A framework for applied quantitative trading strategies in South African equity markets

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SOLEMN DECLARATION

Solemn declaration by student

I **Jacques Francois du Plessis** declare herewith that the assignment which I herewith submit to the North-West University as partial completion of the requirements set for the MBA degree, is my own work.

Signature of student______________________________

Student number: 12603724

Signed at _________________________ this ______ day of _____________20___

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Executive summary

This study discusses the history, origins and use of quantitative trading in the financial sector and it also lays the ground work for a framework of applied quantitative trading strategies in South African equity markets. This framework is then used on actual real world stock data from the Johannesburg Stock Exchange (JSE) to show if the discussed strategies are viable when applied in practise.

It contains a brief literature study around quantitative trading and also gives details for the different trading strategies that can be commonly found in literature. It also contains research on the theoretical aspects of defining measures to see which strategies should be selected as well as a short discussion on guidelines for when positions should be exited.

The study contains empirical research and back testing results around the profitability and feasibility of the various discussed trading strategies and discusses and analyses the suitability of each strategy in the context of a defined trading algorithm.

The trading algorithm is used to find viable strategies over JSE stock price data from 2007/01/02 to 2011/12/30. The first four years are used to find and calibrate profitable trading strategies and then the last year is used to evaluate the results of the selected strategies as if they had been applied in the last year. The returns of each qualified strategy are also shown in the last chapter.

This report contains references to tradable stocks which are listed on the JSE as well as descriptions of trading strategies which can be implemented on those stocks. The author does not accept any responsibility for any damages or loss as a result of implementing the trading strategies contained within this dissertation.

The results in this dissertation are considered to be hypothetical results. Hypothetical performance results have many inherent limitations. Unlike an actual performance record, simulated results do not represent actual trading. Also, since the trades have not actually been executed, the results may have been under or over compensated for. No representation is being made that any account will or is likely to achieve profits or losses similar to those shown. Furthermore, only risk capital should be used for leveraged trading due to the high risk of loss involved.

Trading any financial market involves risk. The content of this dissertation is neither a solicitation nor an offer to Buy/Sell any financial instruments. The content of this dissertation is for general information and educational purposes only.

Although every attempt has been made to assure accuracy, the author does not give any express or implied warranty as to its accuracy. The author does not accept any liability for error or omission. Examples are provided for illustrative purposes only and should not be construed as investment advice or strategy.

Chapter 1

Quantitative trading research introduction

1.1 Introduction

What is quantitative trading? Quantitative trading is the act of buying and selling certain investment assets based on the indicators of some pre-defined strategy that has been programmed into a financial model and has been tested for profitability by using the actual historical data of the asset being considered (Chan, 2009:1).

The chosen strategies are prepared by using a computer algorithm to sift through historical financial datasets in order to fit a preconceived pattern that, if implemented in the past, would have yielded a profit. Based on the assumption that these patterns will remain valid in the present time, the financial model will then derive buy or sell signals for the scrutinized financial instruments which if implemented would hopefully yield a profit.

Algorithmic trading is gaining considerable traction and popularity; it is estimated that as much as 70% of the trading volumes in the United States were made by automated trading platforms in 2009 (Lopez, 2010:1). Yet not much has been published in academia because most of the information is proprietary and kept out of the public domain by investment banks, hedge funds and other financial institutions. The advent of the internet, however, is quickly changing this information blackout (Stone, 2011).

Although many, if not most, financial institutions and hedge funds are heavily invested in the infrastructure and manpower assets required for financial modelling activities, it is not their exclusive domain. There are still many opportunities for small scale start-up enterprises in this field, since smaller enterprises are able to swim in markets to shallow for the big fish of corporate enterprise (Chan, 2009:157).

Indeed, multiple PhDs do not guarantee success in this discipline, as most simple models work just as well if not better than the overly complicated ones dreamt up by the financial wizards of Wall Street (Chan, 2009:3). A small venture with smaller amounts of capital is able to move in and out of positions much more quickly, without disrupting the market and with less cost than the large multi million rand hedges funds are able to do (Chan, 2009:158).This forms the basis for this study, which will explore the business viability of a small scale start up quantitative trading venture within the South African financial environment.

This study will outline the performance and applicability of several quantitative trading strategies in South African markets. It will also give details and statistical analysis around the effectiveness of these strategies when submitted to proper back testing computer algorithms and procedures.

1.2 Problem statement

Quantitative trading strategies are described in literature by authors from around the world. Most of these authors can be found primarily in the developed world and they tend to describe strategies that work well in developed markets. Contrasted with this availability of research and information in the developed world, not a lot has been said about the viability of these strategies in South African markets.

The focus of this study then will be to investigate the viability of quantitative trading strategies in South African retail equity markets. This mini- dissertation will show and describe quantitative trading strategies available in academic literature and it will then practically implement these strategies over historical stock price data.

A common measure or measures will then be shown as well which will allow the different strategies to be compared to each other. This will then allow the dissertation to make comments and recommendations about the quantitative trading strategies which are most applicable to South African retail equity markets.

1.3 Objectives of the study

The following chapter will show which objectives must be undertaken and accomplished in order to successfully complete this dissertation. It will explain the primary objective of the study as well as the secondary objectives that must be met in order to complete the primary objective.

1.3.1 Primary objective

The primary objectives of this study will be to search for and evaluate feasible quantitative trading strategies in South African equity markets.

1.3.2 Secondary objectives

To achieve the primary objective of this study the following steps will need to be taken:

- Research must be done to find different quantitative trading strategies described in literature.
- Research must also be done to find ways of evaluating the effectiveness of the quantitative trading strategies available in literature. These measures of effectiveness should be standardized on each strategy's rate of return in order to allow different strategies to be compared against each other.

The first two objectives mentioned above will be dealt with in the second chapter of this dissertation in which a literature study about quantitative trading will be done.

- The third chapter will deal with empirical research based on the strategies and measures discovered in the second chapter.
- First the strategies will be encoded into a computer algorithm.
- Then 5 years of historical data will be sourced from the top 100 stocks on the Johannesburg Stock Exchange (JSE). The stocks will be ranked in terms of capitalization and liquidity.
- The next step will be to back test the quantitative trading strategies against the top 100 identified stocks and then to record the results.

- The measures described in chapter 2 will then be used to evaluate each strategy's performance.

The next chapter of the dissertation, chapter 4, will deal with discussing the results from the back testing done for chapter 3, and in chapter 4 the question posed by the title of the dissertation will be answered.

1.4 Research methodology

1.4.1 Literature and theoretical review

The literature and theoretical research review will primarily be geared towards the discovery of quantitative trading strategies. An example of a book dedicated to this topic is Pairs trading by Ganapathy Vidyamurthy (Vidyamurthy, 2004) in which the author shows how to craft a strategy around highly correlated stocks.

The review will also include articles and a book detailing the inner workings of quantitative trading as such study is necessary to formulate optimal capital allocation and market risk strategies. A very good example of such a book with this type of information can be found in it is Quantitative trading, a book by Ernest Chan (Chan, 2009.)

These resources, along with other as yet undiscovered material, will allow this feasibility study to create a unique business case specifically tailored to the South African financial market context.

1.4.2 Empirical research

The empirical research of this study will reside in the back testing procedures which will have to be made in order to show if the chosen trading strategies are in fact profitable.

The following procedure will be enacted once a shortlist of suitable trading strategies has been assembled and encoded along with the historical finance data into the quantitative trading computer model.

For each strategy, the program will run in sequence from the oldest historical data to the newest. While running linearly through the data from back to front the program executes buy or sell decisions at certain times in the linear run-through based on the currently active financial strategy.

When making such a decision on a certain time step between the start and end dates, for which data is available, the program will only factor in information that it has already run through.

As an illustrative example, say the program has daily settlement data available for stock ABC from 2 January 2008 up until 2 January 2012. Then starting on 2 January 2008 the program will iteratively evaluate the strategy on each available day up to 2 January 2012. Say also that when the program runs past 3 February 2011 a buy signal is generated by the active financial strategy. That then means that the buy strategy was generated when the program considered data from 2 Jan 2008 up until 3 Feb 2011. At that point the program is blind to the data from 4 Feb 2011 up to 2 Jan 2012 and these data points would have had no influence on the programs decision.

This, given the program's buy decision at 3 Feb 2011, would allow the investor to see if that decision would have been profitable given what happened to the stock's price from 4 Feb 2011 up until 2 Jan 2012. This is how profitable strategies are separated from non-profitable strategies. The investor then assumes that past market behaviour will continue into the future and will then allow the program, after substantial calibration, to make buy and sell decisions in real time as well. The investor will then execute these decisions in real time in hope of making a profit.

1.5 Scope of the study

This study's theoretical background will come from the field of quantitative finance and from quantitative programming as well. This study may take some basic economic principles into consideration but the field of fundamental and value analysis will not be included in any great detail.

Also, due to time and resource constraints this study will only look at South African equity data. Only equities that are actively traded on the Johannesburg Stock Exchange (JSE) will be considered.

For the purposes of quantitative trading strategy formulation only the historical share price datasets of these companies will be used to compile and back test quantitative trading strategies. Financial statements will not be considered. Also, only the top 100 companies, in terms of capitalization and liquidity will be considered in this study. Both long and short positions can be taken in the described strategies.

1.6 Limitations of the study

This study will only consider financial instruments easily accessible to the retail (small) investor, as over the counter derivative information is harder to come by and even if such information could be sourced, the massive nominal amounts that these instruments trade in will severely restrict the size and number of transactions that a start up quantitative trading business would be able to make.

In order to help quantify the profitability of this study a hypothetical amount of capital will be decided on, which will be allocated over the chosen number of strategies. This will enable the reader to subjectively consider the profitability of the venture given the back testing done on the selected strategies. This amount will be decided on at a later date when more research on this particular topic has been done.

1.7 Chapter division

The study will be divided into the following chapters with their contents as described below:

1.7.1 Chapter 1: Dissertation layout

This chapter will discuss the history of quantitative trading in more detail as well as give the layout and describe the methodology for the rest of this study. Further research will also be done with regard to the problem statement which will include details of other similar studies made internationally or in South Africa, if such resources exist at this moment in time.

1.7.2 Chapter 2: Quantitative trading theory

This chapter will contain a brief literature study around quantitative trading and also give details for the different trading strategies that can be found in the literature. Then this chapter will also look at the theoretical aspects of defining measures to see which strategies should be selected and how capital should be allocated between different trading strategies. It will also look at some portfolio performance and risk measures.

1.7.3 Chapter 3: Empirical research

In this section the empirical research and back testing results around the profitability and feasibility of the previously identified trading strategies will be discussed and an analysis of the strategy suitability will also be given. The back testing will be done as shown in the empirical research section of this report.

The best practices of capital allocation and market risk management will be covered by this section of the mini-dissertation. Any obstacles to practical implementation will also be discussed and analyzed in this section.

1.7.4 Chapter 4: Reporting and discussion of results

A report of the findings from the previous chapters will be given in more detail in this chapter and present the final profitability arguments for the feasibility of the described quantitative trading strategies. It will detail what return can be expected after implementing the final selected strategies as well as over which time horizons they can reasonably be expected to run.

Chapter 2

Quantitative trading theory

2.1 Introduction

This chapter will give more insight into the origin and inner workings of quantitative trading. The chapter will start by giving the reader some background information regarding quantitative trading. It will then proceed to describe some quantitative trading strategies that can be found in modern day literature as well as a range of measures which will be used to evaluate these strategies in the next chapter.

2.1.1 What is quantitative trading?

"Quantitative trading, also known as algorithmic trading, is the trading of securities based strictly on the buy/sell decisions of computer algorithms. The computer algorithms are designed and perhaps programmed by the traders themselves, based on the historical performance of the encoded strategy tested against historical financial data. " – Chan, 2009.

Many people believe that quantitative trading is the same thing as technical analysis. This is not entirely true, but neither can it be taken as completely false either. In layman's terms, technical analysis is the practice of trying to explain and predict stock price movements by looking for visual patterns and predictors on stock price movement charts.

Certain technical analysis tools, like moving averages, are very useful and powerful, as will be shown later, and can be used to derive quite a number of quantitative trading strategies, but other parts of this discipline cannot (easily) be used. It would be very difficult and time consuming to encode the search for the next "head and shoulders" stock price pattern, as can be seen in figure 1, in any algorithm. This is because a large part of technical analysis is very subjective and therefore not easily quantifiable (Chan, 2009:1).

Figure 1 - Head and shoulders technical analysis plot (Aboutcurrency, 2007)

Quantitative trading and technical analysis share many of the same tools, as was mentioned earlier, but some of the techniques used in technical analysis cannot be used in quantitative strategies. In the same way some of the techniques in quantitative trading cannot be used in technical analysis.

