60
84	GM8.93 - Coppock System	37	57	1.25
85	GM8.93 - DYRimpliedRsk	67	79	1.31
86	GM8.93 - Offset MO Sys	58	62	1.72
87	GM9.94 - Hybrid System	60	43	0.86
88	GM9.95 - Bottom Fisher	60	50	0.64
89	GM9.95 - CCI OXOver	35	81	0.81
90	GM9.95 - Modified VIX	60	50	1.07
91	GM9.95 - T & N	25	32	0.56
92	GM9.95 - UD% Price chry	59	323	0.92
93	HiHo Silver	23	127	0.88
94	Intermarket Mov Avg	38	115	1.46
95	Intermarket one	54	592	1.19
96	Intermarket three	54	76	1.30
97	Intermarket two	52	234	1.07
98	JJMBook.Four%Model	29	107	0.80
99	Kase 30	46	80	1.38
100	Key Reversal Major	68	47	1.50
101	MACD	32	111	0.93
102	Momentum First	42	55	1.18
103	Mov Avg x2 20	27	79	0.58
104	Mov Avg - Supp/ Res	45	55	0.86
105	Mov Avg (3) Cross Over	42	64	1.24
106	Mov Avg Cross Over	46	71	1.47
107	Neeley 31	38	124	1.21
108	NMP	47	73	1.32
	Page Total	1739	4178	40.37

No	Systems	% Profitable *Total*	No of Trades *Total*	Profit Factor *Total*
109	One Night Stand	51	75	1.01
110	One Night Stand (TK)	53	72	1.23
111	Parabolic	40	117	1.13
112	Pathfinder Currency	47	59	1.32
113	Range Breakout	54	112	0.30
114	RSI	53	77	0.81
115	RSRatio MACD	43	44	0.49
116	S&P 500	43	53	0.63
117	Saidenberg 30	39	212	0.94
118	Simple Futures MA	28	32	0.26
119	Simple Futures MA_Q	28	32	0.26
120	Stochastic Crossover	33	286	0.90
121	Stochastic S&C	52	126	0.88
122	Sys Implementation	33	33	0.81
123	TCBR	36	387	1.04
124	TRIX System S&C	44	323	1.12
125	Turtle P/L Filt +10 wk	33	33	0.39
126	Volitility Breakout	39	451	1.38
127	Wagner 31	61	56	1.22
128	Weighted Avg. Crossover	35	176	0.89
129	William 19	53	45	1.22
130	XAverage Crossover	33	133	1.05
	Page Total	931	2934	19.28
	Grand Total	6382	16381	128
	Total Average	49.09	126.01	0.99

Figure 8.1 Daily Dow Jones Industrial Average Index
25th March 1999 to 15th October 2004
(Subperiod 3)

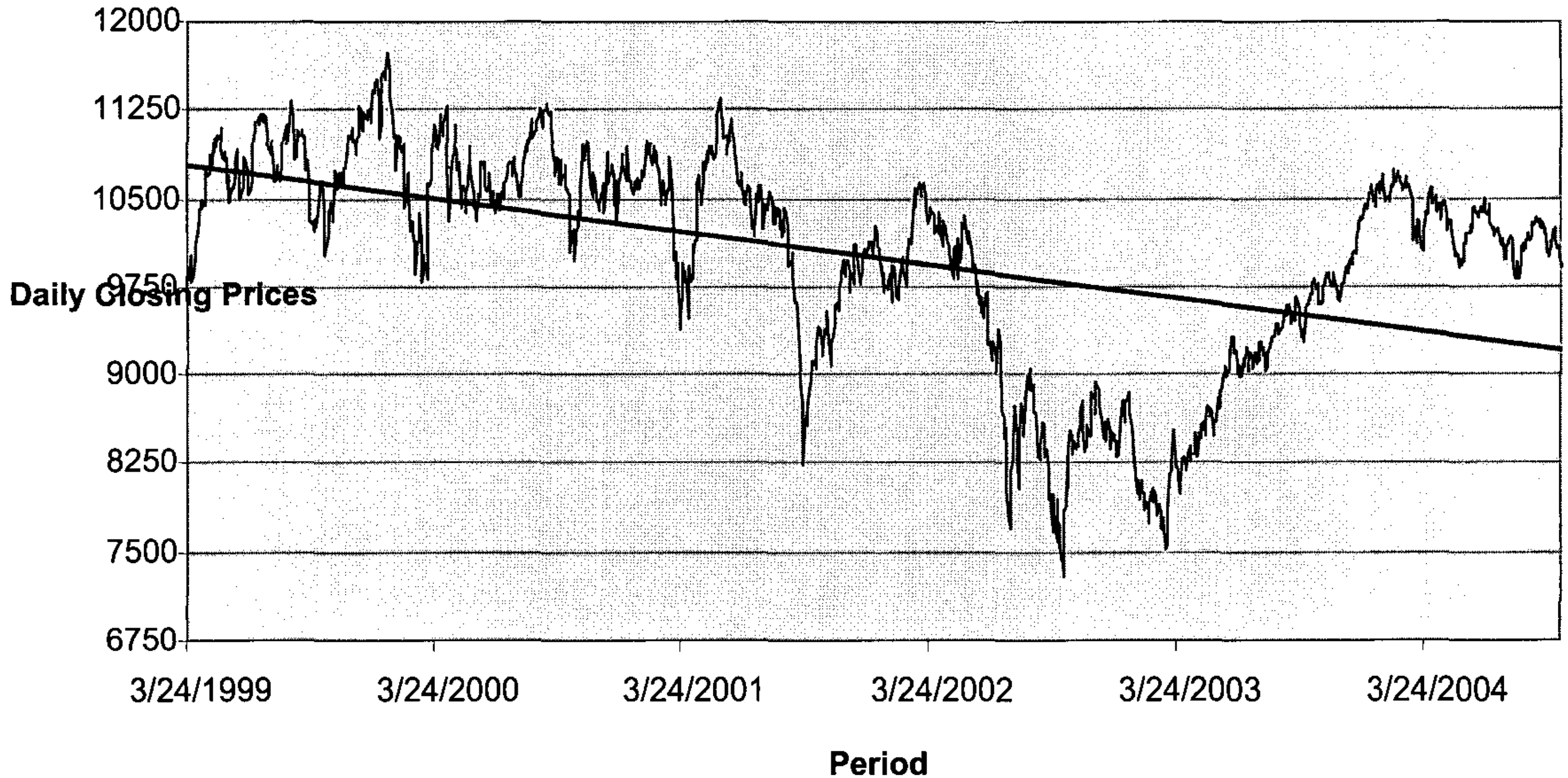
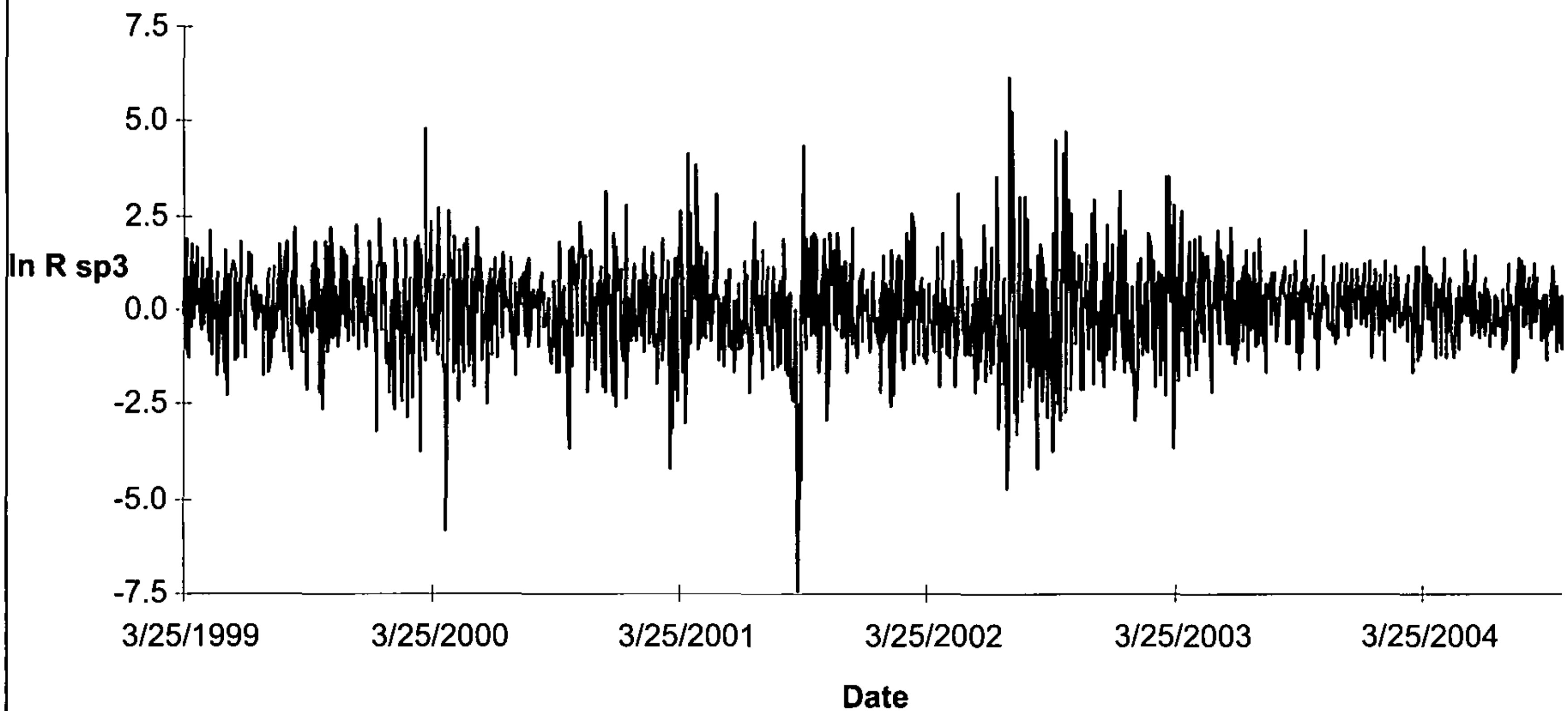


Figure 8.2: Natural Log Returns of Dow Jones Industrial Average Index
25th March 1999 to 15 October 2004
(Subperiod 3)



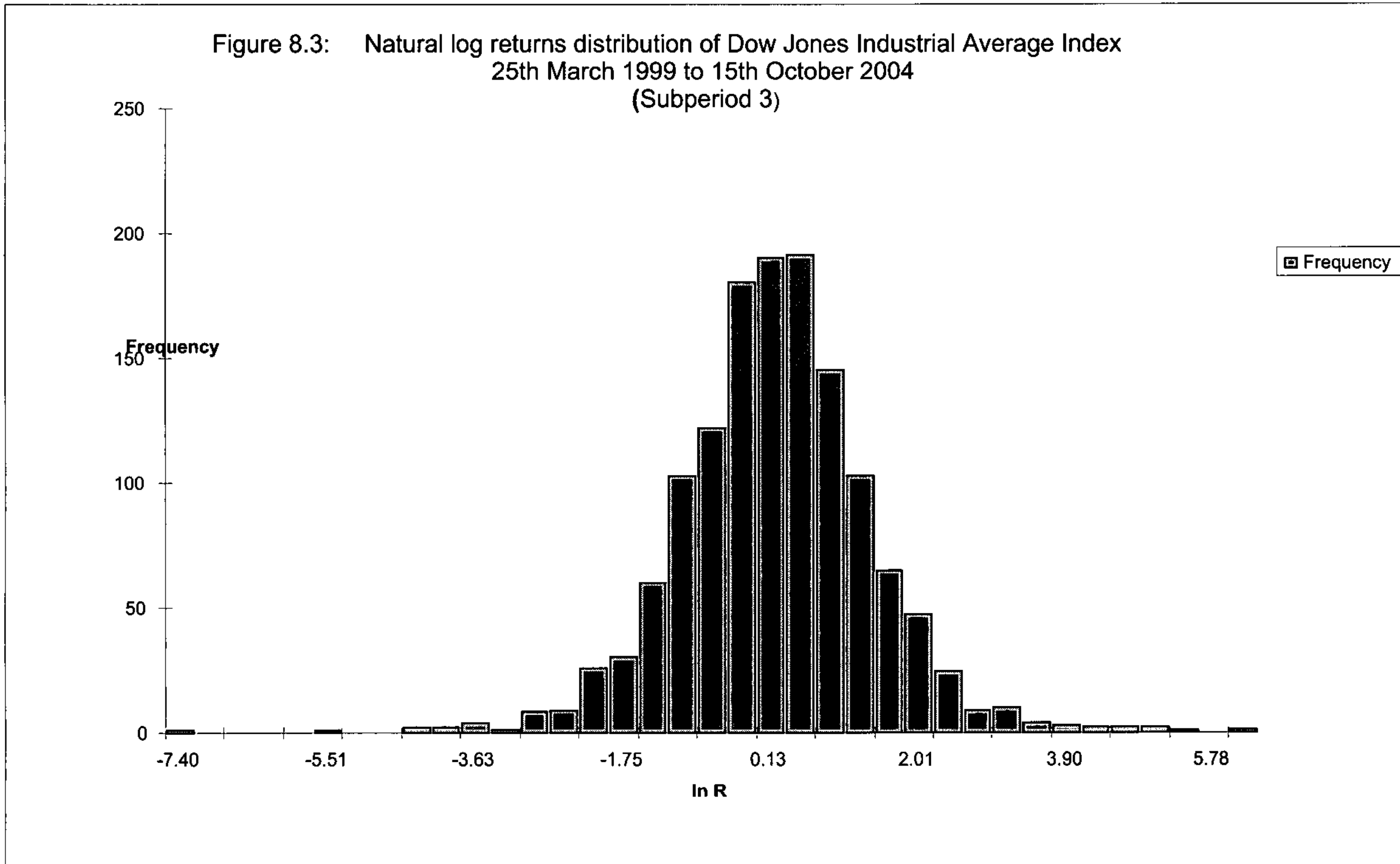


Figure 8.3: Natural log returns distribution of Dow Jones Industrial Average Index
25th March 1999 to 15th October 2004
(Subperiod 3)
Frequency
250
200
150
100
50
0
-7.40
-5.51
-3.63
-1.75
0.13
2.01
3.90
5.78
ln R
Frequency