A quantitative trading strategy or trading algorithm can be as simple as buying a certain stock on Tuesday and selling it on Thursday or it can be extremely complicated, spanning thousands of lines of code and incorporating theory from various and varied disciplines such as time series analysis, stochastic calculus and linear statistics as well as many others.

Any strategy or trading plan that can be broken down and encoded into a computer algorithm, which will then generate buy and sell signals independent of further decision making steps from the user, can be seen as a quantitative trading strategy.

The one facet of quantitative trading which makes it stand out as a robust decision making process is the ability of computers to back test the encoded strategy on historical financial data. This informs the user of how profitable the strategy would have been if it had been implemented it in the past. This allows the user to evaluate the merits of the strategy without having to implement the strategy in the market, in which failure can be very costly.

2.1.2 Does quantitative trading work?

In Kestner (2003, 4) the following example can be found. The Barclay group, which is a group dedicated to the field of hedge funds and managed futures, has recorded the performance of various commodity trading advisers based on the trading style used by them. This allowed for a study to compare quantitative traders against the non-quantitative “discretionary” traders.

Commodity trading advisers are individuals or firms who advise clients about buying or selling certain financial derivatives like futures or options on futures. Some of the largest commodity trading advisers manages portfolios of more than $2 billion.

Discretionary trading is practiced by a subgroup of traders who rely on the intuitive understanding they have of the market and the forces that govern it. These traders trade by “gut feel” and by their innate ability to time and predict the market and have no need for systematic rules to control and guide their actions. This method of trading is very difficult and it is very rare. It requires the individual to have very good control over his or her emotions and to interpret information in an unbiased manner, and only very few individuals have mastered this and been able to be successful and profitable traders.

In a previous study, independent from the study set out in this document, which was done to gauge the effectiveness of quantitative trading against non-quantitative “discretionary” trading the register of commodity trading advisers from Barclay group was divided into two groups based on the trading styles of the advisers (Kestner, 2003:4).Any trader whose trading decisions are made up by using personal judgment more than 75% of the time was classified as a discretionary trader and any trader whose decisions are systematic (derived from fixed and explicit rules) at least 95% of the time was classified as a systematic trader.

After classifying these two groups Barclay was able to track the performance of the trades done under the advisement of the commodity trading advisers. This is done by compiling the Barclays systematic traders' index and the Barclays discretionary traders' index. These indexes are made up of the monthly profit and loss of the underlying trades made upon the advice of these advisers.

Between 1996 and 2001 the average annual return of the discretionary group was 0.58% while the average return of the systematic group was 7.12%. The systematic group also outperformed the discretionary group five out of the six years over the period of the study. These figures speak for themselves.

The Barclay group study was conducted in America, where some of the world's largest and most advanced financial markets can be found. The United states of America is part of the developed world and from the results of the study it can be concluded that there is some merit to systematic trading, also known as quantitative trading, in developed markets. It remains to be seen if these conclusions are also applicable in the developing world and more specifically if the same results would be seen in a much smaller market with less market participants, as found in South Africa.

As part of the study, it will be shown whether there exist systematic trading strategies which can also be viable in South African equity markets.

2.2 The history of quantitative trading

2.2.1 The pioneers

Quantitative trading can be seen as a kind of trading behaviour. Therefore to find the first instances or the origin of quantitative trading one needs to first look at the pioneers of quantitative trading. Some of the first recognized and well known quantitative traders are W.D. Gann, Richard Donchian, Welles Wilder and Thomas DeMark (Kestner, 2003:9).

William D. Gann

In 1909 Gann, a successful young stock broker put his ideas and credibility on the line in an interview with the Ticker and Investment Digest magazine. The magazine published an article in which Gann told of his trading track record. He had the ability to make very accurate forecasts. According to the interview Gann made 286 trades during the month of October 1909 and of those 264 where profitable and only 22 made losses. From some of the books published later in his life, it can be deduced that he used pricing charts independent of time as well as more complex numerology methods, including squares of price and time.

Richard Donchian

Donchian established the first futures fund in 1949. The fund was not profitable for 20 years as Donchian traded commodity markets largely according to the discretionary technical trading style explained previously. Since he started his business in the 1930's during the great depression, he was a renowned bear (bears are typically of the opinion that markets are going down while bulls typically are mostly of the opinion that markets are going to rally) and because of his negative outlooks he missed out on a lot of the commodity rallies of the 1950's and 1960's.

It was only after Donchian discovered and incorporated quantitative trading techniques in the 1970's that his fund started earning steady profits. Among some of Donchain's contribution to quantitative trading are dual moving average crossovers and channel breakout strategies.

Welles Wilder

Wilder was one of the first traders to attempt to take discretionary trading decisions out of the hands of emotional human traders and replace that decision making processes with detailed mathematical trading methodologies. In his book New Concepts in technical trading he introduced the relative strength index, an oscillator in use by almost all trading software packages today, as well as the parabolic stop and reverse system, and numerous other methods.

Thomas DeMark

DeMark, who has been called the "ultimate indicator and systems guy" decided to reveal some of his trade secrets when he published the books *the new science of technical trading* in 1994. This was followed by the sequel *new market timing techniques* in 1997. Among DeMark's quantitative trading contributions are his sequential indicator (which is a countered exhaustion technique), the DeMarker and REI (which is a different kind of oscillator technique), as well as numerous other systematic trading strategies.

2.2.2 Modern day quantitative trading

The trading behaviour, now known as quantitative trading, continues in the modern age and there are many quantitative traders making a living from quantitative trading in the world today. Some of the best money managers in the world are quantitative traders. Traders like Monroe Trout, John Henry, Ken Griffin and Jim Simons (Kestner, 2003:9).

With technological advances in modern day computing quantitative traders are now able to do hundreds of thousands of calculations per second searching for pricing patterns in thousands of securities all over the world. With advances in artificial intelligence quantitative traders are now even able to incorporate news events into their trading strategies (Chan, 2009:2). These artificial intelligences can analyze news broadcast over trading information systems, like Bloomberg or Reuters, and then deduce whether the information in the broadcast will have a negative or positive impact on the market and then place an order in the market in order to take advantage of that deduction. All this can be done in a split seconds with great frequency over thousands of shares, quicker than any human trader could ever hope to react.

2.2.3 Who uses algorithmic trading?

As of the year 2009 algorithmic trading has become very pervasive in the financial industry (Leshik & Cralle, 2011:13). Most if not all large financial institutions are currently actively pursuing systematic quantitative computerized strategies. It is estimated that as much as 70% of the trading volumes in the United States were made by automated trading platforms in 2009 (Lopez, 2010:1).

The guarded hedge funds are some of the largest users of algorithms since the incorporation of algorithmic trading can give the trading operations of the hedge fund a sizable advantage (Leshik & Cralle, 2011:13). Unfortunately there is very little information available on the algorithmic trading strategies used by hedge funds in the public domain as the hedge funds do not need to report on the trades they make in the same way as other publicly funded financial institutions like banks have to.

There are hedge funds doing very well with algorithmic trading. An example would be the Renaissance fund headed up by Jim Simmons. This fund has shown spectacular returns year in and year out (Leshik & Cralle, 2011:13) and it is rumoured that Simmons surrounds himself with up to 50 PhDs which he employed from fields as varied as mathematics, statistics and physics and runs their creations on some of the most powerful and advanced computer systems available.

Major Banks and brokerages have also recognized systematic algorithmic trading as an exploitable competitive advantage and have started moving more and more staff and capital into algorithmic trading divisions or are making algorithmic trading part of the bank's normal operations on a more regular basis (Leshik & Cralle, 2011:13).

Computers become more and more powerful and more affordable all the time, and as market liquidity and efficiency becomes more pronounced the cost of entering and exiting most financial positions are being driven down. This makes it easier and easier for individual traders to enter the algorithmic trading space as well. Although these individuals are up against very intense competition from the big firms there are still many opportunities for small scale operations in this field to take advantage of, since smaller enterprises are able to swim in markets to shallow for the bigger corporate organizations to effectively compete in (Chan, 2009:157).

2.2.4 Why has quantitative trading become popular?

There are various reasons for the popularity of algorithmic trading. One of the main components that have made algorithmic trading so powerful is technological progress. Moore's law states that computational power will double every 18 month (Adee, 2008). This has been observed in the market and today ordinary households have access to desktop computers which are computationally as powerful as the equipment NASA used to put men on the moon and bring them back again. The telecommunications industry has largely kept pace with this increase in computational power which has allowed substantial networking which is keeping pace with exponentially growing data transmission requirements (Leshik & Cralle, 2011:13).

These factors have all contributed immensely to the popularity and viability of quantitative systems trading.

Using computers to place trades in the market also has a unique set of benefits. The immediate benefits which would ensue from implementing algorithmic trading are as follows (Leshik & Cralle, 2011:13):

- Substantial cost per trade reduction. As one computer can send out thousands of trades in a fraction of the time a human trader could at a much lower per trade cost.
- General throughput speed is increased which means more business can be transacted.
- Computers can be set up with a self documenting trade tail in order to meet regulatory requirements.
- Reduction in trading errors as human error is removed.

- Consistent performance. As was shown previously, human discretionary trading can be sidetracked by emotions and computers do not have this problem.
- Less trading staff “burnout” as the emotional side of trading is substantially reduced.
- Computer traders have virtually no limit to their capacity and they do not get bored, lose concentration or forget the instruction they were given to do.

2.2.5 Types of algorithms

Not all trading algorithms are used exclusively to take proprietary positions in the market. There are mainly two types of trading algorithms in literature. The first is where a trader takes positions in a market based on a buy or sell decision of an algorithm in order to make a profit. The second is when computerized algorithms are used to break large block trades into many smaller trades in order to minimize the impact of large orders on the market.These two types of trading algorithms can be further subdivided into more different types.

2.2.6 Large order handling algorithms

Large order handling algorithms are used to minimize the impact of large block trades on the market. If the market knows that a market participant wants to raise or buy a large block of shares other participants could buy up any free floating shares at the current market value and then immediately make them available to sell but at a higher price. The trader wanting to fill his large buy order would then be forced to buy shares at this higher price. This practice is called front running, and it can be done ahead of both large buy and sell orders (Investopedia, 2013).

Even without front running, large share orders would still impact the market forces of supply and demand. If some-one tries to sell a large amount of shares the market becomes oversold and prices drop, the same thing happens with buying large blocks of shares as the market becomes overbought and prices rise. Leshik & Cralle (2011:19) list the following trading algorithms used to deal with the trading of large block orders.

Volume weighted average price

This algorithm uses real-time and historic volume data as a criterion to determine the size of any particular block trade. The main block order is broken down into a desired number of pieces or waves and these pieces are then sold in lot sizes dependant on the currently observed volume of trade in the market. If there is a large volume of shares changing hands the algorithms will buy and sell in large lot sizes and in smaller lot sizes when the trading volume is low.

Trading volume activity is determined by looking at the current amount of shares traded at any particular time in the day when it is compared against the historical trading volume of the share at the same time on past days. For example the historical trading volume for a particular share was 1 million units between 12:00 and 13:00 on average over the last six month and today the trading volume between those times was 2 million then the algorithm would know that trading volumes are higher than normal and that larger orders can be placed in the market without significantly moving prices.

Time weighted average price

This strategy simply divides any large order more or less into many equal parts which are then sent to the market over a predetermined time frame during a particular trading day. Although this is convenient, this might expose the trader to other trades looking to front run on these types of orders. This type of behaviour can be combated by allowing one or more of the predefined trading windows to pass over without placing a trade. The windows to be skipped in this way would be randomly determined beforehand in order to not create a pattern another trader could pick up on.

Percentage of volume

This strategy would allow the algorithm to “stay under the radar” by only trading lots which are a small percentage of the current trade volume. For example if the volume on a share is currently at 1 million and the algorithm is preset to trade orders at 1%

of this number each hour, then it would only trade 10,000 shares an hour so as to not be noticed by any other market participant as these trades will be drowned in the noise of many other trades from many other participants.

2.2.7 Proprietary trading algorithms

Proprietary trading algorithms seek to exploit small market inefficiencies or patterns that form part of the historical price data of market traded securities. These algorithms would identify a possible trade by back testing a pre-programmed strategy on historical data. If the results are profitable the program would then alert the trader when the next sell signal is generated and the trader can then choose to enter the position with the hope that history will repeat itself.

There are two main types of proprietary trading algorithms (Chan, 2009:116). The first is known as momentum or trending algorithms and the second type is known as mean reverting strategies.

Momentum strategies

Momentum strategies look for any market traded security that is about to significantly deviate from its current value. If the algorithm identifies a long entrée signal, it would mean that there is a possibility that the share price is about to increase. If a short entrée signal is generated the algorithm indicates that the share price is about to decrease in value. By taking either long or short positions over the underlying security the trader can attempt to capture this predicted move and exit the security after the price move has occurred booking a profit afterwards.

An example of these types of strategies is the moving average crossover. This strategy seeks a point in time when a security’s short- term moving average crosses its long- term moving average.