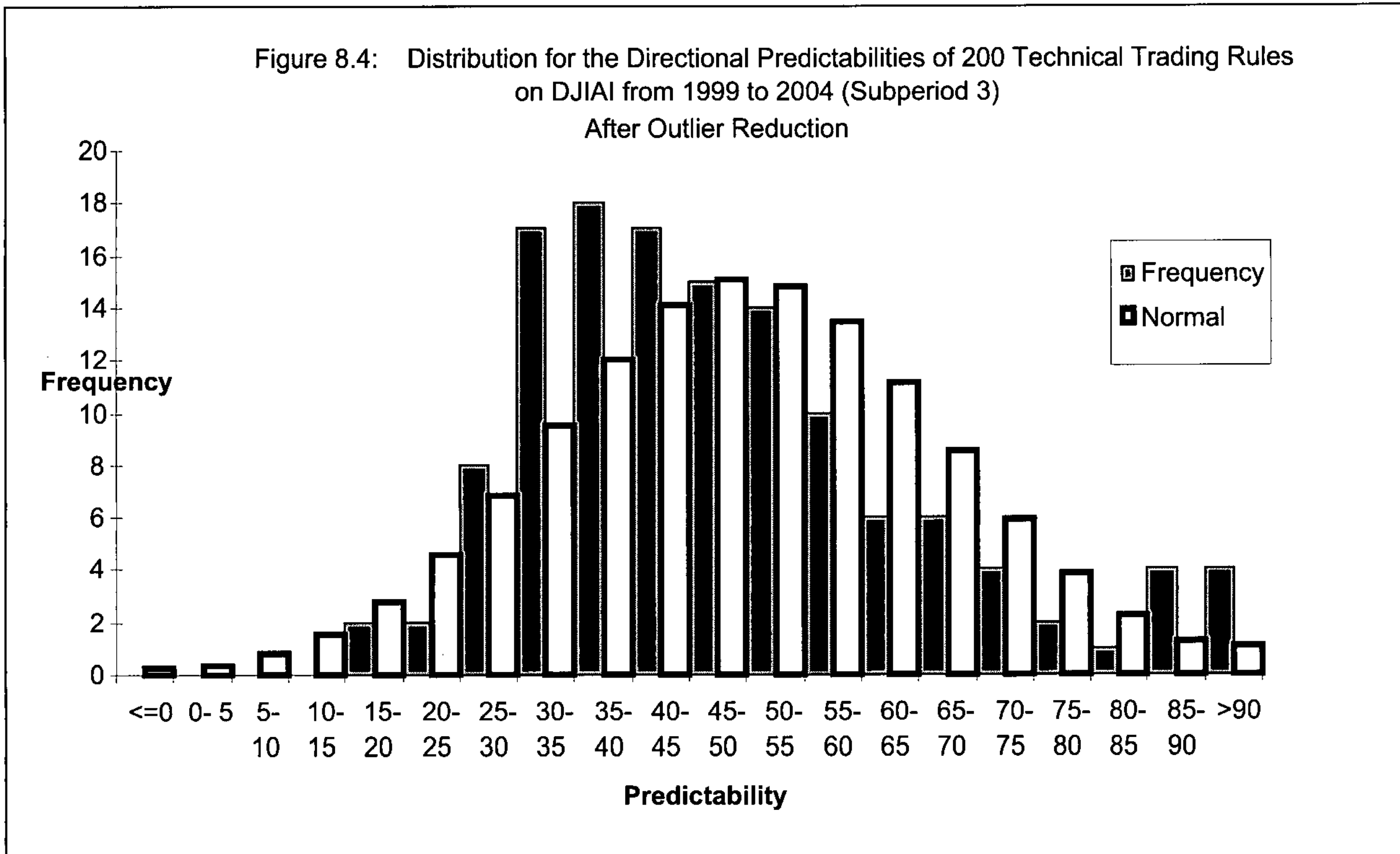
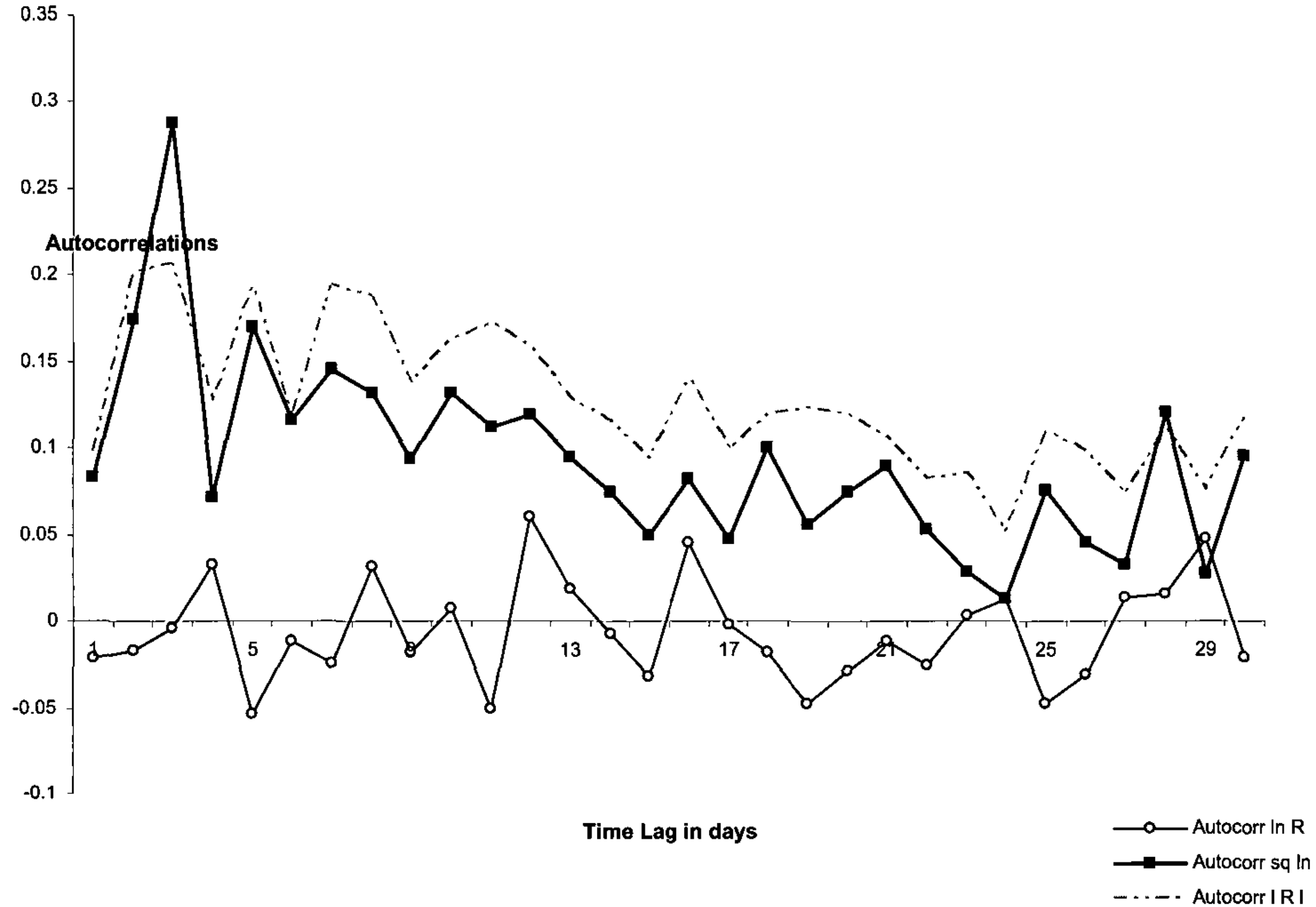


Figure 8.4: Distribution for the Directional Predictabilities of 200 Technical Trading Rules on DJIAI from 1999 to 2004 (Subperiod 3)
After Outlier Reduction
Frequency
Normal
Frequency
0
2
4
6
8
10
12
14
16
18
20
<=0
0- 5
5- 10
10- 15
15- 20
20- 25
25- 30
30- 35
35- 40
40- 45
45- 50
50- 55
55- 60
60- 65
65- 70
70- 75
75- 80
80- 85
85- 90
>90
Predictability

Figure 8.5: Autocorrelations of log returns, squared log returns and absolute log returns for the DJIAI from 25th March 1999 to 15th October 2004 (Subperiod 3)



Chapter 9

Concluding remarks: contributions and trading philosophies

9.1 Conceptual methodology and rationale

This thesis starts off as a "***reverse engineering***" project, whereby a large portfolio of technical trading rules are randomly assembled and tested across different financial markets on over a dozen of variables. Those trading rules which consistently performed well or badly are then analyzed. Some of the initial results are studied and presented here.

9.2 Contributions

We discuss the merits and limitations of quantitative analysis; as well as the justifications and motivations of studying technical trading rules in chapter 1. In chapter 2, we highlighted that technical analysis is gaining momentum as a subject of study in business schools across the Atlantic, including the "Trade Station" software that we use for this thesis.

Chapter 3

9.2.1 Literature review

A comprehensive review of the academic literature on technical trading rules was carried out and some drawbacks on their methodologies as well as possible solutions were proposed, and potential future researches were discussed which either ***can add value or compliment to the existing body of literature*** in the study of technical trading rules.

Chapter 4

9.2.2 Data analyses

In chapter 4, using the traditional linear techniques, we ***detected the usual stylized facts*** on the temporal and distributional properties of daily returns on financial time series for the series under study; we also found that ***autocorrelation is stronger in a predominantly steeper uptrend period.***

Driven by the lack of strong evidences on dependencies in the time series by using traditional linear techniques; we decided to employ several nonparametric techniques designed for brain research, and ***found possibly other forms of dependencies or temporal relationships much more significant than the traditional linear autocorrelation*** for the time series. This result is also in line with Sherry (1992)'s study of the S&P 500 daily price data for the whole year of 1988 using the same techniques.

The argument against randomness test put forward by Los (1999) was particularly highlighted in this chapter.

Chapter 5

9.2.3 Methodology

One of the major contributions of this thesis lies in the ***merits of a distributional study of 200 heterogeneous and published technical trading rules***, with a majority of them published before the test period and thus allowing a spread of out-of-sample testing. The merits of a distributional study with a larger sample of this nature were discussed. The sample size here may not be the largest of its kind; however, it is much more heterogeneous than the thousands of technical trading rules studied by Sullivan et al (1999, 2003). Since Sullivan et al. (1999, 2003) do not publish their directional predictability results; this study is the ***largest in terms of heterogeneity and directional predictability*** to the best of our knowledge. As such, comparison of results is difficult.

The concepts of efficient sample size and post publication testing are introduced to tackle the usual constraints of data snooping and resources.

9.2.3.1 Test of significance: t-test or bootstrap

We notice that most studies in technical trading rules so far provide evidence of same statistical results for both tests in the form of rejecting the null at the standard significance levels such as the 1 and 5 percent. From a statistical perspective, we are tempted to offer two possible explanations here that would basically lead to the same result of rejecting the "null":

(a) Firstly, for the t-test, it ***could be due to the large sample size*** in all these studies rendering the standard statistical t-test to reject the null hypothesis.

(b) Secondly, for the bootstrap, unless the models are grossly misspecified or "bad models", it is quite likely that the ***price dynamic that one is trying to capture would not be there once the time series is scrambled.*** Thus, resulting in the rejection of the "null".

9.2.3.2 Test window

Having discussed the various factors in choosing the size of test window in chapter 5; our overall conclusion is that it all ***depends upon what type of technical trading rules that one is testing.*** For example, to capture a trend in daily data which may occur, say, three times a year, would only provide a limited number of 24 observations over an eight years period, whereas a short term moving average which gives buy and sell (or vice versa) signals of every fifteen trading days would provide a large number of 136 observations over an eight year period (assuming an average of 250 trading days per annum). But then, if one is testing an individual stock which has a market component to it, then the observations may not be independent.