Mean reverting strategies

Mean reverting strategies seeks a single security or a pair whose price is currently deviating from its long term average. A trader using this strategy will look for these deviations and then enter the security with the hope that the price will revert back to its previous mean. When it does the trader exits the positions and books a profit. A very good example of a mean reverting strategy is pairs trading.

Pairs trading exploits the fact that not many shares are mean reverting, but that there exists certain “pairs” of shares and that the difference between the two shares is mean reverting. A pair’s trader would seek moments in time when such a pair is diverging and would then position him to take advantage of the expectation that the two shares will move back into convergence.

In the next section various momentum strategies as well as the pairs trading mean reverting strategy will be discussed in more detail.

2.3 Quantitative trading strategies

In this section a detailed description of the various trading strategies that are described in literature will be given. This will be followed by a section defining measures to quantify the effectiveness of the presented trading strategies when they are back tested on actual South African equity data. This will give an indication of the viability of these strategies in South African financial markets.

These strategies will be defined in the context of equity markets. Some of these strategies could also be applied to foreign exchange markets and, with some imagination, can be applicable to other financial markets as well. However, for the purposes of this study only share data will be considered going forward.

2.3.1 Buy and hold strategy

The first strategy could be considered to be a control strategy and this strategy involves simply buying or selling (shorting) the underlying share. To be truly viable the returns of a trading strategy would have to exceed the return of simply buying and holding the stock over the period under scrutiny.

2.3.2 Momentum strategies

These strategies seek to identify periods in time when a share's price is about to, or has already entered into, a trending period. Trending periods are when the prices move mainly in one direction instead of moving randomly. If a trader can identify such trending times, the trader will be able to position him or herself accordingly.

2.3.2.1 Moving averages

A simple moving average is the average of a share's price over a set time. For example on a certain day the 50- day moving average of that stock would be equal to the average of the previous 50 prices available for that stock. The following day's moving average would again be equal to the average of the previous 50 stock prices, meaning that to calculate the average the last price used in the previous calculation is discarded and the latest day's price is added to the calculation. In this fashion a moving average series can be constructed on a stock's share price data. This moving average series can then be charted next to the stock price chart.

Moving averages are significant as they are studied by almost all market participants. There are two major simple moving averages (SMA) that traders observe, the 50- day SMA and the 200- day SMA (Whistler, 2004:30).

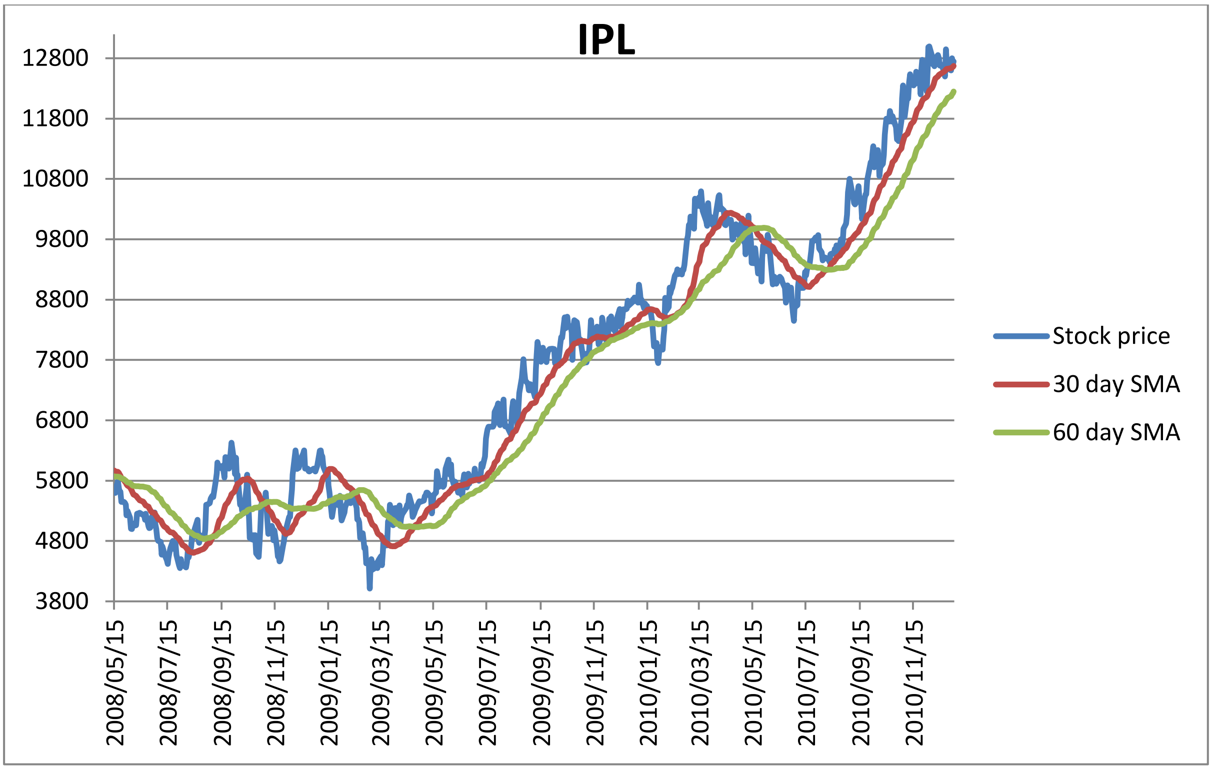

Figure 2 - IPL 30- day and 60- day simple moving average crossover

A 50- day SMA tends to be more volatile than a 200- day SMA simply because the 200- day SMA considers more data points in its calculation and any large individual share price moves are more smoothed out.

Many analysts consider the 50- day SMA crossing above the 200- day SMA as a buy signal as this could be an indicator that the share price is entering a trending phase (Whistler, 2004:30). In the same manner a 50- day moving average crossing below a 200- day moving average would indicate a sell signal.

A famous example of crossing moving averages is known as the golden cross strategy. This strategy creates buy or sell signals at the points where the 50- day SMA and the 100- day SMA crosses.

The strategy works because of the level of noise reduction achieved by the smoothing action of the moving average calculation. The moving average line masks the day to day noise in the data series and only shows the major stock price movements. By using two moving averages with different levels of noise reduction an observer can see when the price sequence picks up more momentum and starts moving more forcefully into a certain direction. With back testing the correct parameters can be found which fit this type of movement the best and the instances where the two moving average lines intersect can then be used as an indicator of possible future movements.

In the same manner crosses of other SMA combinations can also be considered for different stocks. The viability of these different combinations of moving average crossovers will be explored further in the following chapter.

Exponential moving averages (EMA) could also be used. EMAs are fundamentally the same as SMA with the difference that the most recent values are weighted more heavily in the averaging calculation (Whistler, 2004:30). This is done to emphasize the most recent data points over the ones further away.

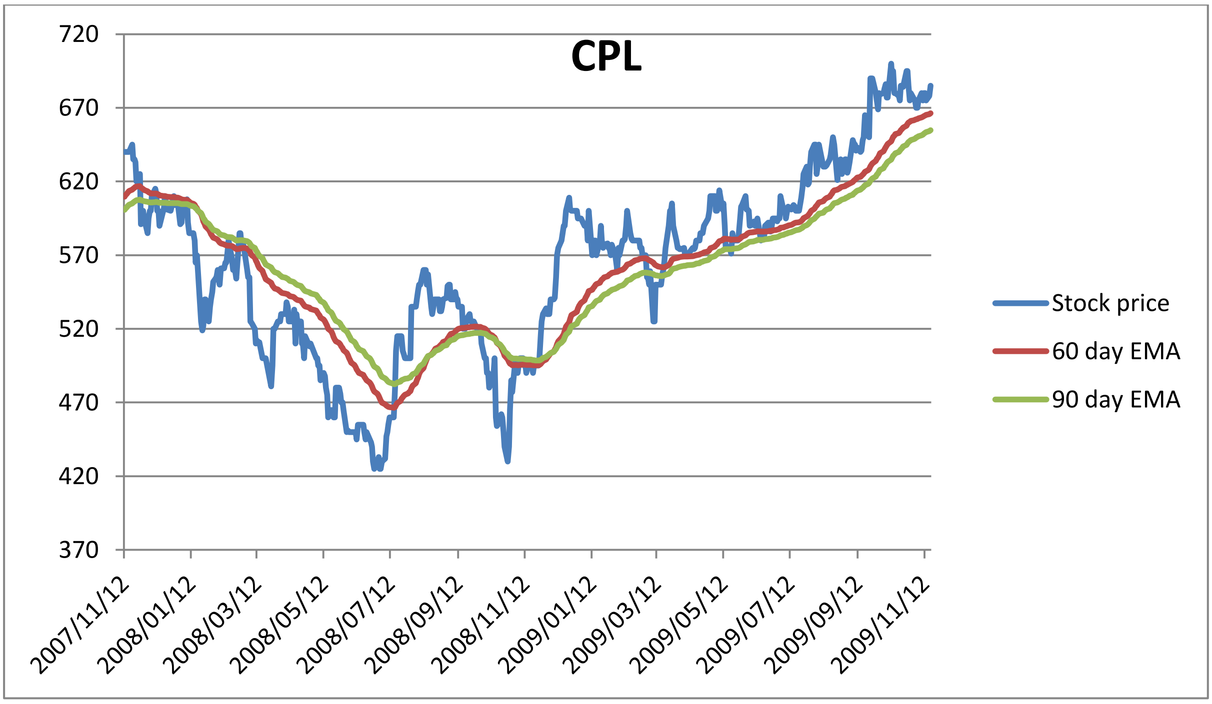

Figure 3 - CPL 60- and 90- day exponential moving average crossover

2.3.2.2 Channel breakouts

Richard Donchian was a pioneer in the futures trading industry, and he is also the first credited user of channel breakouts (Kestner, 2003:60). A channel breakout is a stock trending strategy and works on the simple premise that if a stocks starts to exhibit trending behaviour, then it first has to surpass one of its previous high or low prices.

The channel breakout strategy derives its name from the channel that is created around a stock price when plotting the stocks previous highs and lows next to each stock price. These highs and lows are "moving" in the same way as in moving averages where only the highs and lows of a set time are considered.

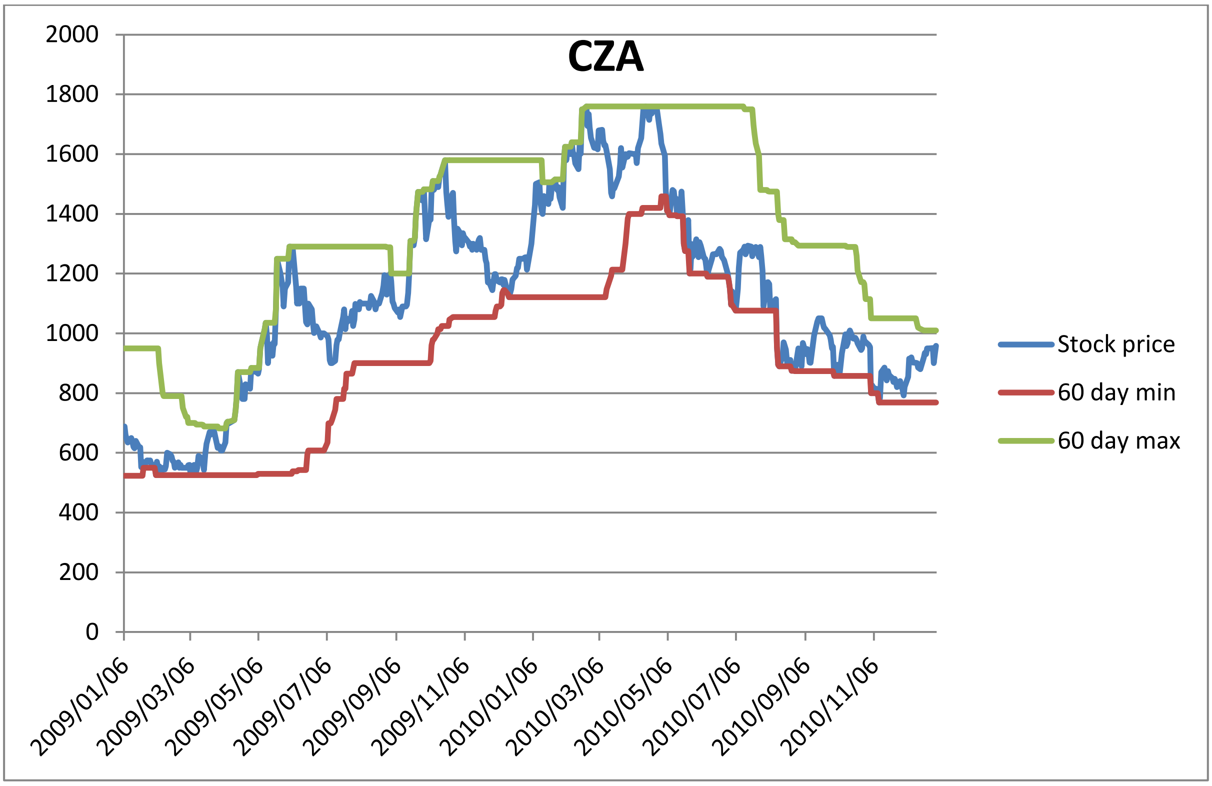

Figure 4 - CZA 60- day channel

For example a 60- day channel break out strategy would plot the high and low of the previous 60 share prices next to each share price. This then has the effect of creating a channel around each share price.