9.2.3.3 Directional predictability or profitability?

We gave personal reasons as to why we prefer to study directional predictability. We also argued that ***with out a correct directional predictability; there would not be profitability to start with, no matter how accurate the closing trade is.*** In addition, ***a large portion of the profit could be due to just a single or a few trades.*** Thus, knowing the directional predictability may be more informative in general and more relevant in our case. We also came out with ***15 factors that one needs to consider in calculating the profitability of technical trading rules.***

9.2.3.4 Issues on empirical testing

We further outlined dozens of issues, as well as bringing works from existing literature, on empirical testing related to technical trading rules in general. They illustrated the complexity and caution needed in choosing the data, developing methodology, applying the various financial econometric models, interpreting the results and so forth. Simple as it may seem for some of the issues on empirical testing; it is surprising that they are often overlooked and ignored. These oversights could and indeed can, ***cast a shadow of doubt on most previous studies on technical trading rules!***

Chapter 6

9.2.4 To predict or not to? – that is "still" the question

8.2.4.1 Time tested

We do not discount the possibility that there may be many other published and unpublished technical trading rules which have higher directional predictability, but given the ***top 20 percent of technical trading rules tested here produces a conditional mean of 73% directional predictability***; this is enough of an indication of the economic significance and continuous practice of technical trading rules.

One may not need to have high predictability to achieve much. To give a hypothetical example, for a predictability of 51%, if it can be capitalized on a weekly basis, it can turn into a return of 52 percent per annum before risks and transaction costs.

Neither does one need to look very far ahead to make a useful prediction. For example, more than 75% of foreign exchange trading takes place within the day (Taylor and Allen, 1992).

9.2.4.2 Expected value as expected: No free lunch

Given that the directional predictability is less than a conditional mean of 50%; there seems to be ***no free lunch on Wall Street***. On the other hand, given the large sample of rules tested, it is not surprising that the conditional mean directional predictability is near to 50%. The conditional mean directional predictability of 46% over the entire period is close to an expected population mean of 50% as suggested by the central limit theorem of normal distribution. However, the t-test rejected the null hypothesis of equality to 50% at the 1 percent level.

9.2.4.3 Is there a message for the technical analysts?

The fact that the conditional mean directional predictability of 46% is significantly different from 50% up to the 1 percent level, may come as a rude shock to those die-hard technical analysis fans, as ***it implies that a random decision making process can do just as well as technical trading rules on the whole or on average, and likely to perform better in the long-run!*** Bear in mind the impact of a large sample, would invariably lead to the rejection of the null hypothesis at the conventional 1 and 5 percent levels.

9.2.4.4 Stability

The results for both before and after outlier reduction for the conditional mean directional predictabilities during total, buy only, and sell only periods, appear to be similar in almost all aspects. Neither are there many differences between the two sub-periods. However, a t-test performed on each of the ***total, buy only and sell only between the two subperiods have all rejected the null hypothesis of equality at the 1 percent level of significance.***

The number of ***buy only and sell only signals are equally generated for all periods***, which is not one would expect from the result of a particular technical trading rule, and this may have to do with the law of large numbers here.

9.2.4.5 Directional predictability

Although the number of buy and sell signals are almost equal, their respective directional predictabilities differ widely with an average ratio of 1.84xs in favour of buy signals for the entire period. If technical trading rules do not have any forecasting power, then one should observe that directional predictability on days when the rules emit buy signals do not differ significantly from directional predictability on days when rules emit sell signals. We do not have comparison with other studies simply because most studies invariably focus on profitability rather than directional predictability and they also usually test a limited number (several in most cases) of technical trading rules.

The high ratio of buy to sell directional predictability is within expectation in a predominantly up-trend time series. By the same token, the ratio for subperiod 2 is expected to be higher than sub-period 1 as it can be seen from figure 4.1 in chapter 4 that the former has a steeper up-trend than the latter.

The large difference in conditional means between buy only and sell only for the entire period is large enough to be relevant.

9.2.4.6 Unconventional: Lower risk but higher return and vice versa

Risk is higher on sell days as measured by the coefficient of variation than on buy days, whereas the conditional mean directional predictability is higher for buy days than sell days. This observation is consistent with the results of several other studies such as Brocks et al. (1992) on the conditional returns of equity indices.

9.2.4.7 Against the odd

The conditional mean of a buy signals having a probability of more than 50% directional predictability is 54 percent compared to only 13 percent of the time for sell signals. This is a staggering ratio of 4.15x and the ratio is comparatively higher for the steeper up-trend subperiod 2 (6.88x) than subperiod 1 (3.31x). This phenomenon of better performance for buy signals is in line with other studies such as Brock et al. (1992) and Mills (1997) on the profitability of technical trading rules whereby buy signals consistently out-perform sell signals.

9.2.4.8 The 80/20 rule

The better performing technical trading rules tend to have smaller differences in the performance of buy and sell signals, whereas the worse performing technical trading rules tend to have larger differences as shown by the ratios of 1.42 x and 2.12 x for the top 20 percent and bottom 80 percent respectively.

These statistics ***may be due to the better designed technical trading rules for the top 20 percent group which can capture both the up and down directions of the time series quite well, whereas, the worse designed technical trading rules have to rely upon the inherited and predominately up-trend component for their performance.***

9.2.4.9 Efficient market?

The overall probability of a more than 50% directional predictability occurs only 36 percent of the time. However, if one adheres to ***buy signals only, then the probability of more than 50% directional predictability is 54 percent of the time.*** This is in contrast to the argument that financial markets are assumed to be random and efficient. Under the null hypothesis that technical trading rules do not produce useful signals, the fractions of conditional mean predictability which are more than 50% should be the same for both buys and sells.

The wide differences in the conditional mean directional predictability, of buy only and sell only signals and the considerable differences in the fraction of buy only and sell only signals with more than 50% conditional mean directional predictability, further support the forecasting ability of technical trading rules.

Furthermore, the differences in conditional mean directional predictability between buy only and sell only are ***not explained by risk***. We are not going to join the debate on efficient market hypothesis. But for those who are in doubt on the hypothesis, a classic argument against the hypothesis is given by Grossman and Stiglitz (1980) and a more up-to-date work is given by Lo and McKinlay (1999).

9.2.4.10 Repeatability

What is more interesting would be whether those higher predictability rules can still continue with their superior performance in ***other time series and over different time frames, frequencies and market structures.*** More importantly, whether there is a ***positive relationship between directional (or sign) predictability and profitability*** of technical trading rules, given the present empirical evidence on directional predictability, is an important subject for further investigation.

Chapter 7

9.2.5 Distributional properties and financial traders' belief

Several authors believe that most successful financial traders have an average technical trading rules' directional predictability in the region of 25% to 50%. These ranges of ***belief roughly coincide with the mode of 35% directional predictability*** for the total (buy and sell) conditional mean distribution generated here. This is an intriguing issue, as it implies a net profitability despite a lower than 50% directional predictability. Our results show that 60 percent of the rules are within the region of 25% to 50% directional predictability. In other words, 60 percent for a quarter or one-fourth or 25 percent of the range is a relatively high area of concentration. Incidentally, the best rule out of a universe of 7,846 rules in Sullivan et al. (1999) has a directional predictability of only 40%, although it has an annualized average return of 17.17 percent.

The overall (total of buy and sell signals) distributional properties of conditional directional predictability are positively skewed with low kurtosis. However, the distributional property of directional predictability of ***sell signals only are more positively skewed and with higher kurtosis than buy signals only*** for both before and after outlier reduction

Chapter 8

9.2.6 In the presence of a downtrend

We observe a counter-intuitive ***relationship between volatility and predictability: the more volatile, the more predictable***. The evidence presented also concurs and ***supports previous researchers' theoretical argument that technical trading rules would out-perform a buy-and-hold strategy during a downtrend period.***

The sum (total) of the first 30 lags of log returns autocorrelations for all the three subperiods are all negative, despite the fact that the first two subperiods are predominately uptrend (please refer to table 8.7). One likely possible explanation for this phenomenon is that the ***panic or bad news factor is more influential or having a greater impact than the greed or good news factor.*** In other words, market participants may be are more averse to risks or losses than to the prospect of gaining or profits. This argument is in line with the now famous Prospect Theory in behavioral finance. The fact that the largest daily negative return is bigger than the largest daily positive return for all three subperiods, further lend supports to our argument (please refer to table 8.1).

It is worth mentioning that the first lag of autocorrelation for the two predominately uptrend subperiods are positive; but it is ***negative for the predominately downtrend subperiod.*** This empirical evidence can be used as one of the criteria for the **definition of an uptrend or downtrend.**

9.3 Parsimony: Too much variables, too little time

The values of various concepts and methodologies proposed in the tackling of the empirical testing of technical trading rules here, lies in their simplicity, parsimony and intuitive appeals possibly to a wider audience. Simplicity is as much a virtue as for any other statistical method (LeBaron, 2000). Armstrong (1986), in his quarter-century review article documents a number of empirical studies on time series forecasts where complex methods fared no better, and often worse, than simple methods.

Indeed, simplicity and parsimony are the appeal of technical trading rules to the investment community. In fact, as mentioned earlier, several studies find that technical trading rules do about as well as some of the statistical models. The concept of simplicity and parsimony is well summarized by Wilcox (1999), "The market structure is always changing and the greatest rewards will likely go to simple, robust methods applied promptly and creatively." On the other hand, one would have difficulty in distinguishing spurious phenomena as a result of over-fitting or data mining when increasing parameters and sophisticated econometric techniques are used (Forcadi et al., 2004).

Similarly, Taylor (1994) argues that the channel rule may be superior when a trading objective is evaluated because it may require less information to learn about a satisfactory value for its one parameter than an ARIMA rule needs to find satisfactory estimates of its AR and MA parameters.

The concept of simplicity is also advocated by Diebold (1998), "... note that simple models, of course, should not be confused with naïve models. All this is well formalized in the KISS principle (appropriately modified for forecasting): Keep it sophisticatedly simple."

9.4 Caveat: what the numbers tell you and what they do not

As there are as many technical trading rules as one can imagine, it does not seem to be meaningful to make any claim on their effectiveness in general, but rather a claim based on categories or a particular category or group of technical trading rules may be more fruitful. As such, this study could be interpreted within the sphere of published and computable technical trading rules.

9.5 Further research

Hopefully, this paper has opened up new avenues of research on nonparametric analyses, directional predictability, financial traders' belief, in the presence of a downtrend, volatility and predictability, on technical trading rules; rather than the usual bootstrapped returns and the alternative null hypotheses. In addition, our discussions on the following issues and those on empirical testing would hopefully, inspire more debates:

(a) The drawback of buy-and-hold strategy as a benchmark and some proposed alternatives.

(b) Dilemma on the size of test window: power and stability.

(c) Performance measurement based on downside risk.

(d) Risk management in the application of technical trading rules.

(e) Inter-markets dynamics.

(f) The linkage between prospect theory and the rationale behind support and resistant levels.

(g) Efficient sample size and homogeneity.

(h) Data snooping: issue and motivation.

(i) Test of significance: bootstrap or t-test?

9.6 Trading philosophy: A tale of profitable and unprofitable trading rules

The storey that a group of unprofitable trading rules pleaded to the researcher that they should not be sent for disposal for three good reasons: (a) Time will come when those profitable trading rules will no longer be useful when more people become aware of their existence. (b) Time will come when the market microstructure changes that will render those existing profitable no longer profitable. For example, the change of settlement delivery procedure from a T+7 to T+3 may make a 3 days moving average more profitable than a 7 days moving average. (c) For those extremely unprofitable trading rules, why not test them by changing the trading signals generated by them. For instance, if it is a long or buy signal, rather than long, change it in to a short or sell signal. In this way, the unprofitable trading rules may become profitable. Since then, the researcher has given those unprofitable trading rules a different look. Although the story is fictitious and concocted as we go along, nevertheless, it does sum up quite well some of ***our philosophies*** behind technical trading rules in general.

9.7 Predicament of inference in the present of a large *N:* adjusted t-test and adjusted expected value?

As all too often in the process of research, what initially appeared to be a good idea and/or an interesting discovery would subsequently evaporated on further literature search: someone along the way had proposed for a sample adjusted t-test. For instance, Lindley (1957) and Connolly (1989).

9.8 A thought on forecasting and predictability: physical or biological (evolutionary)?

9.8.1 Expectation gap

A finance professor once issued a controversial challenge to anybody who can give him seven equations that can explain the evolution of the New York Stock Exchange index (Lo, 1997. p.65). We took up his challenge, but did not receive any response. Speculative markets being as complex and dynamics as they are, where the ***signals to noise ratio is comparatively much lower than that of physical science experiment;*** is it not then to expect too much for just one or two formulae to forecast and predict them in good accuracy?

9.8.2 Application of physical science

Financial markets, unlike physical science, where Newton's three laws can almost explain 99% of all physical phenomena, and they are also time invariant and stable across space. Unfortunately, financial markets are extremely complex and constantly evolving. They involve a diverse and large number of participants ranging from institutions to homemakers, each with different backgrounds, knowledge, information, objectives, and constraints. Above all, they are human beings with emotions and may occasionally react irrationally in times of greed and fear. Thus, one does not have that luxury of physical science phenomena in the financial markets, but rather an evolutionary process much like that of biological science: Darwin's evolutionary theory of natural selection. For example, a forecasting tool that works today is subject to the resultant force of a particular equilibrium in supply and demand at that particular point in time. Any departure from that may render the forecasting tool ineffective.