The strategy then would be to buy the share if the share price hits the top of the channel, in other words when the 60- day high equals the current share price, and a sell signal is generated when the bottom of the channel is hit by the share price when the current share price is equal to the lowest share price observed over the last 60 days.

Stocks usually trade in stable price ranges, and when the market learns of some news event the stock tends to break out of this range and move in the same direction for a time long enough to be exploited by a watching investor. Such a move by a stock is known as a breakout. Channel breakouts are an attempt to predict and take advantage of these stock price path breaks.

2.3.2.3 Momentum

A momentum strategy considers the Change in share price over time to derive some idea of the strength of the stocks trending behaviour (Leshik & Cralle, 2011:13). To calculate this indicator, simply deduct the share price of *n* periods ago from the current share price. If the result is positive it is an indicator that the stock is increasing in value and if it is negative the opposite is shown.

This indicator can be used to detect a trending period in a stock's price or if the behaviour is studied over time, can be an indicator of mean reversion once a certain amount of "momentum" has been generated with a suitable large difference between past and present data points.

For example, to calculate the 20- day momentum indicator the share price from 20 days ago will be deducted from the most recent one which will show whether prices have been increasing or decreasing.

A momentum strategy is another, much simpler, attempt to take advantage of the breakouts of stock price paths.

2.3.2.4 Volatility breakout

The volatility break out rule was devised to take advantage of the fact that large stock moves are often preceded by other relatively large stock price moves (Kestner, 2003:65). This could possibly be caused by large institutions mobilizing their resources for large block trades, since deciding to do a large multi million rand trade can be ponderous at best.

The volatility break out buy/sell signal is generated by using three measures. Firstly the Reference value which could be yesterday's close, today's open or a short term moving average. Second the volatility multiplier, which is a decided upon integer. Lastly the volatility measure which can be the standard deviation of price returns, the average true range or the standard deviation of price.

The true range can be chosen as a moving average of the maximum daily value of the following prices (choose only the maximum of the following values each day, and then calculate a moving average).

- Today's high minus today's low
- Today's high minus yesterday's close
- Yesterday's close minus today's low

The moving average of the true range is then known as the volatility measure, and the last price or settlement price of the stock can be used as the reference value.

After the volatility measure has been calculated the strategy is then implemented as follows:

- Buy if today's close price is greater than the reference value plus the volatility multiplier times the volatility measure.
- Sell if today's close price is smaller than the reference value minus the volatility multiplier times the volatility measure.

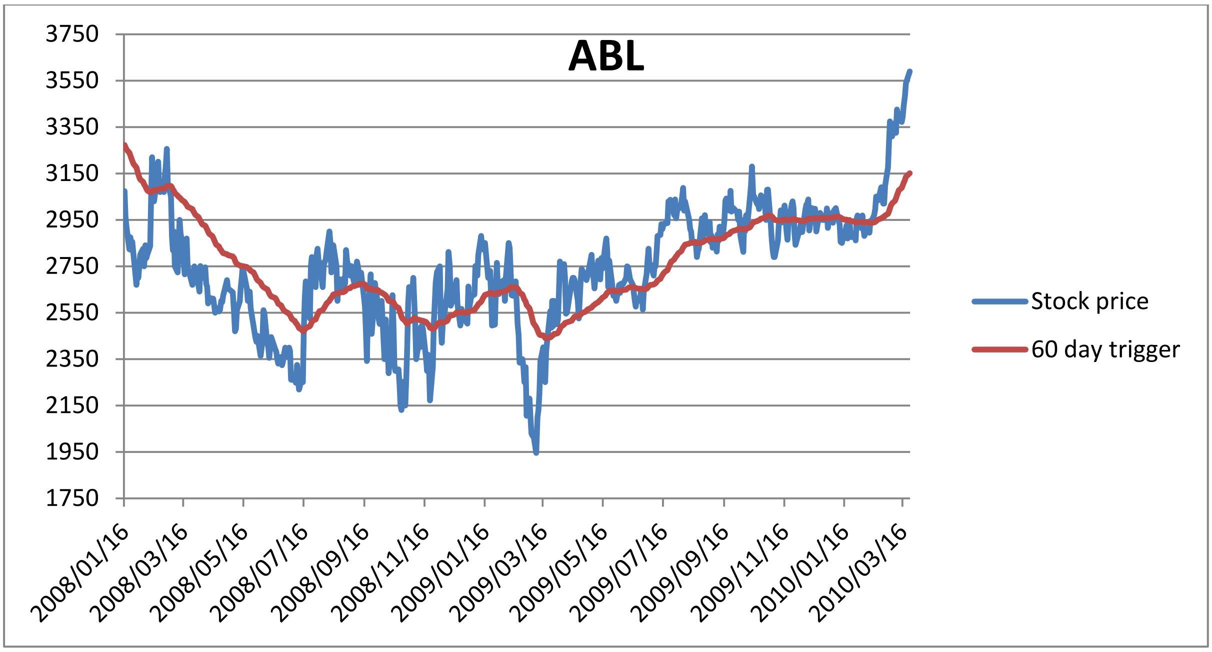

Figure 5 - ABL volatility breakout with 60- day trigger

2.3.2.5 Bollinger Bands

A Bollinger band can be taken as the 20- day exponential moving averages (EMA) with two bands plotted above and below this moving average spaced 2 standard deviations apart (Leshik & Cralle, 2011:121). The standard deviations are calculated on the same values used to calculate the moving average. When the share price touches or crosses the upper Bollinger band a sell signal is generated, when it touches or crosses the bottom Bollinger band a buy signal is generated. The strategy works as it assumes that the price of the underlying security will mean revert back to previous levels after the market overreacted during a sudden price swing.

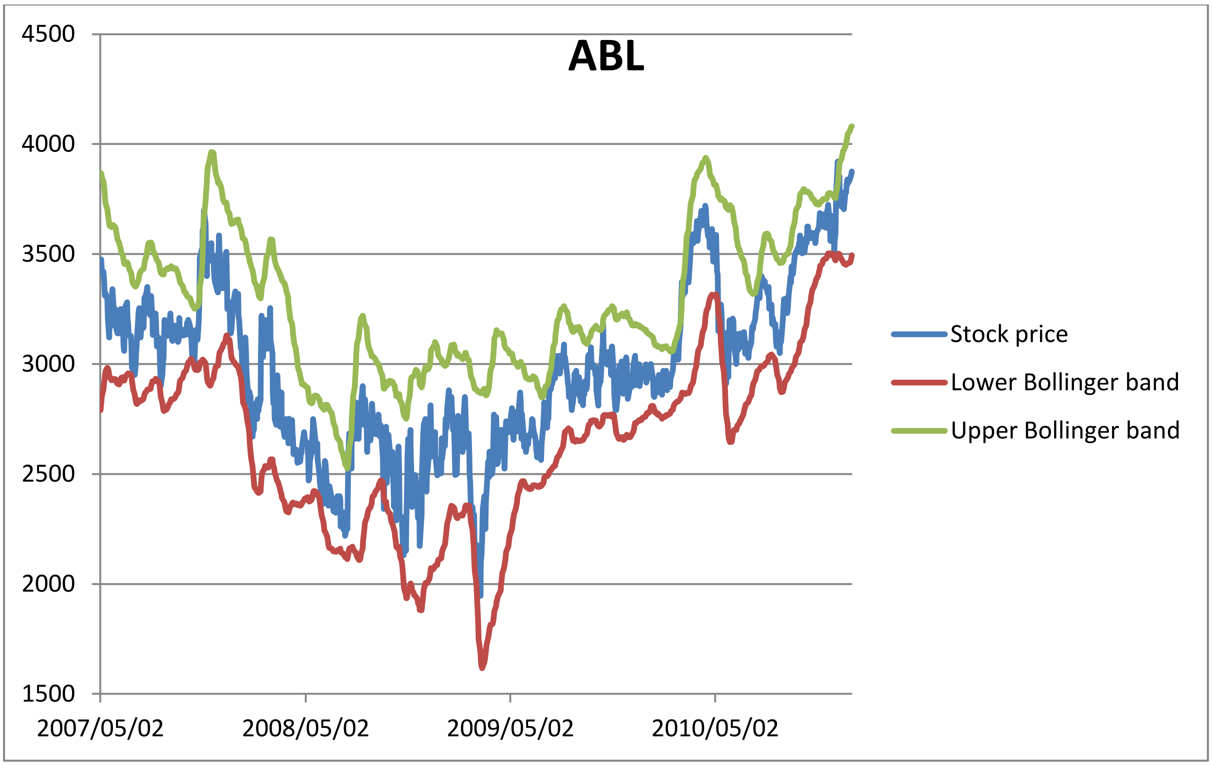

Figure 6 - ABL Bollinger bands

2.3.2.6 Trix oscillator

The Trix is a triple exponential average oscillator which indicates oversold and overbought markets and oscillates centre a centre or zero line (Leshik & Cralle 2011, 121). Buy and sell signals are generated when the oscillator crosses the zero line.

The Trix is calculated as follows:

$$EMA1 = EMA1n\text{-}1 + ((2 / (n + 1)) * (Pn - EMA1n\text{-}1))$$

$$EMA2 = EMA2n\text{-}1 + ((2 / (n + 1)) * (EMA1n - EMA2n\text{-}1))$$

$$EMA3 = EMA3n\text{-}1 + ((2 / (n + 1)) * (EMA2n - EMA3n\text{-}1))$$

$$T = (EMA3n - EMA3n\text{-}1) / EMA3n\text{-}1$$

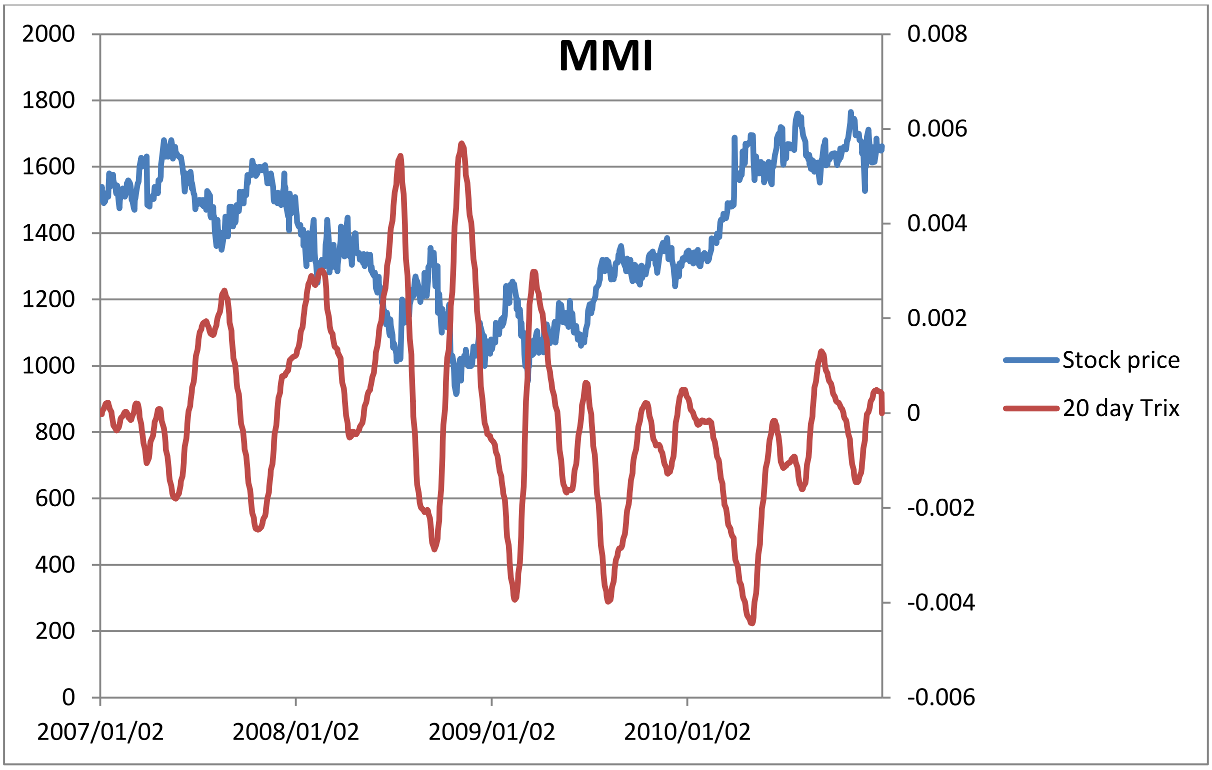

Figure 7 - MMI 20- day Trix oscillator

2.3.3 Mean reverting strategies

These strategies seek to identify periods in time when a share's price has diverged from its mean and is possible about to revert to a point of previous stability. The trader can then take advantage of this mean reverting behaviour by position him or herself accordingly.

2.3.3.1 Relative strength index

The relative strength index (RSI) is an oscillator which compares a stock's recent gains with its losses. First used by Welles Wilder in 1978 it uses a stock's price gains and losses to calculate a range from 0 to 100 (Whistler, 2004:36). The index is calculated as follows:

RSI = 100 – (100/(1 +RS))

Where:

RS = mean gain/ mean loss

mean gain = total stock price gains in *n* periods

mean loss = total stock price losses in *n* periods

Most traders prepare to sell a market if the oscillator moves above 70 and prepares to buy into a market if the oscillator dips below 30. Most technical analysts typically use 14- days worth of data for the RSI.

If a stock experienced a lot of gains the mean gain amount will be a lot bigger than the mean loss amount which means that the RS value will be quite huge. A large RS value means that the right side of the RSI calculation will be quite small as the 100 numerator on the right is divided by a larger number. This means a smaller number will be deducted from the 100 on the left which means a bigger RSI closer to 100 than zero. If a stock's price path experienced a lot of gains a contrarian might expect that the stock is overbought and that it might start losing value when the market realizes this. A contrarian could then implement a short position to take advantage of such a possible price move.

In periods where more losses were experienced than gains a small RSI value will result and a contrarian could then implement a long position to take advantage of a possible rally in that stock once the market realizes that the stock was oversold.

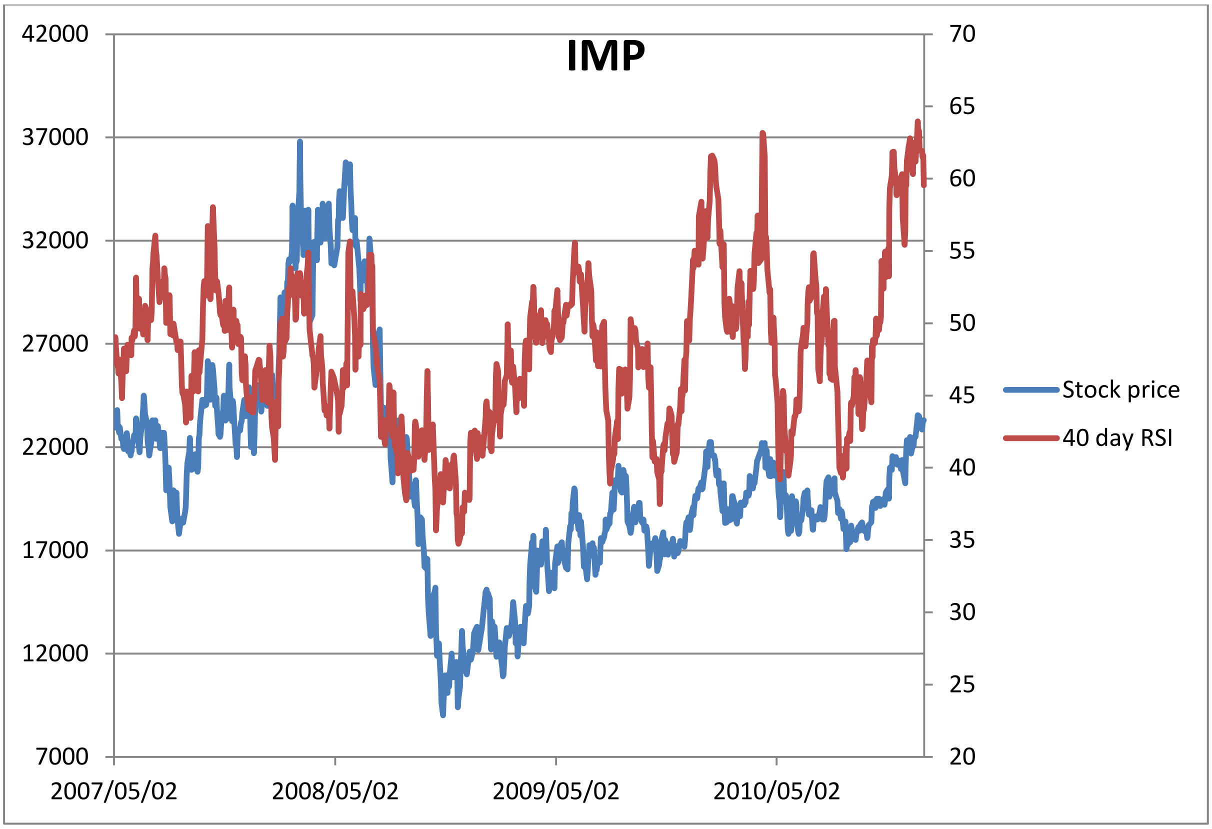

Figure 8 - IMP 40- day relative strength index

2.3.3.2 Stochastic

The Stochastic trading strategy is another type of oscillator, similar to the RSI (Whistler, 2004:30). It also ranges from 0 to 100 with 20 indicating oversold markets and 80 indicating overbought markets. The stochastic consists of two moving lines called %k and %d. These move about one another in a similar manner that moving averages do, and it is thought that the crossings of %k and %d can also be used as buy and sell signals. This oscillator is calculated as follows:

$$\%k = 100*(C - Ll)/(Hh-Ll)$$

Where:

Ll = lowest low for the last *n* intervals

Hh = highest high for last *n* intervals

C = close of the latest

The %d is calculated in the following way:

%d = 100*(HP/LP)

Where:

HP = *n* periods sum of (C - Ll)

LP = *n* periods sum of (Hh - Ll)

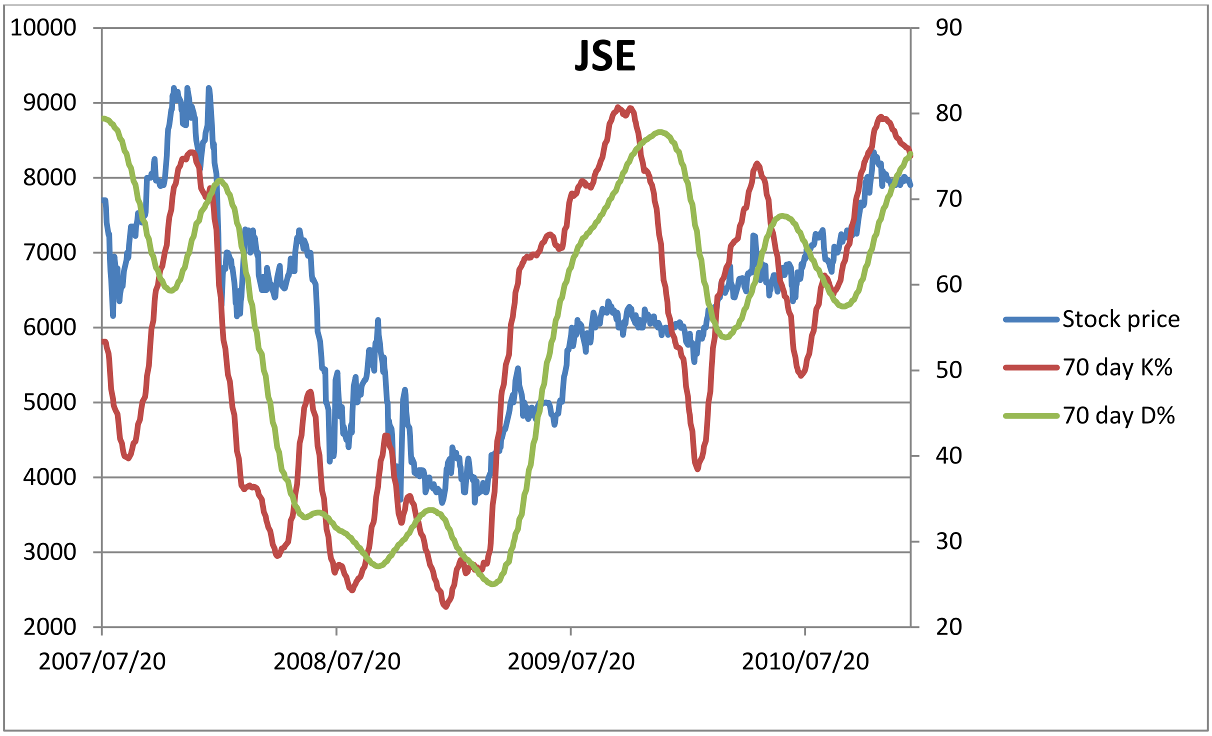

Figure 9 - JSE 70- day Stochastic

2.3.3.3 Moving average convergence/divergence

The Moving average convergence/divergence (MACD) oscillator was developed by Gerald Apple during the 1980's (Kestner, 2003:68). It is created by taking the difference between two exponential averages. In some cases a 12- day EMA with exponential weighting alpha = 0.15 and a 26- day EMA with exponential weighting alpha = 0.075 is used. An EMA is then taking from the MACD and both are plotted on a graph. If the MACD rallies (crosses from below) over the signal line, it can be taken as a signal that the market is oversold and long positions should be taken. Conversely if the MACD crosses the signal line from above it could be an indicator that the market is overbought and short positions should be taken. The MACD and signal line is calculated as follows:

MACD = 12- day EMA of close – 26 EMA of close

MACD signal line = 9- day EMA of MACD

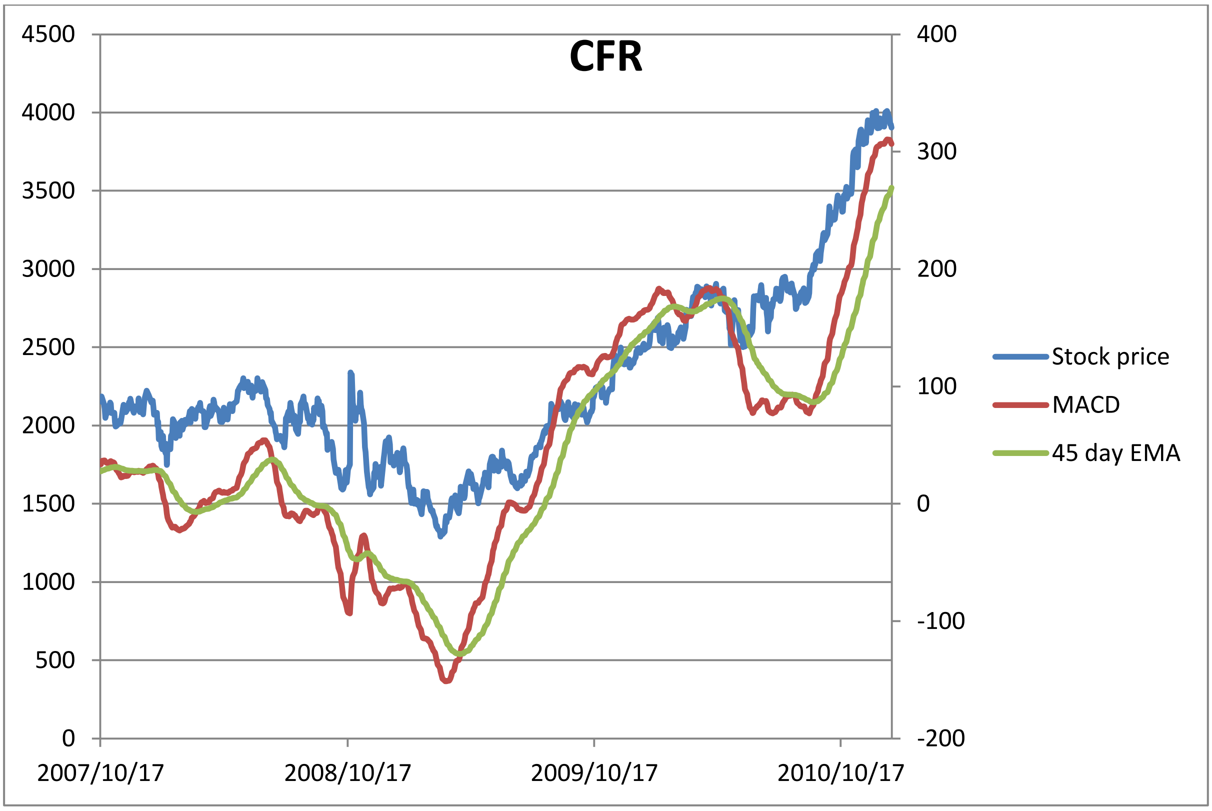

Figure 10 - CFR Moving average convergence/divergence oscillator

2.3.3.4 On- balance volume

On- balance volume (OBV) is an indicator derived from stock volume movements. The OBV is simply a cumulative graph of the daily volume of shares traded on the exchange (Whistler, 2004:36). If the share price closed higher than the previous day's close the entire volume total for that day is added to the cumulative OBV. If the share price at close is lower than the previous close the volume amount is subtracted. This indicator shows underlying strength or weakness in the share price and if limits are set at certain levels this indicator could be transformed into a trade entrée indicator.