In this age of technological and informational advancements, coupled with the force of globalization; ***the point of equilibrium can be constantly shifting***. This is already evidenced by the strong empirical facts that profits decline over time for those much published technical trading rules in recent years. Thus, if one is to subscribe to the above argument, then what works today may not work tomorrow, and that may become the motto for predicting financial markets. In that respect, it is more like an evolutionary science. If that is the case, researchers perhaps should have more empathy in the study of human behavior (behavioral finance) in speculative markets; and also more on ***a competitive evolutionary model rather than the straight application of physical science models.***

9.8.3 Endorsement from an artificial stock market simulation

In an article at the web site of Complexica, a consulting company in data mining and complexity study, Dr. John L. Casti's article entitled "The Simply Complex" concludes the results of an artificial stock market simulation experiment done at the Santa Fe Institute, which happen to be in line with our thought:

> "After many time periods of trading and modification of the traders' decision rules, what emerges is a kind of "ecology" of predictors, with different traders employing different rules to make their decisions. Furthermore, it is observed that the stock price always settles down to a random fluctuation about its fundamental value. But within these fluctuations a very rich behavior is seen: price bubbles and crashes,

psychological market "moods," overreactions to price movements and all the other things associated with speculative market in the real world."

The article's second conclusion on the simulation experiment is more interesting, in particular for those who attempt to predict the market. We highlighted those statements which are more relevant to our investigation here:

> "Also as in the real markets, the population of predictors in the artificial market continually coevolves, showing <u>no evidence of settling down to a single best predictor for all occasions.</u> Rather, the optimal way to proceed at any time is seen to depend critically upon what everyone else is doing at that time. In addition, we see <u>mutually-reinforcing trend-following or technical-analysis-like rules appearing in the predictor population.</u>"

9.8.4 From artificial modeling to reality

In the world of financial trading and investment, a combination of technical trading rules and fundamental analysis are likely to be the norm in practice. As summarized by the Chicago Board of Trade (1998, p.157):

> "Traders frequently <u>use a combination of fundamental and technical methods to forecast price</u>. For example, many traders obtain a forecast of price movement using fundamental analysis and then choose the time for initiating or liquidating a position based on technical factors.
>
> Regardless of which method or combination of methods a technical trader uses for price analysis, none is foolproof. The price discovery process in the futures markets represents the collective wisdom of all market participants trying to estimate future prices."

References

Part I

Acar, E. (1993) **Economic evaluation of financial forecasting**, Ph.D. Thesis, City University, London.

Acar, E. (1998) **Expected returns of directional forecasters**, in Acar, E. and Satchell, S. (Ed) *Advanced Trading Rules*, Butterworth-Heinemann.

Acar, E. and Loqueux, P. (1995) **Trading rules profits and the underlying time series properties**, *First International Conference on High Frequency Data in Finance*, Zurich, Switzerland.

Acar, E. and Satchell, S. (1997) **A theoretical analysis of trading rules: An application to the moving average case with markovian returns**, *Applied Mathematical Finance*, 4, 1-16.

.... (1998) **The portfolio distribution of directional strategies**, in Acar, E. and Satchell, S. (ed) Advanced trading rules, Butterworth-Heinemann.

Acar, E. and Toffel, R. (2000) **Stop-loss and investment returns,** Investment conference, Faculty and Institute of Actuaries, Hatfield Health, June.

Albright, S.C., Winston, W.L. and Zappe, C. (1999) **Data analysis and decision making with Microsoft Excel**, Duxbury Press.

Alexander, C. (2001) **Market models-a guide to financial data analysis**, Wiley.

Alexander, S.S (1961) **Price movements in speculative markets: Trends or random walks**, *Industrial Management Review*, II, 7-26.

------- (1964) **Price movements in speculative markets: Trends or random walks no.2**, *Industrial Management Review*, V, 25-46.

Allen, F. and Karjalainen, R. (1999) **Using genetic algorithms find technical trading rules**, *Journal of Financial Economics*, 51, 245-271.

Allen, H. and Taylor, M.P. (1990) **Chart, noise and fundamentals in the London foreign exchange market**, *Economic Journal*, 100, 49-59.

Amihud, Y. and Mendelson, H. (1986) **Asset pricing and the bid-ask spread**, *Journal of Financial Economics*, 17, 223-249.

Armstrong, S. (1986) **Research on forecasting: A quarter-century review, 1960-1984**, *Interfaces*, 16, 89-103.

Badrinath S.G. and Chatterjee, S. (1988) **On measuring skewness and elongation in common stock distributions: the case of the market index**, *Journal of Business*, 61, 451-472.

Baillie, R.T. and Bollerslev, T. (1989) **The message in daily exchange rates: a conditional-variance tale**, *Journal of Business and Economic statistics*, 7(3), 297-305.

Baker, M. and Stein, J.C. (2002) **Market liquidity as a sentiment indicator**, NBER working paper.

Ball, R., Kothari, S.P. and Wasley, C.E. (1995) **Can we implement research on stock trading rules**, *Journal of Portfolio Management*, Winter, 54-63.

Barberis, N., Shleifer, A., and Vishny, R. (1998) **A model of investor sentiment,** *Journal of Financial Economics*, 49, 307-343.

Bekaert, G. and Harvey C.R. (1995) **Time-varying world market integration,** *Journal of Finance,* 50, 403-444.

Bekaert, G., Erb, C.B., Harvey, C.R. and Viskanta, T.E. (1998) **The behaviour of emerging market returns**, in Levich, R. (ed.) *Emerging Market Capital Flows*, Kluwer Academic Publishers.

Bensaid, B. and DeBandt, O. (1998) **Stop-loss rules as a monitoring device: theory and evidence from the bond futures market**, in Acar and Satchell (ed.) *Advanced Trading Rules*, Butterworth-Heinemenn, 176-208.

Bessembinder, H. and Chan, K. (1995) **The profitability of technical trading rules in the Asian stock markets,** *Pacific-Basin Finance Journal*, 3, 257-284.

...... (1998) **Market efficiency and the returns to technical analysis,** *Financial Management*, 27, 5-17.

Bird, P.J.W.N. (1985) **The weak form efficiency of the London Metal Exchange,** *Applied Economics*, 17, 571-87.

Black, F. (1976) **Studies of stock market volatility changes**. Proceedings of the 1976 meetings of the American Statistical Association, Business and Economics Statistics Section, 177-181.

Black, F. and Perold, A.F. (1992) **Theory of constant proportion portfolio insurance,** *Journal of Economic Dynamics and Control*, 16, 403-26.

Blattberg, R.C. and Gonedes, R.C. (1974) **A comparison of the stable and student distributions as statistical models for stock prices,** *Journal of Business*, 47, 244-80.

Blume L., Easley D, and O'Hara M. (1994) **Market statistics and technical analysis: the role of volume,** *Journal of Finance*, 49, 153-181.

Bookstaber, R. (1985) **The complete investment book: Trading stocks, bonds, and options with computer applications**, Glen view, IL: Scott Foresman.

Brennan, M., Chordia, T. and Subrahmanyam, A. (1998) **Alternative factor specifications, security characteristics, and the cross-section of expected stock returns,** *Journal of Financial Economics*, 49, 345-373.

Brock, W., Lakonishok, J. and LeBaron, B. (1992) **Simple technical trading rules and the stochastic properties of stock returns,** *Journal of Finance*, 47, 1731-1764.

Brooks, C. (1996a) **Testing for and forecasting nonlinearity in sterling foreign exchange market**, Ph.D. Thesis, ISMA, University of Reading.

……. (1996b) **Testing for nonlinearity in daily pound exchange rates,** *Applied Financial Economics*, 6, 307-17.

……. (2002) **Introductory econometrics of finance**, Cambridge University Press.

Brooks, C., Hinich, M.J. and Smith, M.J. (1999) **Nonlinear evolution in UK stock returns and volume**, in Rothman, P. (ed.) *Nonlinear Time Series Analysis of Economic and Financial Data*, Kluwer Academic Publishers.

Brorsen, B.W., and S.H. Irwin. **Futures funds and price volatility**. *The review of futures markets,* 6 (1987): 118-135.

Brown, D.P. and Jennings, R.H. (1989) **On Technical analysis**, *Review of Financial Studies*, 2, 527-551.

Brown, S., Goetzmann W.N. and Kumar, A. (1998) **The Dow theory: William Peter Hamilton's track record reconsidered**, Stern School of Business, New York University.

Burke, G. (1994) **A sharper sharp ratio**, The Computerized Traders, March.

Burstein, G. (1999) **Macrotrading and investment strategies: Macroeconomic arbitrage in global markets**, Wiley, New York.

Caginalp, G and Laurent, H. (1998) **The predictive power of price patterns.** *Applied Mathematical Finance*, 5, 181-205.

Campbell, J. Y., Grossman, S. J. and Wang, J. (1993) **Trading volume and serial correlation in stock returns**, *Quarterly Journal of Economics*, 108, 905-939.

Campbell J.Y., Lo A.W. and Mackinlay A.C. (1997) **The Econometrics of Financial Markets**, Princeton.

Casti J.L. (2004) **The simply complex**, Complexica (http;//internet.cybermesa.com/~rfrye/complexica).

Chan, L., Jegadesh, N. and Lakonishok, J. (1996) **Momentum strategies**, *Journal of Finance*, 51, 1681-1713.

Chang, P.H.K. and Osler, C.L. (1998) **Is more always better? Head-and-shoulders and filter rules in foreign exchange markets**, in Acar, E. and Satchell, S. (Ed.) Advanced Trading Rules, Butterwork-Heinemann.

.......(1999) **Methodical madness: Technical analysis and the irrationality of exchange-rate forecasts.** *Economic Journal,* 109, 636-661.

Chen, S.J. (2003) **Exploring the predictability in technical trading rules**, Department of Economics, Washington University.

Cheung, Y.W. and Chinn, M.D. (2001) **Currency traders and exchange rate dynamics: a survey of the US market,** *Journal of International Money and finance*, 20, 439-471.

Cheung, Y.W., and Wong, C.Y.P. (2000) **A survey of market practitioners' views on exchange rate dynamics.** *Journal of International economics,* 51, 401-419.

Cheung, Y.W., Chinn, M.D. and Marsh, I.W. (2000) **"How do UK-Based foreign exchange dealers think their market operates?"** *NBER working paper*, no. 7524.

Chicago Board of Trade (1998) **Trading in futures: an introduction for speculators,** CBOT, Glenlake Publishing Company Ltd.

Christie, A.A. (1982) **The stochastic behavior of common stock variances: value, leverage, and interest rate effects,** *Journal of Financial Economics*, 23, 407-432.

Chui, A.C.W., Titman, S. and Wei, K.C.J. (2000) **Momentum, legal systems and ownership structure: An analysis of Asian stock markets,** *Working paper*, HK Polytechnic.

Clark, P.K. (1973) **A subordinated stochastic process with finite variance for speculative prices,** Econometrica, 41, 135-55.

Clyde, W.C. and Osler, C.L. (1997) **Charting: Chaos theory in disguise?** *Journal of Futures Markets*, 17, 489-514.

Cochrane, J.H. (1999) **New facts in finance**, Graduate School of Business, University of Chicago.

Colby, R.W. (2003) **The encyclopedia of technical market indicators**, McGraw Hill. Second edition.

Connolly, R. (1989) **An examination of the robustness of the weekend effect,** *Journal of Financial and Quantitative Analysis*, 24, 133-169.

Conrad, J., Hameed, A. and Niden, C. (1994) **Volume and autocovariances in short-horizn individual security returns,** *Journal of Finance*, 49, 1305-1330.

Conway, O. (1996) **Cover story about John W. Henry& Company, Inc.**, *Managed Derivatives*, May.

Cooper, M and Gulen, H. (2004) **Is time-series based predictability evident in real-time?** Working Paper, Purdue University.

Coutts, J.A. and Cheung, K. (2000) **Trading rules and stock returns: some preliminary short run evidence from the Hang Seng 1985-1997**, *Applied Financial Economics*, 10, 579-586.

Covel, M. (2004) **Trend following**, Prentice Hall.

Cowles, A. (1934) **Can stock market forecasters forecast?** *Econometrica*; 1, 309-324.

Cox, J.C. and Rubinstein, M. (1985) **Options markets**, Prentice Hall.

Curcio, R., Goodheart, C. Guilaume, D. and Payne, R. (1997) **Do technical trading rules generate profits? Evidence from the intra-day foreign exchange market,** *International Journey of Finance and Economics,* Special Issue of Technical Analysis and Financial Markets.

Dacorogna, M.M., Gencay, R., Muller, U., Olsen, R.B. and Pictet, O.V. (2001) **An introduction to high-frequency finance**, Academic Press.

Datar, V., Naik, N. and Radcliffe, R. (1998) **Liquidity and asset returns: an alternative test,** *Journal of Financial Markets,* 1, 203-220.

Davison, A.C. and Hinkley, D.V. (1997) **Bootstrap methods and their application,** Cambridge University Press.

Dawson, E R and Steeley, J (2003) **On the existence of visual technical patterns in the UK stock market.** *Journal of Business Finance & Accounting*, 30, 263-293.

Day, T.E. and Wang, P. (2002) **Dividends, nonsynchronous prices, and the returns from trading the Dow Jones industrial Average,** *Journal of Empirical Finance*, 9, 431-454.

De Long, J.B., Shleifer, A., Summers, L.H. and Waldmann, R.J. (1990) **Noise trader risk in financial markets.** *Journal of Political Economy*, 98, 703-738.

...... (1991) **The survival of noise traders in financial markets.** *Journal of Business,* 64, 1-19.

Dempster, M.A.H. and Jones, C.M. (2002) **Can channel pattern trading be profitably automated?** *The European Journal of Finance*, 8, 275-301.