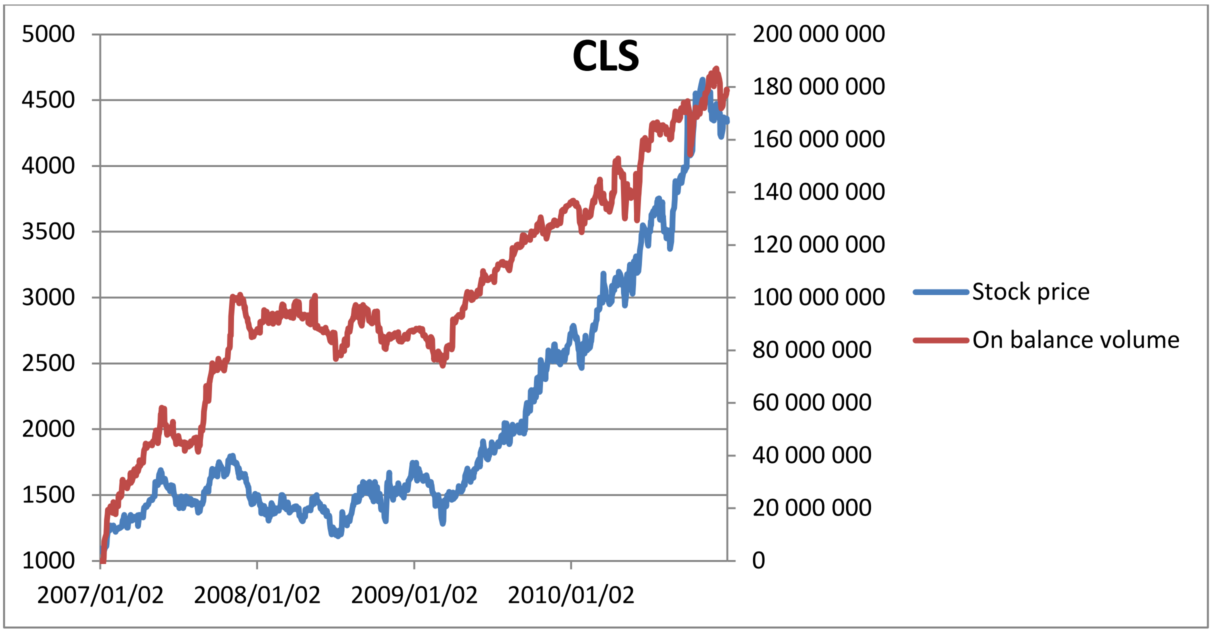

Figure 11 - CLS on balance volume

2.3.3.5 Williams %R

The Williams %R is another oscillator developed by Larry Williams (Leshik & Cralle 2011,121). It ranges from 0 to -100 and any answer between 0 and -20 is thought to indicate overbought markets and any answers between -80 and -100 indicates oversold markets. The Williams %R is calculated as follows:

$$\%R = ((MAXn - \text{Today's close})/(MAXn - MINn))*100$$

Where:

MAXn = maximum share price over *n* periods.

MINn = minimum share price over *n* periods.

2.3.4 Trading strategy exits

According to Kestner (2003:69) trading strategy exits are an aspect of quantitative trading which most authors tend to neglect. A comprehensive exit strategy is an integral part of each complete trading system, for exits are responsible for converting trade entries into closed profits. Entries show a trader when to create profitable trades, but exits determine when to exit both profitable trades as well as unprofitable ones.

Each exit point exemplifies the fine balance between risk and reward. If an exit is too strict then the strategy, while protecting against losses, will exit profitable trades too quickly. If an exit is too lenient large losses can be accrued before the exits closes out the position.The trading strategy exit must be built in such a way that it will allow profitable trades to run its course while cutting unprofitable trades before it becomes unmanageably large.

To truly be useful in quantitative trading, the exit strategy must be quantifiable and should be included in the back testing procedure built to test the entree signals. This will give the best indication to the trader if the entrée and exit combination is profitable for a particular share. The following basic exit strategies can be found in Kestner (2003:70).

2.3.4.1 Profit targets

This strategy exits a trade when a certain predetermined price range is met. These exits could be calculated using the standard deviation of closes, standard deviation of prices movements, the average true range or can simply be arbitrarily chosen, depending on the risk apatite of the trader using it. These exits can be placed to create cut off points for losses as well.

2.3.4.2 Trailing exits

Trailing exits can be used to allow a profitable position to run over time while locking in a profit. A trailing exit is updated with each new high or low price, depending if the position is long or short, over the entire life of the trade. The strategy will exit when a predetermined deviation from the remembered high or low is detected. For example a trailing exit could be defined as a price 5% lower than the maximum price seen over the course of a long share position.

2.3.4.3 Time target

This exit strategy is met simply after a predetermined time has passed. These strategies are useful for planning cash flows stages in a portfolio of trading strategies.The strategies mentioned can be used individually or in concert, depending on the creativity and risk apatite of the trader.

2.4 Measures of performance

When back testing any particular trading strategy there needs to be some quantifiable and programmable measure of its performance in order to determine to what degree the strategy is working, profitable and whether it compares favourably against other trading strategies. The following measures of performance are popular amongst quantitative traders (Kestner, 2003:76 and Chan, 2009:17):

2.4.1 Net profit

Net profit is the most popular measure of determining a trading strategies performance. It is simply a number denoting the profit made over the course of the trades created in the back testing algorithm. While it is good to know if a strategy is profitable or not, using the net profit measure as the only selection criteria could be very costly and misleading. The net profit measure alone does not show how consistent the returns was on each trade or which losses were incurred in the generation of that profit.

The profit displayed could have been due to a single large profitable outlying event while all other trades were not as profitable or even unprofitable. In the same way, an otherwise good strategy could be disqualified if only net profit is used as selection criteria as the trade could have had one large loss, due to an unforeseen random event, while the strategy is quite viable and profitable in most other cases.

2.4.2 Profit factor

This measures attempts to rectify some of the shortcomings of the net profit measure by taking losses into account as well. The profit factor is calculated by dividing the total profit gained from the strategy on winning trades by the total losses made from all the losing trades in the back test. If the strategy was more profitable than unprofitable the factor answer will be greater than one and if it was more unprofitable then the factor will be smaller than one.

The profit factor measure goes some way to reveal the risk inherent in any strategy, as smaller profit factors will show risk as these strategies have larger losses associated with them while large profit factors are indicative of strategies with small inherent losses.

However, as all profits are summed the profit factor measure does not show how consistent the profits or losses are over time. It could still happen that all profits come from a single big trade while most other trades are not as profitable.

Consistent trading strategies are more preferable than inconsistent ones as consistent ones have shown that at a time in the past the stock exhibited a predictive pattern and the trader can then choose to position himself in a way to take advantage of the identified pattern in the hopes that the pattern is going to repeat itself.

2.4.3 Maximum drawdown

A drawdown is the amount net profits falls from its highest point. The drawdown can be seen as the cost of making a trade and is generally tolerated by the quantitative trader in the pursuit of more profitable expected position. This measure is equal to the maximum value of all observed drawdowns during the times positions were held by the trading strategy and shows the trader what the biggest drop in price was while a trade was held by the back testing procedure. This gives the trader an idea of what kind of drawdowns to expect when entering the trade under the tested share (Kestner, 2003:80).

2.4.4 Profit to draw-down

This measure simply takes the net profit of the strategy and divides it by the maximum drawdown already described. This factor also gives a measure of the riskiness associated with the trading strategy over the tested share in the same way that the profit factor does. This is true since the strategy could indicate an entry signal into the trade before the momentum of the share price has changed. This is especially true of mean reverting strategies since a trader, acting on a quantitative trading signal, could enter a possible mean reversion position before the share price starts moving back towards its long term mean. The trader could wait until the share price starts to convincingly turn, but by that time a lot of upside could have been sacrificed in order to get more certainty. On the other hand, initial losses when entering a mean reverting strategy is the cost of entering the position sooner.

The profit to drawdown measure gives a trader an indication of how big the initial loss on such a position was in the past before the share price started acting beneficially. However, this measure also suffers from the same drawback as the profit factor measure in that it does not give any indication about how consistent the observed returns were. This is true since the measure only looks at the maximum drawdown and the net profit generated at the end of the strategy. The measure does not care if the profit was generated in the very first trade and the other trades all produced losses since it only uses the net profit and maximum drawdown, regardless of when and how the constituents of these measures were generated.

2.4.5 Percent of profitable trades

The percentage of profitable trades is used in order to reveal how consistent a trading strategy is and how many of its trades are profitable. The measure is calculated by simply dividing the number of profitable trades by the total number of trades carried out in the back test. This then gives a percentage equal to the percentage of profitable trades observed by the back testing procedure.

A very consistent strategy will give a high percentage while an inconsistent strategy will give a very low percentage. While the percentage of profitable trades measure does solve the consistency drawback from the previous measures, it then falls short in determining if, and by what degree, a particular strategy is profitable or not. It cannot distinguish between the types of profits and considers a large profit on the same scale as a small profit. What it makes up for in showing consistency of returns it loses in showing the quality of those returns.

2.4.6 Sharp ratio

The Sharp ratio was developed by Nobel Laureate William Sharp and is a standard in the money managing industry. The ratio is calculated by using the mean and standard deviation of excess returns and in this way solves both the consistency of returns and the quality of returns problems that was identified with the other previous measures.

By using the mean of the excess returns, the ratio takes into consideration the sizes of the returns and by taking the standard deviation into account the ratio takes the riskiness of returns into consideration.

The ratio also has a scaling factor, which is used to standardize the returns over time. This allows different returns over different time periods from different asset classes to be compared against one another as the time frame as well as size and risk are all taken into consideration by the Sharp ratio. The Sharp ratio is calculated as follows:

Sharp ratio = Scaling factor x Average excess return/Standard deviation of excess returns

Where:

Excess return = strategy return – risk free rate.

Scaling factor = the square root of the timescale of the returns.

If the returns are daily then a timescale of 252 could be used as there are about 252 trading days in the year. Then the scaling factor would simply be equal to the square root of 252, which is 15.87451.If the strategy has a high average return then numerator will be large which will give a large ratio. If however there are a few large returns and a few negative returns (if the returns vary a lot) then the standard deviation will cause a big denominator which will create a smaller ratio.

Returns increase linearly with time, therefore to prevent longer dated returns from giving higher Sharp ratios than shorter dated returns the square root of the periods in a year is used as the standard deviation scales proportionately to the square root of time. This standardizes returns over all time frames which allow any Sharp ratio to be compared with any other Sharp ratio. This makes Sharp ratios an excellent tool to compare different strategies with each other.

Sharp ratios greater than 1 are considered to be good.

2.5 Chapter summary and conclusion

In this chapter the history and origin of quantitative trading was presented. Where after various popular quantitative trading strategies which are found in literature was described along with measures to judge their effectiveness during back testing procedures.

In the next chapter the identified strategies will be put to the test on South African equity data. The described measures will then be used to judge each strategy's performance.

Chapter 3

Applied quantitative trading

3.1 Introduction

In this chapter the different quantitative trading strategies described in the literature study of the previous chapter will be applied to historical South African equity data. The different strategies will be applied via a back testing procedure as described in chapter 1. The results of the applications will be measured and judged according to the measures described at the end of chapter 2.

The historical equity data will be selected as set out in chapter 1. In order to derive consistent results the strategies will be applied to high quality high tier stocks. These stocks have large market capital value, expressed as the amount equal to the amount of shares the company has issued multiplied by the share price of the company, and they are also actively traded in the open market.

3.2 Share selection

Large companies with a distinguished track record offer much more security than small companies which are usually hit the hardest in times of market turmoil. In fact legislation bars pension funds from obtaining large stock positions in small cap companies for precisely this reason. Large companies also have generally longer and more consistent share price histories to work with.

High liquidity is also a requirement. Liquidity is expressed in terms of the amount of shares traded on any day on which the markets were open. High liquidity is a sign of a healthy market as high liquidity allows the share price to move more accurately to reflect the current market perception of the “fair value” price of that particular share.

In order to conduct this study South African equity market data was obtained for the last five years, from 2007 to 2011. This data consists of daily high, low, close and open prices for each trading day for each share between 2007 and 2011.

The daily high data set records the highest price the share reached during the trading day. In the same way the daily low gives the lowest recorded share price during the trading day and the open and close shows at which prices trading opened and closed on that trading day. These measures can be used to see how volatile a share's price was during any particular trading day.