Dickey, D.A. and Fuller, W.A. (1979) **Distribution of the estimators for autoregressive time series with a unit root**, *Journal of the American Statistical Association*, 74(366): 427-431.

Diebold, F.X. (1998) **Elements of forecasting**, International Thomson Publishing.

Dijk, V.D., Franses, P.H. and Lucas, A. (1996a) **Testing for smooth transition auto regression in the presence of outliers**, Econometric Institute Report 9622, Erasmus University.

...... (1996b) **Testing for ARCH in the presence of additive outliers**, Econometric Institute Report 9659, Erasmus University.

Ding, Z., Granger, C.W.J. and Engle, R.F. (1993) A **long memory property of stock market returns and a new model**, *Journal of Empirical Finance*, 1, 83-106.

Edmonds, D. (1998) **Commodity trading advisors and their role in managed futures**, in Acar, E. and Satchell, S. (Ed.) *Advanced Trading Rules*, Butterworth-Heinemann.

Edwards, R.D. and Magee, J. (2001) **Technical analysis of stock trends**, St. Lucie Press, 8th Edition.

Efron, B. (1982) **The jackknife, the bootstrap and other resampling plans**, Society for Industrail and Applied Mathematics, Philadelphia.

.... (1979) **Bootstrap methods: another look at the jackknife**, *Annals of Statistics*, 7(1), 1-26.

El-Galfy, A.M. and Forbes, W.P. (2004) **Are forecast of corporate profit rational? A note and further evidence**, *Journal of Empirical Finance*, 11 (4) 617-626.

Engle, R.F. (1995) **ARCH: Selected readings**, Oxford University Press, Oxford.

Fama, E. (1965) **The behaviour of stock prices,** *Journal of Business*, 47, 244-80.

Fama, E.F. and Blume, M.E. (1966) **Filter rules and stock market trading,** *Journal of Business*, 39, 226-241.

Fama, E. F. and French, K. R. (1992) **The cross section of expected stock returns,** *Journal of Finance*, pp. 427-465.

Fang, y. and Xu, D. (2003) **The predictability of asset returns: an approach combining technical analysis and time series forecasts,** *International Journal of Forecasting*, 19, 369-385.

Fernandez-Rodriguez, F., Gonzalez-Martel, C and Sosvilla-Rivero, S. (2000) **On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market.** *Economic Letters*, 69, 89-94.

Fernandez-Rodriguez, F., Gonzalez-Martel, C and Sosvilla-Rivero, S. and Andrada-Felix, J. (2003) **Technical analysis in foreign exchange markets: Evidence from the EMS.** *Applied Financial Economics,* 13, 113-122.

Fishburn, P. C. (1977) **Mean-risk analysis with risk associated with below target returns,** *American Economic Review*, 67 (2), 116-126.

Focardi, S. and Johas, C. (1997) **Modeling the market: new theories and techniques,** Frank J. Fabozzi Associates.

Forcadi, S.M., Kolm, P.N. and Fabozzi, F. J. (2004) **New kids on the block: Trend in quantitative finance and their impact on investment management,** *Journal of Portfolio Management*, 30th Anniversary Issue

Frankel, J.A., and Froot, K.A. (1990) **Chartist, fundamentalists, and trading in the foreign exchange market.** *American economic review,* 80, 181-185.

Franses P.H. (1998) **Time series models for business and economics forecasting,** Cambridge University Press.

Franses, P.H. and Dijk, D.V. (1997) **Do we often find ARCH because of neglected outliers?** Economic Institute Report 9706, Erasmus University.

Franses, P.H. and Dijk, D.V. (2000) **Non-linear time series models in empirical finance,** Cambridge University Press.

Froot, K.A., Scharfstein, D.S and Stein, J.C (1992) **Herd on the street: Informational inefficiencies in a market with short-term speculation.** *Journal of Finance*, 47, 1461-1484.

Fuhmars, V. and Mongan, C. (1999) **It is all in their heads,** *The Asian Wall Street Journal,* May 3.

Gencay, R. (1998) **The predictability of security returns with simple technical trading rules,** *Journal of Empirical Finance*, 5, 347-359.

...... (1999) **Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules.** *Journal of International Economics,* 47, 91-107.

Gencay, R and Stengos, T (1998) **Moving average rules, volume and the predictability of security returns with feedforward networks.** *Journal of Forecasting*, 17, 401-414.

Ghysels, E., Granger, C.W.J. and Siklos, P.L. (1996) **Is seasonal adjustment a linear or nonlinear data filtering process?** *Journal of Business and Economic Statistics*, 14,374-386.

Goodacre, A., Bosher, J. and Dove, A. (1999) **Testing the CRISMA trading system: evidence from the UK market,** *Applied Financial Economics*, 9, 455-468.

Goodhart, C.A.E. (1989) **News and the foreign exchange market,** Proceedings of the Manchester Statistical Society.

Goodhart, C.A.E. and Figliuoli, L. (1991) **Every minute counts in financial markets,** *Journal of International Money and Finance*, 10, 23-52.

Gorener, R., Demirel, O. and Norsworthy J.R. (2004) **Generating autocorrelated financial time series by bootstrap**, Working paper, Rensselaer Polytechnic Institute.

Granger, C.W.J. (1999) **Empirical modeling in economics: specification and evaluation**, Cambridge University Press.

Granger, C.W.J. and Ding, Z. (1994) **Stylized facts on the temporal and distributional properties of daily data from speculative markets**, Mimeo, University of California San Diego.

Griffin, J.M., Ji, S. and Martin, J.S. (2002) **Momentum investing and business cycle risk: Evidence from pole to pole,** *Working paper,* Arizona State University.

Grossman, S. and Stiglitz, J. (1980) **On the impossibility of informationally efficient markets,** *American Economic Review*, June.

Group of Thirty (1985) **The foreign exchange market in the 1980s**, New York, NY: Group of Thirty.

Grundy, B.D. and Martin, J.S. (2001) **Understanding the nature of the risks and the source of the rewards to momentum investing**, *Review of Financial Studies* 14, 29-78

Guillaume, D.M (2000) **Intradaily exchange rate movements.** Boston, MA: Kluwer Academic Publihers.

Gunasekarage, A. and Power, D.M. (2001) **The profitability of moving average trading rules in South Asian stock markets**, *Emerging markets Review*, 2, 17-33.

Hamao, Y., Masulis, R.W. and Ng, V. (1990) **Correlation in price changes and volatility across international stock markets**, *Review of financial Studies*, 3, 281-307.

Hansen, P.R. (2003) **Asymptotic tests of composite hypotheses**. Working Paper, Brown University.

......(2004) **A test for superior predictive ability**. Working Paper, Brown University.

Harvey, C. and Siddique, A. (2000) **Conditional skewness in asset pricing tests**, *Journal of Finance*, 55, 1263-1295

Hellwig, M.F. (1982) **Rational expectations equilibrium with conditioning on past prices: a mean variance example**, *Journal of Economic Theory*, 26, 279-312.

Hinich, M.J. and Patterson, D.M. (1985) **Evidence of nonlinearity in daily stock returns**, *Journal of Business and Economic Statistics*, 3(1), 69-77.

Hong, H. and Stein, J.C. (1999) **A unified theory of underreaction, momentum trading, and overreaction in asset markets**, *Journal of Finance*, 54, 2143-2184.

Hsieh, D.A. (1989) **Testing for nonlinear dependence in daily foreign exchange rates**, *Journal of Business*, 62(3), 339-68.

……. (1991) **Chaos and non-linear dynamics: Application to financial markets,** *Journal of Finance*, 46,1839-1877.

Hudson, R., Dempsey, M. and Keasey, K. (1996) **A note on the weak form efficiency of capital markets: the application of simple technical trading rules to UK stock prices -1935 to 1994,** *Journal of Banking and Finance*, 20,1121-1132.

Hwang, S. and Salmon, M. (2004) **Market stress and herding,** *Journal of Empirical Finance*, 11 (4) 585-616.

Ito, A. (1999) **Profit on technical trading rules and time-varying expected returns: evidence from Pacific-Basin equity markets,** *Pacific-Basin Finance Journal*, 7, 283-330.

Jegadeesh, N. and Titman, S. (1993) **Returns to buying winners and selling losers: implications for stock market efficiency,** *Journal of Finance*, 48,65-91.

……. (2001) **Profitability of momentum strategies: An evaluation of alternative explanations,** *Journal of Finance* 56, 699-720.

Jasic, T. and Wood, D. (2004) **The profitability of daily stock market indices trades based on neural network predictions: case study for the S&P500, the DAX, the TOPIX and the FTSE in the period 1965-1999,** *Applied Financial Economics*, 14, 285-297.

Kahneman, D. (2002) **Nobel lecture**, Stockholm, Sweden.

Kahneman, D. and Tversky, A. (1979) **Prospect theory: an analysis of choice under risk,** *Econometrica*, 47, 263-291.

Kalman, R.E. (1994) **Randomness reexamined,** *Modeling, Identification and Control,* 15(3):141-151.

.... (1995a) **Randomness and probability,** *Mathematica Japonica,* 41(1):41-58.

.... (1995b) **Addendum to "Randomness and probability",** *Mathematica Japonica,* 41(2):463.

Kaufman, P.J. (1998) **Trading systems and methods,** Wiley.

Kavajecz, K.A and Odders-White, E.R (2004) **Technical analysis and liquidity provision.** *Review of Financial Studies,* 17, 1043-1071.

Keane, M.P. and Runkle, D.E. (1998) **Are financial analysts' forecast of corporate profits rational?** *Journal of Political Economy,* 106, 768-805.

Kho, B (1996) **Time-varying risk premia, volatility, and technical trading rule profits, evidence from foreign currency futures markets,** *Journal of Financial Economics,* 41, 249-290.

Kidd, W.V., and Brorsen, B.W. (2004) **Why has the returns to technical analysis decreased?,** *Journal of Economics and Business,* 56, 159-176.

Kon, S.J. (1984) **Models of stock returns: a comparison,** Journal of Finance, 39,147-165.

Koza, J. (1992) **Genetic programming: on the programming of computers by means of natural selection,** Cambridge, MA: MIT Press.

Kraus, A. and Litzenberger (1976) **Skewness preference and the valuation of risk assets,** *Journal of Finance,* September 1085-1100.

Kritzman, M.P. (2000) **Puzzles of finance**, John Wiley & Son Inc.

Krugman, P. and Miller, M. (1993) **Why have a target zone,** Carnegie-Rochester conference series on public policy, 38, 279-314.

Kuo, G.W. (1998) **Some exact results for moving-average trading rules with applications to UK indices**, in Acar, E. and Satchell, S. (ed) Advanced trading rules, Butterworth-Heinemann.

LeBaron, B. (1999) **Technical trading rule profitability and foreign exchange intervention,** *Journal of International Economics*, 49, 125-143.

LeBaron, B. (2000) **The stability of moving average technical trading rules on the Dow Jones Index,** *Derivatives Use, Trading & Regulation*, 5, 324-338.

LeBaron, D. and Vaitilingam, R. (2002) **Treasury of investment wisdom**, Wiley.

Lee, C. and Swaminathan, B. (2000) **Price momentum and trading volume,** *Journal of Finance* 55, 2017-2069.

Leigh, W., Modani, N., Purvis, R and Roberts, T (2002) **Stock market trading rule discovery using technical charting heuristics**. *Expert Systems with Applications,* 23, 155-159.

Leigh, W., Paz, N and Purvis R (2002) **Market timing: A test of a charting heuristic.** *Economic Letters*, 77, 55-63.

Levich, R. and Thomas, L. (1993) **The significance of technical trading rules profits in the foreign exchange market: A bootstrap approach,** *Journal of International Money and Finance*, 12, 451-474.

Lindley, D. (1957) **A statistical paradox,** *Biometrica*, 44, 187-192.

Lo, A. (1997) **On the fundamentals of technical analysis,** *Technical Analysis of Stocks and Commodities*, December.

Lo, A and MacKinlay, A. C (1990) **Data snooping biases in tests of financial asset pricing models.** *Review of Financial Studies*, 3, 431-467.

...... (1999) **A nonrandom walk down Wall Street,** Princeton University Press.

Lo, A., Mamaysky, H. and Wang, J. (2000) **Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation,** *Journal of Finance*, 55, 1705-1765.

Los, C.A. (1999) **Nonparametric efficiency testing of Asian stock markets using weekly data**, Centre for Research in Financial Services, Working paper No. 99-01, Nanyang Technological University.

Lucke, B (2003) **Are technical trading rules profitable: Evidence for head-and-shoulder rules.** *Applied Economics*, 35, 33-40.

Lui, Y.H., and Mole, D. (1998) **The use of fundamental and technical analysis by foreign exchange dealers: Hong Kong evidence,** *Journal of international money and finance*, 17, 535-545.

Lukac, L.P. and Brorsen, B. W. (1989) **The usefulness of historical data in selecting parameters for technical trading systems,** *The Journal of Futures Markets*, 9, 55-65.

Lukac, L.P., Brorsen, B.W. and Irwin, S.H. (1988) **A test of futures market disequilibrium using twelve different technical trading systems**, *Applied Economics*, 20, 623-639.

Maddala, G.S. and Li, H. (1996) **Bootstrap based tests in financial models**, in Maddala, G.S. and Rao, R.C. (ed.) *Handbook of Statistics 14*, Elsevier Science.

Malkiel, B. (1981) **A random walk down Wall Street**, 2nd edition, New York, Norton.

Mandelbrot, B. (1963) **The variations of certain speculative prices**, Journal of Business, 36, 394-419.

Markellos, R.N. (2004) **Diversification benefits in trading?** *Applied Financial Economics*, 14, 13-17.

Markellos, R.N. and Mills, T.C. (1997) **EXPO/Econometric user's guide**, Leading Market Technologies Inc. Cambridge, Massachusetts.

Markellos, R.N., Mills, T.C. and Gavridis, M. (1998) **High frequency random walks?** Economics research paper No.98/8, Department of Economics, Loughborough University.

Markowitz, H. (1959) **Portfolio selection**, Yale University Press.

Markowitz, H. and Xu, G. (1994) **Data mining corrections**, *Journal of Portfolio Management*, 21, 60-69.

Marmer, H. S. and Ng, F. K. (1993) **Mean-semivariance anlysis of option-based strategies: a total mix perspective**, *Financial Analysts Journal*, May/June, 47-54.

McCullough, B.D. (2000) **Is it safe to assume that software is accurate?**, *International Journal of Forecasting*, 16, 383-397.

Menkhoff, L. (1997) **Examining the use of technical currency analysis,** *International Journal of Finance and Economics,* 2, 307-318.

Merriken, H. E. (1994) **Analytical approaches to limit down risk: semivariance and the need for liquidity,** *Journal of Investing,* 3 (3), 65-72.

Merton R. (1976) **Option pricing when underlying stock returns are discontinuous,** Journal of Financial Economics, 3, 125-44.

Mills, T.C. (1996) **Modeling returns distributions: A survey of recent developments and some new evidence**, Economic Research Paper, Loughborough University.

...... (1997a) **Technical analysis and London stock exchange: testing trading rules using the FT30,** *International Journal of Finance and Economics,* 2, 319-331. Special Issue on Technical Analysis and Financial Markets.

...... (1997b) **Stylized facts on the temporal and distributional properties of daily FT-SE returns,** *Applied Financial Economics,* 7, 599-604.

.... (1999) **The econometric modeling of financial time series,** Cambridge University Press, Second Edition.

...... (2000) **Business cycle asymmetry and duration dependence: an international perspective,** *Business cycle volatility and economic growth research paper 00/2.* Department of Economics, Loughborough University.

Moore, G.H. (1990) **Leading indicators for the 1990s,** Dow Jones-Irwin.

Murphy, J.J. (1999) **Technical analysis of the financial market,** New York Institute of Finance.

Neely, C.J. (2002) **The temporal pattern of trading rule returns and exchange rate intervention: intervention does not generate technical trading profits,** *Journal of International Economics*, 58, 211-232.

Neely, C., Weller, P. and Dittmar, R. (1997) **Is technical analysis in the foreign exchange market profitable? A Genetic programming approach**, *Journal of Financial and Quantitative Analysis*, 32, 405-426.

Neely, C.J and Weller, P.A (2001) **Technical analysis and central bank intervention.** *Journal of International Money and Finance,* 20, 949-970.

Neftci, S. N. (1991) **Naive trading rules in financial markets and Wiener-Kologorow prediction theory: a study of technical analysis,** *Journal of Business*, 64, 549-571.

Nelson, D. B. (1991) **Conditional heteroskedasticity in asset returns,** *Econometrica*, 59, 347-370.

Oberlechner, T. (2001) **Importance of technical and fundamental analysis in the European foreign exchange market,** *International Journal of Finance and Economics,* 6, 81-93.

Olson, D. (2004) **Have trading rule profits in the currency markets declined over time?** *Journal of Banking and Finance*, 28, 85-105.

Omega Research (1996a) **Trade Station version 4: user's manual**, Omega Research Inc.

...... (1996b) **Getting started manual: trade station version 4**, Omega Research Inc.

...... (1996c) **Omega server: user's manual,** Omega Research Inc.

...... (1996d) **Omega downloader: user's manual**, Omega Research Inc.

...... (1996e) **Easy language: user's manual**, Omega Research Inc.

...... (1996f) **Analysis techniques: reference manual**, omega research Inc.

Oscar W. (1893) **Lady Windermere's fan**, Penguin Popular Classics 1995.

Osler, C.L. (2000) **Support for resistance: technical analysis and intraday exchange rates**, *Federal Reserve Bank of New York Economic Policy Review*, July.

...... (2003) **Currency orders and exchange rate dynamics: an explanation for the predictive success of technical analysis**, *Journal of Finance*, 58, 1791-1819.

Quandt, R. (1960) **Test of the hypothesis that a linear regression system obeys two separate regimes**, *Journal of the American Statistical Association*, 55(290): 324-330.

Park, C. and Irwin, S.H. (2004) **The profitability of technical analysis: a review**, AgMAS project Research Report no. 2004-04.

Parker, S.P. Editor-in –chief (1994) **McGraw-hill dictionary of mathematics**, McGraw-Hill.

Praetz, P.D. (1976) **Rate of return on filter tests**, *Journal of Finance*, 31, 71-5.

Pring, M.J. (2002) **Technical analysis explained**, McGraw Hill.

Pruitt, S.W., Tse, K.M. and White,R.E. (1992) **The CRISMA trading system : the next five years**, *Journal of Portfolio Management*, Spring, 22-25.

Pruitt S. W. and White, R.E. (1988) **The CRISMA Trading System: who says technical analysis can't beat the market**, *Journal of Portfolio Management*, Spring, 55-58.

Qi, M. and Wu, Y. (2002) **Technical trading rule profitability, data snooping, and reality check: evidence from the foreign exchange market**, Working Paper, Kent State University.

Raj, M. and Thurston, D. (1996) **Effectiveness of simple technical trading rules in the Hong Kong futures markets.** *Applied Economics letters*, 3, 33-36.

Ratner,M. and Leal, R.P.C. (1999) **Tests of technical trading strategies in the emerging equity markets of Latin America and Asia**, *Journal of Banking and Finance*, 23, 1887-1905.

Ready, M.J. (2002) **Profits from technical trading rules**, *Financial Management*, 31, 43-61.

Reitz, S. (2001) **Why technical trading rules works – A simple illustration**, Research Center, Deutsche Bundesbank.

Robert, M.C. (2003) **Technical analysis in commodity markets: risk, returns and value**, NCR-134 conference, St. Louis, Missouri.

Rotella, R.P. (1992) **The elements of successful trading**, New York Institute of Finance.

Rouwenhorst, K.G. (1998) **International momentum strategies**, *Journal of Finance*, 53, 267-284.

Rubinstein, M. (1973) **The fundamental theorem of parameter preference security valuation**, *Journal of Financial and Quantitative Analysis*, 8 (1), 61-69.

Ruiz, E. and Pascual, L. (2002) **Bootstrapping financial time series,** *Journal of Economic Surveys*, 16, 271-300.

Rydberg, T.H. (2000) **Realistic statistical modeling of financial data,** *International Statistical Review*, 68, 3, 233-258.

Saacke, P. (2002) **Technical analysis and the effectiveness of central bank intervention,** *Journal of International money and Finance*, 21, 459-479.

Samuel, K.T. and Raffalovich, P.M. (1995) **Indicators and trading systems**, volume 1 to 9, G. Morris Corporation.

Sapp, S. (2004) **Are all central bank interventions created equal? An empirical investigation.** *Journal of Banking & Finance,* 28. 443-474.

Schiller, R. (1981) **Do stock prices move to be justified by subsequent changes in dividends?** *American Economic Review*, June 71, 3, 421-435.

Schmidt, A.B. (2002) **Why technical trading may be successful? A lesson from the agent-based modeling.** *Physica A*, 303, 185-188.

Schwager, J.D. (1996) **Schwager on Futures: Technical Analysis.** New York, NY: John Wiley & Sons.

Schwert, G.W. (2003) **Anomalies and market efficiency**. In G. Constantinides, M. Harris and R. Stulz (ed.) *Handbook of the Economics of Finance* (p. 937-972). North-Holland.

Sherry, C.J. (1992) **Mathematics of technical analysis**, Probus Publishing Company.

.... (1994) **The new science of technical analysis**, Probus Publishing Company.

Smidt, S. (1965) **Amateur Speculators**, Ithaca, NY: Graduate School of business and public administration, Cornell University.

Smith, C. (2001) **Controlling risk with money management techniques,** in Bensignor, R. (ed.), *New Thinking in Technical Analysis*, John Wiley & Sons.

Sortino, F. and van der Meer, R.A.H. (1991) **Downside risk**, *Journal of Portfolio Management*, Summer, 27-31.

Sortino, F. and Price, L. (1994) **Performance measurement in a downside risk-framework,** *Journal of Investing*, Fall, 59-65.

Sortino, F.R., van der Meer and Plantinga, A. (1999a) **The Dutch triangle: a framework to measure upside potential relative to down side risk**, *Journal of Portfolio Management*, Fall, 50-58.

...... (1999b) **The upside potential ratio,** *Journal of Performance Measurement*, 4 (1), 10-15.

Sosvilla-Rivero, S., Andrada-Felix, J. and Fernandez-Rodriguez, F. (2002) **Further evidence on technical trade profitability and foreign exchange intervention.** *Applied Economics Letter,* 9, 827-832.

Stewart, B. (1949) **An analysis of speculative trading in Grain Futures,** *Technical bulletin,* No.1001, US Department of Agriculture, Washington, D.C..

Stock, J.H. and Watson, M.W. (2003) **Introduction to econometrics**, Addison Wesley.

Stridsman, T. (2001) **Trading systems that work,** McGraw Hill.

Strong, R.A. (1988) **A Behavioral investigations of three paradigms in finance,** *North East Journal of Business and Economics*, Spring/Summer, 1-28.

Sullivan, R., Timmermann, A. and White, H. (1999) **Data-snooping, technical trading rule performance and the bootstrap,** *Journal of Finance*, 54, 647-1691.

……. (2003) **Forecast evaluation with shared data sets.** *International Journal of Forecasting,* 19, 217-227.

Swanson, N.R. and Franses P.H. (1999) **Nonlinear econometric modeling: a selective review,** in Rothman, P. (ed.) *Nonlinear Time Series Analysis of Economic and Financial Data*, Kluwer Academic Publishers.

Sweeney, R.J. (1986) **Beating the foreign exchange market,** *Journal of Finance*, 41, 163-82.

……. (1988) **Some new filter tests, Methods and Results,** *Journal of Financial and Quantitative Analysis*, 23, 285-300.

Tan, R.S.K. and Wong, N.T. (1998) **The diminishing calendar anomalies in the stock exchange of Singapore,** *Applied Financial Economics,* 1, 119-125.

Taylor, M.P. and Allen, H. (1992) **The use of technical analysis in the foreign exchange markets,** *Journal of International Money and Finance,* 11, 304-314.

Taylor, S.J. (1986) **Modeling financial time series,** John Wiley & Sons Ltd..

……. (1994) **Trading futures using a channel rule: a study of the predictive power of technical analysis with currency examples,** *Journal of Futures Markets*, 14, 215-235.

.... (2000) **Stock index and price dynamics in the UK and the US: new evidence from a trading rule and statistical analysis,** *The European Journal of Finance*, 6, 39-69.

The Economist (1999) **School brief-Finance: Trick or treat?** October 23rd.

The Economist (2004) **Finance and economics-Currency trading: The buck doesn't stop here**, Oct.2-8th.

Timmermann, A. and Granger, C.W.J. (2004) **Efficient market hypothesis and forecasting,** *International Journal of forecasting*, 20, 141-163.

Treynor, J. and Ferguson, R. (1985) **In defence of technical analysis,** *Journal of Finance,* XL, 3.

Tucker, A.L. (1992) **A reexamination of finite-and infinite-variance distributions as models of daily stock returns,** *Journal of Business and Economics Statistics*, 10, 73-81.

Van Vliet, B. and Hendry, R. (2004) **Modeling financial markets**, McGraw Hill.

Vince, R. (1990) **Portfolio management formulas,** New York: Wiley.

Wang, J. (2000) **Trading and hedging in S&P 500 spot and futures markets using genetic programming,** *Journal of futures Markets*, 20, 911-942.

White, H. (2000) **A reality check for data snooping**. *Econometrica,* 68, 1097-1126

Wilcox, J.W. (1999) ***Investing by the numbers***, Frank J. Fabozzi Associates.

Wong, Y.K. and Koh, A. (1994) **Technical analysis of Nikkei 225 stock index futures using an expert system advisor,** *Review of Futures Market*, 1005-1025.

Zielonka (2004) **Technical analysis as the representation of typical cognitive biases,** *International Review of Financial Analysis*, 13, 217-225.