The data set also includes daily volume (total amount of shares traded on the day) as well as the daily current market capitalization values of each share as well.Publicly traded shares are traded over the Johannesburg Stock Exchange (JSE) in South Africa and the exchange releases the total amount of shares that changed hands on a daily basis as well. However, the exchange does not show between which market participants the trades were done, it only shows the amount of shares that changed hands during the trading day.

The market capitalization amount also varies from day to day since this value is a direct function of the share price since the amount of shares in issue is generally stable from day to day. This is true since the market capitalization is equal to the current share price multiplied by the number of shares in issue and the share price of liquid stocks changes after each trade day.

The amount of shares in issue can change when a company does a stock split or issues more shares to the market, but this does not happen often, and when it does the share price will immediately change to reflect the new market capitalization. For example if a company's share price was equal to R100 per share and the company decided to do a stock split by splitting each share in two shares then the share price should immediately change to R50 per share so as to maintain the current market capitalization value of the company. Companies cannot make substantial changes to market capitalization by using share splits in much the same way that a person can't increase the mass of an apple by slicing it into two or more parts.

Share splits will not be considered to be part of the scope of this study, as the price movements created by splits are not market related and do not add any economic value. Such share price movements, if allowed, would have major repercussions on any quantitative trading strategy as any profits or losses generated by a strategy because of such share price moves would be misleading.

In order to mitigate the effect of stock splits share prices will be adjusted in order lessen the impact of a share split. For example PPC did a share split on 2007/07/05 when one share was split into 10 shares. As a result the share price decreased by a factor of 90%, but the amount of shares in issue increased by 90% as well so overall there was no impact on the market capitalization of the company since the number of shares in issue increased by a factor of 9 but the value of each share decreased by a factor of 9 so the net effect on the company market capitalization was negligible.

In order to mitigate the effects of share splits in this study, the share prices of each day before the split will be divided by the amount each share was split into. In other words each PPC share price from 2007/01/02 up to 2007/07/05 will be divided by 10 to create a more consistent price pattern. This can be seen in the following graph for the share spilt of PPC. The raw unadjusted dataset would have created false mean reversion buy signal or false momentum sell signals and if a position was held before the spilt. If price alone was considered, then a truly massive profit or loss would have been show which would have been false since no real material wealth was generated by the share split as previously explained.

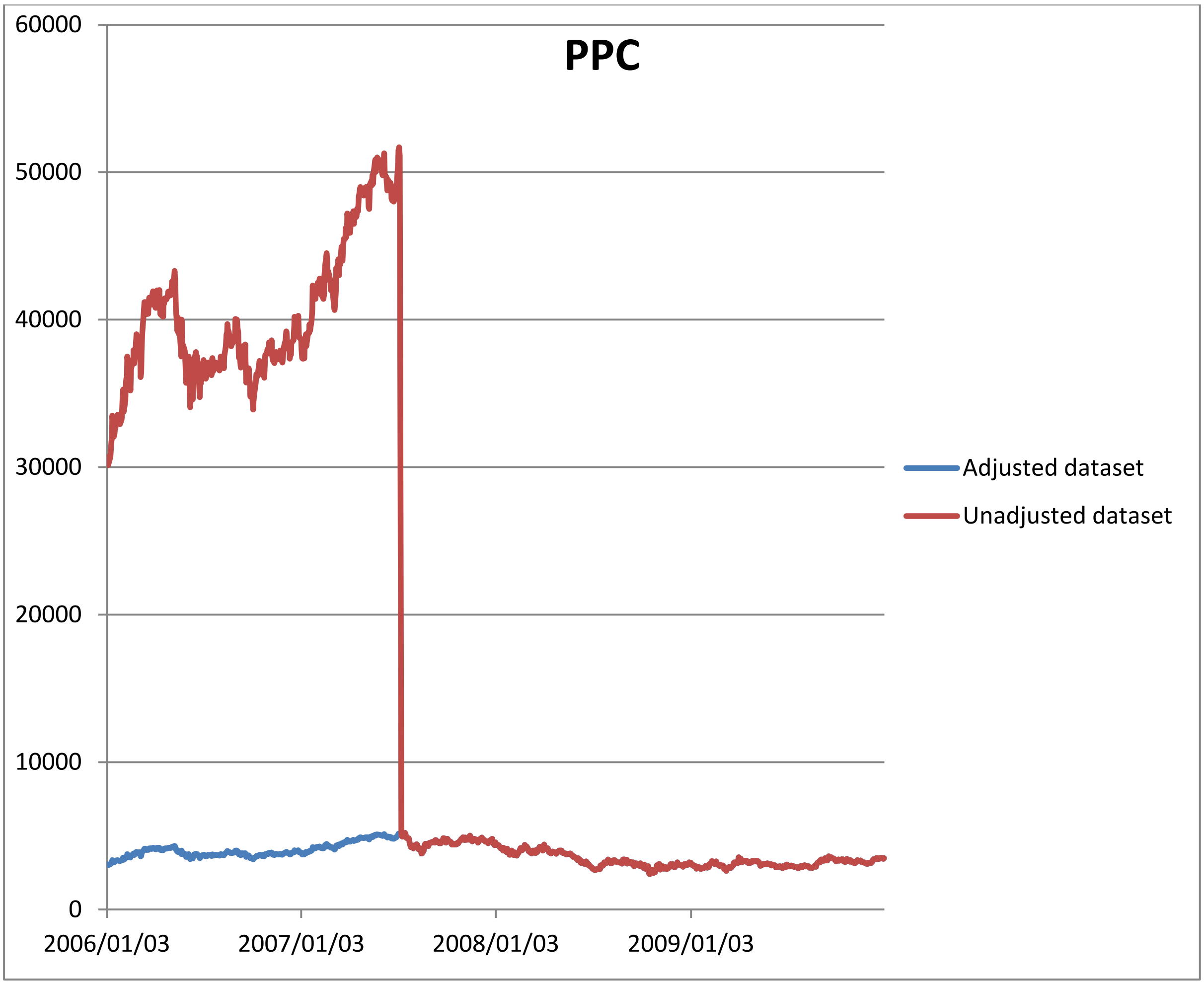

Figure 12 - PPC share split adjustment explanation

To reflect to the high cap and high liquidity requirements, the stocks selected to participate in this study were selected as follows: Only stocks with a full price history from 2007/01/02 to 2011/12/30 were selected. Any stock delisted before or during this period was excluded. Any stocks listed during or after this period will also be excluded. This was done to give an adequate and homogenous data set for each stock as some stocks may be given an unfair advantage over other stocks if those stocks have more data points to fit strategies onto than others.

The stock history from 2007/01/02 up to 2010/12/30 constitutes approximately four years or 80% of the total period of five years under consideration. This portion of the data set will be used to find an appropriate frame work for applied quantitative trading strategies. This dataset will be used to calibrate and identify the “best” trading strategies. The overall “goodness” of the strategies will be judged according to the previously defined measures in chapter 3.

Once the “best” trading strategies and the best parameters sets have been determined by back testing all the quantitative trading strategies over the 2007 to 2010 dataset, these strategies will be applied to the last year’s or remaining 20%, in other words the 2011 data set and the results of this application will be given in chapter 4 of this study.

As previously discussed and for practical and logistical reasons only the top 100 shares according to market capitalization and liquidity were selected for this study.

The 1 year daily average number of shares traded will be used as a measure for liquidity. This measure is calculated by adding the volumes traded for the last year and then dividing that number by the amount of days in a year. Using the average will prevent large trading events on single days to skew the results.

The measure used for the market capitalization will be the rand amount or rand value of all shares issued by the company and is equal to the amount of shares in issue multiplied by the rand value or last price of the share on that day. In order to make this selection the averages of the daily volumes for each stock were calculated for each data point in the 2010 portion of the data set. This 1 year daily average volume number of each stock was then multiplied by the market capitalization value of that stock on the 2010/12/30. This measure then gives a ranking in terms of both liquidity and market capitalization. For example ASA or ABSA had a market capitalization of R100.5 billion on the 31st of December 2010. During the year of 2010 ASA traded on average 1.46 million shares per day. If these two amounts are multiplied and divided by 1 million, to make the resulting number manageable, a rank number of 146 562 would be generated. If this same calculation was done to all the other stocks on the JSE and the rank numbers were ranked from big to small ASA would be the 15th company in this selection.

The top 100 stocks were then selected to form part of the study while the rest of the stocks were discarded. A table with the stock names, market capitalization, 1 year daily average volume and the selection measure can be found in appendix I along with each companies market cap on that date as well as 2010's liquidity average. Number 1 was BIL or BHP Billiton with a rank number of 5 692 957.

3.3 Back testing procedure

The back testing procedure will consider both long and short trading positions when the suitable buy/sell signals are generated by the active trading strategy. A long trading position is achieved by simply buying a stock and holding it in a portfolio. In order to make a profit on a long position the stock needs to rise in value. Therefore if the stock is sold back in the market, and if the selling price is higher than the buying price a profit would have been made.

It is also possible however to make a profit when a share price falls. This is done by entering into a short trading position. Essentially a "short" is when an investor borrows a share from a broker and then sells it in the market. At the completion of the trade the investor buys the share back in the market and returns it to the stock broker. If the share's price fell after the investor borrowed and sold it, the investor will be able to buy it back for less than it originally cost. The difference between the money received from selling the share and then spent on buying it back translates into a profit or a loss made by the trade.

For example a trader could borrow stock X from a broker and could then sell this stock for R100 in the market. After a while the stock price goes down to R90. The trader, who still has the R100 in his bank account, can then buy the stock back for R90 in the market. But the trader still owes the broker the stock and has to give the stock back after a certain time period. The net effect is that the broker borrowed a stock and received his stock back so the broker is no worse or no better off than he was before, however the trader is now R10 richer than she was before the transaction. In this way the trader could show a profit from a decline in a stock's value. Of course if the stock had gone up in value the trader would have had to buy the stock for more than she received from selling it and would have shown a loss afterwards.

If the trader works for a smaller firm which does not have the same access to script lending that bigger firms enjoy, profits can still be made via shorting by purchasing short Contract for difference (CFD) or future contracts from bigger financial institutions.

The back testing procedure will use the computer encoded strategies, and evaluate each strategy to each stock's price data series in sequence. Each strategy will run sequentially over each price path of each stock. If a stock's price path generates a buy or sell signal during such a price run the algorithm will create a fake trade by saving the price of the stock at the time of the buy/sell signal and remembering it until the trade is completed and the share is sold or bought back again. Once a trade is completed the algorithm will save the exit price as well. By saving the exit and entree prices the algorithm can calculate how much profit or what loss would have been generated.

It is important to note that the algorithm can enter and exit many trades in the course of the strategy run over each stock's share price path simply by relying on the pre-defined trade rules and trade signals generated by the relevant trading strategy.

Basic trading rules for all strategies:

- Strategies will only be considered if the profit from trading the strategy produces a greater return than buying and holding the stock over the pre-defined trading period.
- Each individual trade will be held for a minimum of 20 trading days.
- Each individual trade will be held for a maximum of 40 trading days.
- Only strategies that made a profit will be considered.
- Only strategies with a Sharp ratio greater than 0 will be considered.

- If a trade makes a loss of 7.5% of the initial trade value, and the trade has been held for more than 20 trading days, the position will be closed out.
- All strategies are assumed to start with an available capital limit of R10,000. This means that a buy signal is generated for a particular share the algorithm will buy as much stock as possible for R10,000. (If a sell trigger is generated the algorithm will sell (short) as much stock as possible until it has reached a R10,000 sell limit as well.)
- All profits/losses generated by a trade are added to the initial capital amount of R10,000 and the additional profits/losses will be taken into account when the next trade is generated. This means that if the very first trade made a profit of R1,000 then the next trade of the same stock in the same strategy run will have R11,000 available, which it will use in full, to buy or sell shares for the next buy/sell signal. This is done to reward or penalize consistently good or bad strategies.
- Brokerage or trading costs are not taken into consideration and are assumed to be zero.
- Dividends will not be taken into consideration and are assumed to be zero in all cases. The dividend's effect on the share price will still be seen in the graphs and its effect will be implied in that way, but the dividend cash flow payments will be ignored.

3.4 Algorithm results

The following test results were obtained when the algorithm was run for each trading strategy and each trading strategy was run for a diverse set of different parameters as well. The parameters will be given in each strategy's results section.

The results for all the strategies that were profitable and outperformed their own stocks were then listed and the tables were aggregated by the parameters. The following tables show the average outcome for each strategy for each of its most successful parameter sets.

The most successful parameter sets were chosen in the following order. In cases where one particular strategy’s parameter set was the better of two successive categories the next best parameter set was chosen in such a way that each parameter set was only selected once. This means that 8 parameter sets were chosen for each strategy.

For each measure and for each strategy only the best or highest measured parameter set implementation will be selected for the next phase of testing. If the same parameter set yielded the highest measure in two or more measures only the one parameter set will be chosen as the parameter of choice for the measures it was identified in.