References

Part II

Sources of 200 Technical Trading Rules

(TASC = Technical Analysis of Stocks and Commodities)

Rule No	Name	Source
1	123 Reversal	Jensen,Ulf (1992) *"How I triple my money in the futures*
		market" , Probus Publishing
2	25x25 Bond	Le Beau, Charles and Tan, Terence (1998) *"The 25x25*
		Bond trading system version 1.0", System Traders Club
3	A Price-&Vol Based	Saitta, Alex (1996) "A price and volume based system"
		TASC, Volume 14:3 (103-105) : March
4	Adaptive Mov Avg	Kaufman, Perry J. (1995)*"Smarter Trading",* McGraw Hill
5	AMA	Kaufman, Perry J. (1998) *" TASC",* Bonus issue
6	Aztec Real Oil	Krutsinger, Joe (1994) *"The trading systems toolkit",*
		McGraw Hill
7	B. Williams 19	Krutsinger, Joe (1997) *"Trading Systems",* McGraw Hill
8	Bottom Fishing	Chande, T.S. (1995) "A market bottom pattern for S&P
		Futures", *TASC,* Volume 13:3 (99-101) : March
		Chande, T.S. (1997) " A pattern for bottom fishing", *Beyond Technical Analysis,* Wiley
9	Buy Mon, 1400 stXMOC	Krutsinger, Joe (1997) *"Trading Systems",* McGraw Hill
10	CCI Avg. Crossover	Trade Station (1996) *"Analysis techniques reference*
		manual" Omega Research
		Reference: Lambert, D.R. (1980) *"Commodities*
		magazine" : October
11	Channel Breakout	Ruggiero, Murray A. Jr. (1997) *"Cybernetic Trading*
		Strategies", Wiley
12	Channel Brk IntraBar	Trade Station (1996) *"Analysis techniques reference*

		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
13	Channel Brk On Close	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
14	Channel Brk Weighted	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
15	Conner 19	Krutsinger, Joe (1997) *"Trading systems"* ,McGraw Hill
16	Consecutive Closes	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
17	DeTrend	Krutsinger, Joe (1997) "*Trading Systems"*, McGraw Hill
18	Dinapoli 5	Krutsinger, Joe (1997) "*Trading Systems"*, McGraw Hill
19	Derivative MA	White, A. (1996) "The Derivative Moving Average" *TASC,*
		Volume 14:6 (253-257) : June
20	Divergence	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
21	Dunnigan ST	Ruggiero, Murray A. Jr. (1998) "The Dunnigan's Way"
		Futures, November
22	Ehrlich 7	Krutsinger, Joe (1997) "*Trading Systems"*, McGraw Hill
23	EZ Bonder	Krutsinger, Joe (1997) "*Trading Systems"*, McGraw Hill
24	Gap1 System	Schwager, Jack (1999) "Turning chart patterns into trading
		systems Part I, Part II and Part III" *Futures :* April, May

		and June
25	Gap2 System	Schwager, Jack (1999) "Turning chart patterns into trading
		systems Part I, Part II and Part III" *Futures :* April, May
		and June
26	Gap3 System	Schwager, Jack (1999) "Turning chart patterns into trading
		systems Part I, Part II and Part III" *Futures :* May and June
27	Gap4 System	Schwager, Jack (1999) "Turning chart patterns into trading
		systems Part I, Part II and Part III" *Futures :* May and June
28	Gap5 System	Schwager, Jack (1999) "Turning chart patterns into trading
		systems Part I, Part II and Part III" *Futures :* May and June
29	Generation 1197	Ruggiero, Murray A. Jr. (1997) "Cybernetic Trading
		Strategies", Wiley
30	Generation 1723	Ruggiero, Murray A. Jr. (1997) "Cybernetic Trading
		Strategies", Wiley
31	Gettess-30	Krutsinger, Joe (1997) "*Trading Systems",* McGraw Hill
32	GM1.Arms EOM (Norm)	Arms, Richard (1990) "Ease of Movement" *TASC,*
		Volume 8:5 (187-190)
33	GM1.Generic Osc w/MA	G. Morris Corporation, "Generic Oscillator with Moving
		Average" *Indicators & trading systems*
		Tradewind Publishing Inc.
34	GM1.PrVol Trend w/MA	G. Morris Corporation, "Generic Oscillator with Moving
		Average" *Indicators & trading systems*
		Tradewind Publishing Inc.
35	GM1. sKST-Vol w/Mavg	Pring, Martin (1997) "Martin Pring on market momentum",
		McGraw Hill
36	GM2.% R (20/80)Xover	G. Morris Corporation: William, Larry (1995) "Percentage
		return (20/80) Crossover" *Indicators & trading systems*
		Tradewind Publishing Inc.
37	GM2.% R(20/80)E/X/Chg	G. Morris Corporation: William, Larry (1995) "Percentage
		return (20/80) Crossover entry/exit with stops - change"

		Indicators & trading systems, Tradewind Publishing Inc.
38	GM2.% R (20/80) Stop/MA	G. Morris Corporation: William, Larry (1995) "Percentage
		return (20/80) Crossover entry/exit with stops - moving
		average" *Indicators & trading systems*, Tradewind
		Publishing Inc.
39	GM2.% R (20/80) w/Stops	G. Morris Corporation: William, Larry "Percentage return
		(20/80) Crossover with stops"
		Indicators & trading systems, Tradewind Publishing Inc.
40	GM2.CCI(+/-) Cross Over	Lambert, Donald R. (1982-1983) "Commodity Channel
		Index : Tool for trading cyclic Trends" *TASC*, Volume 1:5
		(120-122) : May
41	GM2.CCI(+/-) XO/ Exchg	Lambert, Donald R. (1982-1983) "Commodity Channel
		Index : Tool for trading cyclic Trends" *TASC*, Volume 1:5
		(120-122) : May
42	GM2.CCI(+/-) XO/ ExMAV	Lambert, Donald R. (1982-1983) "The market direction
		indicator anticipating moving average crossovers" *TASC*,
		Volume 1:7 (166-167) : July
		Lambert, Donald R. (1984) "Exponential smoothed moving
		average" *TASC*, Volume 2:5 (182-183) : May
43	GM2.CCI(+/-) XO/Stops	Lambert, Donald R. (1982-1983) "The market direction
		indicator anticipating moving average crossovers" *TASC*,
		Volume 1:7 (166-167) : July
		Lambert, Donald R. (1984) "Exponential smoothed moving
		average" *TASC*, Volume 2:5 (182-183) : May
44	GM2.Chaikin w/stops	G. Morris Corporation: Chaikin, Marc "Chaikin entry/exit
		with stops" *Indicators & trading systems*
		Tradewind Publishing Inc.
45	GM2.GenOsc/Mov.Avg	G. Morris Corporation, " Generic Oscillator with moving
		and moving average" *Indicators & trading systems*
		Tradewind Publishing Inc.

46	GM2.GenOsc/Thresh/MA	G. Morris Corporation, " Generic Oscillator with threshold
		and moving average" *Indicators & trading systems*
		Tradewind Publishing Inc.
47	GM2.Parabol.SAR.Xover	G. Morris Corporation: Wilder, Welles (1978)
		"Parabolic SAR Crossover" *Indicators & trading systems*
		Tradewind Publishing Inc.
48	GM2.ROC Cross Over	G. Morris Corporation, "Rate of Change Crossover"
		Indicators & trading systems, Tradewind Publishing Inc.
49	GM2.ROC/Xover/Stops	G. Morris Corporation, "Rate of Change Crossover with
		stops" *Indicators & trading systems,*
		Tradewind Publishing Inc.
50	GM2.RSI/Xover/Stops	Wilder, Welles (1986) "Relative strength index" *TASC,*
		Volume 4:9 (343-346): September
51	GM2.RSI(30/70)Xover	G. Morris Corporation: Wilder, Welles "RSI (30/70)
		crossover" *Indicators & trading systems,*
		Tradewind Publishing Inc.
52	GM2.RSI(30/70)XO/MA	G. Morris Corporation: Wilder, Welles "RSI (30/70)
		crossover entry/exit with stops- moving average"
		Indicators & trading systems,
		Tradewind Publishing Inc.
53	GM2.RSI(30/70)XO/chg	G. Morris Corporation: Wilder, Welles "RSI (30/70)
		crossover entry/exit with stops- change"
		Indicators & trading systems,
		Tradewind Publishing Inc.
54	GM2.StocD/Xover/Stop	Lanes, George C. (1984) "Lane's stochastics" *TASC,*
		Volume 2:3 (87-90) : March
55	GM2.StocK Crossover	G. Morris Corporation: Lanes, George C.
		"Stochastics %K (20/80) crossover"
		Indicators & trading systems, Tradewind Publishing Inc.
56	GM2.StocK/XO/Stop/MA	G. Morris Corporation: Lanes, George C.

		"Stochastics %K (20/80) entry/exit with stops - moving
		average" *Indicators & trading systems,*
		Tradewind Publishing Inc.
57	GM2.StocK/Xover/Stop	G. Morris Corporation: Lanes, George C.
		"Stochastics %K (20/80) crossover with stops"
		Indicators & trading systems, Tradewind Publishing Inc.
58	GM2.Trix En/Ex-chng	Hutson, Jack K. (1982-1983) "Good Trix" *TASC,*
		Volume 1:5 (105-108) : May
		Hutson, Jack K. (1984) "TRIX : Triple exponential
		smoothing oscillator" *TASC,* Volume 2:3 (91-93) : March
59	GM2.Trix En/Ex-mavg	Hutson, Jack K. (1982-1983) "Good Trix" *TASC,*
		Volume 1:5 (105-108) : May
		Hutson, Jack K. (1984) "TRIX : Triple exponential
		smoothing oscillator" *TASC,* Volume 2:3 (91-93) : March
60	GM2.Trix Stops-chng	Hutson, Jack K. (1982-1983) "Good Trix" *TASC,*
		Volume 1:5 (105-108) : May
		Hutson, Jack K. (1984) "TRIX : Triple exponential
		smoothing oscillator" *TASC,* Volume 2:3 (91-93) : March
61	GM3.All%D Long	Morris, Greg (1992) "*Candle Power*" Probus Publishing
62	GM3.All%D Short	Morris, Greg (1992) "*Candle Power*" Probus Publishing
63	GM3.All CCI Long	Morris, Greg (1992) "*Candle Power*" Probus Publishing
64	GM3.All Short	Morris, Greg (1992) "*Candle Power*" Probus Publishing
65	GM3.All MFI Long	Morris, Greg (1992) "*Candle Power*" Probus Publishing
66	GM3.All MFI Short	Morris, Greg (1992) "*Candle Power*" Probus Publishing
67	GM3.All RSI Short	Morris, Greg (1992) "*Candle Power*" Probus Publishing
68	GM3.All with % D	Morris, Greg (1992) "*Candle Power*" Probus Publishing
69	GM3.All with CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
70	GM3.All with MFI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
71	GM3.All with RSI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
72	GM3.DKkcld/PrcL in CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing

73	GM3.Doji Stars & CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
74	GM3.Doji Stars & MFI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
75	GM3.Engulfing & %D	Morris, Greg (1992) "*Candle Power*" Probus Publishing
76	GM3.Engulfing & CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
77	GM3.Engulfing & MFI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
78	GM3.Harami & %D	Morris, Greg (1992) "*Candle Power*" Probus Publishing
79	GM3.Harami & CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
80	GM3.Harami & MFI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
81	GM3.Harami & RSI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
82	GM3.HngMn/Ham&CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
83	GM3.HngMn/Ham&MFI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
84	GM3.HngMn/Ham&RSI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
85	GM3.Stars and %D	Morris, Greg (1992) "*Candle Power*" Probus Publishing
86	GM3.Stars and CCI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
87	GM3.Stars and MFI	Morris, Greg (1992) "*Candle Power*" Probus Publishing
88	GM4.DirMov. ROC/MA	G. Morris Corporation, "Directional movement rate of
		change/moving average system" *Indicators & trading*
		systems, Tradewind Publishing Inc.
89	GM4.DirectMove ROC	G. Morris Corporation, "Directional movement rate of
		change" *Indicators & trading systems,*
		Tradewind Publishing Inc.
90	GM4.Envelopes Crossing	G. Morris Corporation, "Envelopes crossing"
		Indicators & trading systems, Tradewind Publishing Inc.
91	GM4.GenOSC w/Mavg	G. Morris Corporation, "Generic oscillator with moving
		average" *Indicators & trading systems,*
		Tradewind Publishing Inc.
92	GM4.GenOSC w/thr & MAV	G. Morris Corporation, "Generic oscillator with threshold
		and moving average" *Indicators & trading systems,*
		Tradewind Publishing Inc.

93	GM4.GenOSC w/thresh	G. Morris Corporation, "Generic oscillator with threshold"
		Indicators & trading systems, Tradewind Publishing Inc.
94	GM4.LinearTrend	G. Morris Corporation, "Linear Trend System"
		Indicators & trading systems, Tradewind Publishing Inc.
95	GM4.LinTrend w/Mavg	G. Morris Corporation, "Linear Trend System with moving
		average" *Indicators & trading systems,*
		Tradewind Publishing Inc.
96	GM4.LinTrend w/E/X/ch	G. Morris Corporation, "Linear Trend System with/entry/
		exit - change" *Indicators & trading systems,*
		Tradewind Publishing Inc.
97	GM4.MACD (True)	G. Morris Corporation, "Moving average convergence
		divergence (True)" *Indicators & trading systems,*
		Tradewind Publishing Inc.
98	GM4.Morris Db1MomOsc	G. Morris Corporation, "Double momentum oscillator
		system" *Indicators & trading systems,*
		Tradewind Publishing Inc.
99	GM4.Morris Mstr Tradr	G. Morris Corporation, "Morris master trader"
		Indicators & trading systems, Tradewind Publishing Inc.
100	GM4.Morris Volume RSI	Morris, Greg (1985) "Facelift for an old favourite" *TASC,*
		Volume 3:5 (159-161) : May
101	GM4.RSI,%D and CCI	G. Morris Corporation, "RSI, %D and CCI trader"
		Indicators & trading systems, Tradewind Publishing Inc.
102	GM4.sKSTd/MA/Bands	Pring, Martin (1997) "Pring's KST with threshold and
		moving average" *Martin Pring on market momentum*
		McGraw Hill
103	GM4.sKSTd w/Mavg	Pring, Martin (1997) "Pring's KST with moving average"
		Martin Pring on market momentum, McGraw Hill
104	GM4.Triple MA in Sync	G. Morris Corporation, "Triple averages in - sync"
		Indicators & trading systems, Tradewind Publishing Inc.
105	GM6.83 - CCI+100/-100	Lambert, Donald (1983) "Commodity Channel Index : Tool

		for trading cyclic trends" *Commodities (Futures now)*
		magazine, Volume 1, p.120
106	GM6.83 - CCI ZeroCross	Lambert, Donald (1983) "Commodity Channel Index : Tool
		for trading cyclic trends" *Commodities (Futures now)*
		magazine, Volume 1, p.120
107	GM6.83 - SwingLineCross	Arnold, Curtis (1983) "GANN" *Commodities (Futures now)*
		magazine, Volume 1, p.48
108	GM6.85 - Morris VolRSI	Morris, Greg (1985) "Facelift for an old favourite" *TASC,*
		Volume 3:5 (159-161) : May
109	GM6.86 - RSI Quality	Jones, Donald & Stromquist, Tod (1986) "The relative
		strength quality factor" *TASC,* Volume 4:7 (275-277) : July
110	GM6.87 - EnhancedIndex	Kinder, Robert J. (1987) "Enhanced Williams % R" *TASC,*
		Volume 5:5 (180-182) : May
111	GM6.88 - MACD - MOTrader	Aspray, Thomas (1988) "MACD - momentum" *TASC,*
		Volume 6:8 (294-297) Part 1 : June
		Volume 6:9 (350-353) Part 2 : June
112	GM6.89 - %V Systems	Notis, Steve (1989) "CompuTrak makes technical analysis
		a SNAP!" *TASC,* Volume 7:9 (315-320) : September
113	GM6.89 - Channel - 8	Aan, Peter (1989) "Channel Breakout" *TASC,*
		Volume 7:9 (295-297) : September
114	GM6.89 - Channel - 12	Aan, Peter (1989) "Channel Breakout" *TASC,*
		Volume 7:9 (295-297) : September
115	GM6.89 - EOM BasLin XO	Arms, Richard (1989) "What volume is it ?" *TASC,*
		Volume 7:12 (456-457) : December
116	GM6.89 - VA Cross Over	G. Morris Corporation, (1989) "Volume accumulation
		crossover system" *Indicators & trading systems,*
		Tradewind Publishing Inc.
117	GM6.89 - Volatility	Notis, Steve (1989) "CompuTrak makes technical analysis
		a SNAP!" *TASC,* Volume 7:9 (315-320) : September

118	GM7.90 - Shrt Sigs DJI	Toombs, John (1991) "A short-term buy signal for the DJIA"
		TASC, Volume 8:7 (245-247) : July
119	GM7.91 - %M and StdDev	Chande, Tushar (1991) "Midpoint oscillator" *TASC*,
		Volume 9:11 (431-434) : November
120	GM7.91 - %M Zero Cross	Chande, Tushar (1991) "Midpoint oscillator" *TASC*,
		Volume 9:11 (431-434) : November
121	GM7.91 - ADX System	Hartle, Thom (1991) "The average directional movement
		index" *TASC*, Volume 9:3 (101-102) : March
122	GM7.91 - Double Stoc	Blau, William (1991) "Double smoothed - stochastics"
		TASC, Volume 9:1 (14-16) : January
123	GM7.91 - HLC Index	Blau, William (1991) "Double smoothed - stochastics"
		TASC, Volume 9:1 (14-16) : January
124	GM7.91 - Maddox System	Maddox, Darrly (1991) "Calculating momentum a new way"
		TASC, Volume 9:4 (158-159) : April
125	GM7.91 - PivotPNt Fast	Kosar, John (1991) "Supports and resistance levels" *TASC*,
		Volume 9:1 (17-19) : January
126	GM7.91 - True Strengh	Blau, William (1991) "True strength index"
		TASC, Volume 9:11 (438-446) : November
127	GM7.91 - Var.MA Cross	Arrington, George (1991) "Building a variable - length
		moving average" *TASC*, Volume 9:6 (219-223) : June
128	GM8.92 - 2% Model	Kardenian, Bob C.M.T. (1992) "The 4% model : Using the
		value line composite" *TASC*, Volume 10:3(127-128) :March
129	GM8.92 - 4% Model	Kardenian, Bob C.M.T. (1992) "The 4% model : Using the
		value line composite" *TASC*, Volume 10:3(127-128) :March
130	GM8.92 - 2 Stochastics	Meibuhr, Stuart (1992) "Multiple - length stochastics"
		TASC, Volume 10:12 (501-506) : December

131	GM8.92 - DM Trade Model	G. Morris Corporation (1992) "DM trading model"
		Indicators & trading systems, Tradewind Publishing Inc.
132	GM8.92 - Mass Index	Dorsey, Donald (1992) "The mass index" *TASC,*
		Volume 10:6 (265-267) : June
133	GM8.92 - Pring KST XO	Pring, Martin (1992) " Technician's Technician" *TASC,*
		Volume 10:2 (55-60) : February
134	GM8.92 - RM1#2 System	Altman, Roger (1993) "Relative momentum index:
		modifying RSI" *TASC,* Volume 11:2 (57-60) : February
135	GM8.92 - Tai System	White, Adam (1992) "Filtering trades with a moving average
		slope" *TASC,* Volume 10:8 (358-360) : August
136	GM8.92 - TRIX MO System	Downs, Ed (1992) "Looking at momentum with TRIX"
		TASC, Volume 10:12 (537-540) : December
137	GM8.92 - TRIX System	Downs, Ed (1992) "Looking at momentum with TRIX"
		TASC, Volume 10:12 (537-540) : December
138	GM8.92 - Vol RSI System	G. Morris Corporation (1992) "Volume weighted RSI"
		Indicators & trading systems, Tradewind Publishing Inc.
139	GM8.93 - Coppock System	Hayes, Tim (1993) "The Coppock Guide"
		TASC, Volume 11:3 (125-126) : March
140	GM8.93 - DYRimpliedRsk	Yates, Jim (1993) "Through the years"
		TASC, Volume 11:6 (235-242) : June
141	GM8.93 - Offset MO Sys	Star, Barbara (1993) "Oscillator variations"
		TASC, Volume 11:4 (174-177) : April
142	GM8.93 - Raff OBV Sys	Raff, Gilbert (1993) "Time and indicator design"
		TASC, Volume 11:2 (92-97) : February
143	GM9.94 - Hybrid System	Ritter, Jim (1994) "Create a hybrid indicator"
		TASC, Volume 12:12 (534-534) : December
144	GM9.94 - PFE System	Hannula, Hans (1994) "Polarized Fractal Efficiency"
		TASC, Volume 12:1 (38-41) : January

145	GM9.95 - Bottom Fisher	Chande, Tushar (1995) "A market bottom pattern for
		S&P futures" *TASC*, Volume 13:3 (99-101) : March
146	GM9.95 - CCI OXOver	G. Morris Corporation (1995) "CCI zero crossover"
		Indicators & trading systems, Tradewind Publishing Inc.
147	GM9.95 - DJROC System	Kappel, Jay (1995) "A DJIA long-term momentum indicator"
		TASC, Volume 13:5 (200-203) : May
148	GM9.95 - Modified VIX	Karczewski, S. Jack (1995) "Modifying the volatility index"
		TASC, Volume 13:4 (174-179) : April
149	GM9.95 - T & N	G. Morris Corporation (1995) "T & N"
		Indicators & trading systems, Tradewind Publishing Inc.
150	GM9.95 - UD% Price chny	Meyers, Dennis (1995) "UD Price change indicator"
		TASC, Volume 13:7 (298-303) : July
151	GM9.95 - Vol. Mom.Sys	G. Morris Corporation : Star, Barbara (1995) "Volume
		variations" *Indicators & trading systems,*
		Tradewind Publishing Inc.
152	GM9.95 - Weekly S&P	White, Adams (1995) "A weekly trading system"
		TASC, Volume 13:6 (233-237) : June
153	HiHo Silver	Krutsinger, Joe (1994) *The trading system toolkit,*
		McGraw Hill
154	His Vol w/patterns	Connors, Laurence A and Raschke, Linda Bradford (1996)
		"Historical volatility and pattern recognition" *TASC,*
		Volume 14:8 (338-341) : August
155	Intermarket Mov Avg	I. Jurik, Mark (1999) *"Computerized trading"* Prentice Hall
156	Intermarket one	I. Jurik, Mark (1999) *"Computerized trading"*
		Prentice Hall
157	Intermarket three	I. Jurik, Mark (1999) *"Computerized trading"*
		Prentice Hall
158	Intermarket two	I. Jurik, Mark (1999) *"Computerized trading"*
		Prentice Hall

159	JJMBook.Four%Model	Murphy, John J. (1999) "*Technical analysis of the*
		financial market", Prentice Hall
160	Kase 30	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
161	Key Reversal Major	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
162	Long Bomb	Chande, Tushar S. (1996) "*Beyond Technical Analysis*"
		Wiley
163	MACD	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
164	Momentum First	Ruggiero, Murray A. Jr. (1997) "*Cybernetic trading*
		strategies" Wiley
165	Mov Avg x2 20	Landry, David S. (1996) "The 2/20 - Day EMA breakout
		system" *TASC*, Volume 14:12 (526-529) : December
166	Mov Avg - Supp/ Res	Tilley, Dennis L. (1998) "Moving averages with resistance
		and support" *TASC*, Volume 16:9 (428-433) : September
167	Mov Avg (3) Cross Over	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
168	Mov Avg Cross Over	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
169	Neeley 31	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
170	NMP	Downs, Walter T. (1998) "Mutated variables volatility and
		a new market paradigm" *TASC*, Volume 16:6 (265-272) :

		June
171	OBVDI	Holt, Phillip C. (1996) "Enhancing on-balance and negative
		volume" *TASC*, Volume 14:6 (265-270) : June
172	One Night Stand	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
173	One Night Stand (TK)	Krutsinger, Joe (1994) "*The trading systems toolkit*",
		McGraw Hill
174	Parabolic	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Wilder, Welles Jr. (1978)"*New concepts in*
		technical trading systems "
175	Pathfinder Currency	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
176	Percent R Oscillator	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Williams, Larry (1979) "*How I made $1,000,000 last year trading commodities* " Windsor
177	Range Breakout	Saitta, Alex (1995) "Range breakout trading in treasury
		bonds" *TASC*, Volume 13:4 (149-152) : April
178	RSI Oscillator	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Wilder, Welles Jr. (1978) "*New concepts in*
		technical trading systems "
179	RSI	Ruggiero, Murray A. Jr. (1998) "Getting a new angle on an
		old indicator" *Futures* : December
180	RS Ratio MACD	Raff, Gilbert (1994) "The relative strength ratio MACD
		crossover" *TASC*, Volume 12:11 (451-454) : November
181	S&P 500	Katz, Jeffrey Owen & McCormick, Donna L. (1997)
		"Sunspots and market activity" *TASC*, Volume 15:9
		(401-406) : September
182	Saidenberg 30	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
183	Simple Futures MA	Kaeppel, Jay (1997) "Genesis of a simple futures trading

		system, interview" *TASC,* Volume 15:5 (225-234) : May
184	Simple Futures MA_Q	Kaeppel, Jay (1997) "Genesis of a simple futures trading
		system, interview" *TASC,* Volume 15:5 (225-234) : May
185	Stochastic Crossover	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
186	Stochastic S&C	Zellner, Robert (1999) "Tales from the front Robert Zellner,
		interview" *TASC,* Volume 17:3 (116-123) : March
187	Stuckey 19	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
188	Sys Implementation	Stridsman, Thomas (1999) "Running together" *Futures :*
		July
189	T-AT	Chande, Tushar S. (1996) "*Beyond Technical Analysis*"
		Wiley
190	TCBR	Matheny, Brad (1999) "The Japanese Way" *Futures :* April
191	TRIX System S&C	Luisi, Joe (1997) "Playing TRIX : The triple exponential
		smoothing oscillator" *TASC,* Volume 15:6 (280-284) : June
192	Turtle #1,#2,#3	McNutt, Malcolm S. and Sands, R. (1991) "Turtle Trading
		Concepts", Turtle Talk.
193	Turtle P/L Filt +10 wk	McNutt, Malcolm S. and Sands, R. (1991) "Turtle Trading
		Concepts", Turtle Talk.
194	Turtle P/L Filter	McNutt, Malcolm S. and Sands, R. (1991) "Turtle Trading
		Concepts", Turtle Talk.
195	Utility Average	Meyers, Dennis (1997) "A new utility average stock market
		system" *TASC,* Volume 15:2 (101-111) : March
196	Volatility Breakout	Ruggiero, Murray A., Jr., (1997) "Cybernetic Trading
		Strategies", Wiley
197	Wagner 31	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill

198	Weighted Avg. Crossover	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley
199	William 19	Krutsinger, Joe (1997) "*Trading Systems*", McGraw Hill
200	XAverage Crossover	Trade Station (1996) "*Analysis techniques reference*
		manual" Omega Research
		Reference : Kaufman, P.J.(1987) "*The new commodities*
		trading systems and methods" Wiley