As has been shown each discussed strategy can be run with a different set of parameters and each parameter set will give higher or lower measures. For example a simple moving average strategy needs two parameters. A small moving average and a big moving average are needed in order to generate crossover points which then show a buy or sell signal. For example the parameter set 30, 60 can be used to create a 30- day moving average and a 60- day moving average and the crossover point will then give the buy or sell signals. In the same manner a 40, 80 parameter set can be used to create a 40- day moving average and a 80- day moving average and the crossover points of the 40, 80 parameter set will be different and generate different buy or sell signals than the 30, 60 parameter set and the different buy or sell signals will generate different trade times which will produce lower or higher measures of performance.

Parameters of different magnitudes can be run over the same stock but certain parameters will be more attuned to the particular trading algorithm that has been defined and will yield better results given the stated set of trading rules.

In the below table 6 parameter sets can be seen for the example strategy. All these parameters will be used over all stocks and the measures of performance of each will be saved and used later.

Table 1 - example strategy parameter sets

Example strategy parameters					
Pair number	**1**	**2**	**3**	**4**	**5**
Small parameter	100	200	300	400	500
Large parameter	200	350	500	650	800

The measures of performance that will be used are the Sharp ratio, the net profit, the percentage of profitable trades and the profit factor.

Table 2 – Selected example parameter set

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
100	200	Short	X	X		X
300	500	Long			X	

For example in table 1 above the selected parameter sets for the example strategy is shown. 100, 200, short is a parameter set and 300, 500, long is the second parameter set. The parameter sets shows that this strategy uses three parameters to seek buy (for long) or sell (for short) signals on each of the 100 stocks in the test dataset over the first four years. The strategy was run for each available parameter set over each of the 100 stocks and over the four years of data and the Sharp ratio, net profit, percentage of profitable trades and the profit factor was recorded for each parameter set and each stock.

Then the average values of all the sharp ratios and other measurements were calculated for each parameter set. Basically all the measurements created by the strategy for a specific parameter set was added together and divided by 100. This would give the average measurement over a single parameter set for all the stocks it was run over.

Then the highest average measurements of all the parameter sets in a strategy was selected and displayed in the above mentioned table. In other words in example table 1 the parameter set 300, 500, Long produced the highest average percentage of profitable trades measurement of all the parameter sets considered. This means that when all the parameter sets were run over all the stocks only the parameter set 300, 500, Long produced the most consistent and highest average percentage of profitable trades when this single strategy was considered.

It can be seen then also be seen that the parameter set 100, 200, short yielded the best or highest measurement of each of the Sharp ratio, net profit and profit factor measurements. The results for each of the previously discussed trading strategies are as follows:

3.4.1 Moving averages

A moving average strategy is a momentum strategy and entails the calculation of two moving averages. One moving average is calculated with less values at a time (in other words with a smaller parameter) than the other, this means that in effect the small moving average oscillates around the larger moving average as it contains more noise from the underlying stock's price series. A buy or sell signal is generated when the small moving average crosses the big moving average from below or from above respectively.

In this study two types of moving average were considered. Simple and exponential moving averages. Simple moving averages assign equal weight to each observation in the chain of stock prices used to calculate the moving average number while in an exponential moving average the values closer to the present date are assigned a larger weight in the averaging calculation than the older values. The weightings from the recent dates to the past dates decrease exponentially.

The following table lists the parameter sets which were back tested for. Each parameter set gives the big and small numbers of the moving averages used. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 3 - Moving average parameters

Moving average parameters					
Pair number	**1**	**2**	**3**	**4**	**5**
Small parameter	30	40	50	60	70
Large parameter	60	80	100	120	140

The table shows that for parameter pair 1 a 30 moving average and a 60- day moving average were used. This means that for this parameter set a buy or sell signal would be generated each time the small 30- day moving average crosses the large 60- day moving average line.

The same parameter sets are used for both simple and exponential moving averages and the same set is also used for both buy signals (long) and sell signals (short). The outcome of the back test was that over the 100 stocks, 5 parameter sets and 2 methods that one thousand price paths were generated and tested for both the buy signal and sell signal searches which equates to two thousand searches in total.

Of the two thousand price path searches 177 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 177 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage are given by the following tables:

Simple moving averages

Table 4 - Selected simple moving average parameter sets

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
40	80	Long		X		
30	60	Short	X			
70	140	Long			X	
70	140	Short				X

Exponential moving averages

Table 5 - Selected exponential moving average strategies

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
30	60	Long	X	X		X
70	140	Short			X	

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Simple moving averages

Table 6 - Simple moving averages first run results

Parm1	40	30	70	70
Parm2	80	60	140	140
Direction	Long	Short	Long	Short
Net Profit	3 220	2 941	2 368	1 539
Sharp Ratio	0.2650	0.2980	0.2923	0.1084
Profit trade %	61.90%	55.54%	66.23%	58.26%
Profit Factor	2.75	2.25	5.74	13.11
Trades per strategy	5.56	7.87	3.42	2.95
Profitable price paths	16	24	19	22

Exponential moving averages

Table 7 - Exponential moving averages first run results

Parm1	30	70
Parm2	60	140
Direction	Long	Short
Net Profit	2 493	1 316
Sharp Ratio	0.2436	-0.0001
Profit trade %	61.03%	80.59%
Profit Factor	6.68	0.99
Trades per strategy	5.21	1.93
Profitable price paths	19	31

3.4.2 Channel breakouts

A channel breakout strategy is a momentum strategy that generates a buy or sell signal when the current stock price is bigger or smaller than the maximum or minimum of a set number of previous stock price observations. In this way the strategy attempts to gain an advantage from situations in which a stock price “breaks out” from a previous range of similar stock price values.

The following table lists the parameter sets which were back tested for. Each parameter gives the number of past days over which the minimum or maximum is taken. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 8 - Channel breakout parameters

Channel breakout						
Parameter	**1**	**2**	**3**	**4**	**5**	**6**
Number of days	20	40	60	80	100	120

A buy signal is generated when the current stock price is greater than the maximum over the set number of previous days and a sell signal is generated when the current stock price is smaller than the minimum of the price series.

The outcome of the back test was that over the 100 stocks and 6 parameters that six hundred price paths were generated and tested for both the buy signal and sell signal searches which equates to one thousand two hundred searches in total.

Of the one thousand two hundred price path searches 265 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 265 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 9 - Selected channel breakout parameter sets

Parameter	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
60	Long	X	X		
80	Long			X	
100	Long				X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 10 - Channel breakout first run results

Parameter	60	80	100
Direction	Long	Long	Long
Net Profit	7 559.89	4 145.90	3 489.06
Sharp Ratio	0.5154	0.3890	0.3030
Profit trade %	63.34%	63.59%	57.14%
Profit Factor	4.04	3.97	39.17
Trades per strategy	9.32	7.89	6.63
Profitable price paths	19	18	19

3.4.3 Momentum

The momentum trading strategy is very simple. Simply choose a number of days and then look at the price of a stock that many days ago. Then if today's stock price is bigger than that past price buy the stock or if today's price is lower sell that stock.

For example, say 60 is chosen. For each day of the price series you would look at the stock price 60 days ago and buy if today's price is higher or sell if it is lower.

The following table lists the parameter sets which were back tested for. Each parameter gives the number of past days over which the minimum or maximum is taken. The same parameter set is used to find both the buy signal (long) or sell signal (short).

Table 11 - Momentum parameters

Momentum						
Parameter	**1**	**2**	**3**	**4**	**5**	**6**
Number of days	20	40	60	80	100	120

A buy signal is generated when the current stock price is greater than the stock price the indicated number of days ago and a sell signal is generated when the current stock price is smaller than this past price.

The outcome of the back test was that over the 100 stocks and 6 parameters that six hundred price paths were generated and tested for both the buy signal and sell signal searches which equates to one thousand two hundred searches in total.

Of the one thousand two hundred price path searches 212 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 212 profitable price paths the best strategies in terms of

Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 12 - Selected momentum parameter sets

Parameter	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
60	Long	X	X	X	
120	Long				X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 13 - Momentum first run results

Parameter	60	120
Direction	Long	Long
Net Profit	10 779	5 874
Sharp Ratio	0.5761	0.4487
Profit trade %	57.24%	57.07%
Profit Factor	1.99	2.34
Trades per strategy	22.63	18.93
Profitable price paths	16	28

3.4.4 Bollinger Bands

This trading strategy creates a channel around a stock's price range and if the stock breaches this channel a buy or sell signal is generated. The channel is created by taking the stocks exponential moving average and placing this average above and below the stock price. The distance off the EMA from the stock price is created as a function of the stock's standard deviation. In this way the channel will expand in volatile times and shrink in quieter times. A buy signal (long) is generated when the share price crosses the top EMA from below and a sell signal (short) is generated when the stock price crosses the bottom EMA from above.

Strategies for each combination of values in the following two tables were back tested. A total of 90 trading strategies were back tested over 100 stocks for both buy and sell signals. In other words eighteen thousand price path profitability tests were done. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 14 - Bollinger band parameters

EMA days	Standard deviation multiplier
20	0.1
40	0.15
60	0.25
80	0.5
100	0.75
120	1
140	1.25
160	1.5
180	1.75
200	

Of the eighteen thousand price path searches only 2 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 2 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 15 - Selected Bollinger band parameter set

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
180	0.75	Short	X	X	X	X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 16 - Bollinger band first run results

Parameter1	180
Parameter2	1
Direction	Short
Net Profit	962
Sharp Ratio	0.1227
Profit trade %	70.00%
Profit Factor	1.42
Trades per strategy	10.00
Profitable price paths	1

3.4.5 Trix oscillator

The Trix oscillator makes use of a triple exponential average calculation. The first EMA is calculated from the share price time series. The second EMA is calculated from the first EMA and the third from the second. The resulting graph oscillates around the zero axis as can be seen in the graph. A buy signal is generated when the third EMA crosses the zero line from below and a sell signal is generated when the EMA crosses the zero line from above.

The following table lists the parameter sets which were back tested for. Each parameter gives the number of past days over which each of the exponential moving averages is calculated. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 17 - Trix oscillator parameters

Trix Oscillator						
Parameter	**1**	**2**	**3**	**4**	**5**	**6**
Number of days	10	20	30	40	50	60

The outcome of the back test was that over the 100 stocks and 6 parameters that six hundred price paths were generated and tested for both the buy signal and sell signal searches which equates to one thousand two hundred searches in total.

Of the one thousand two hundred price path searches 261 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 261 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 18 - Selected Trix oscillator parameter sets

Parameter	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
20	Long	X	X		
40	Long				X
60	Short			X	

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 19 - Trix oscillator first run results

Parameter	20	40	60
Direction	Long	Long	Short
Net Profit	4 441	2 788	1 078
Sharp Ratio	0.3906	0.2749	0.0345
Profit trade %	62.73%	65.85%	69.55%
Profit Factor	2.89	29.34	2.35
Trades per strategy	9.09	4.74	2.58
Profitable price paths	22	19	26

3.4.6 Relative strength index

The relative strength index (RSI) is an oscillator which compares a stock's recent gains with its losses. It uses a stock's price gains and losses to calculate a range from 0 to 100. Most traders prepare to sell a market if the oscillator moves above 70 and prepares to buy into a market if the oscillator dips below 30. In this way the RSI is a mean reverting strategy. Varying cut off levels was considered for the implementation of this strategy.

Strategies for each combination of values in the following two tables were back tested. A total of 30 trading strategies were back tested over 100 stocks for both buy and sell signals. In other words six thousand price path profitability tests were done. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 20 - Relative strength index parameters

Past number of days	Index cut off level
20	0.05
40	0.1
60	0.2
80	0.3
100	0.4
120	

The cut off level was multiplied by 100. This number was then equal to the bottom cut off number and the number was then also subtracted from 100 to create the top cut off value.

For example if 0.2 was selected then the bottom cut off value would be 20 and the top cut off value would be 80. If the index value is calculated to be more than 80 then a sell signal is generated and if the index value is less than the bottom cut off level a buy signal is generated.

Of the six thousand price path searches 470 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 470 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 21 - Selected relative strength index parameter sets

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
80	0.05	Short	X	X		
60	0.05	Long			X	
100	0.05	Long				X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 22 - Relative strength index first run results

Parameter1	80	60	100
Parameter2	0.05	0.05	0.05
Direction	Short	Long	Long
Net Profit	8 965	4 870	4 989
Sharp Ratio	0.5326	0.3404	0.3915
Profit trade %	53.57%	55.27%	54.78%
Profit Factor	1.11	1.49	1.52
Trades per strategy	35.50	33.56	32.75
Profitable price paths	2	18	12

3.4.7 Moving average convergence/divergence

The Moving average convergence/divergence (MACD) is created by taking the difference between two exponential averages. An EMA is then taking from the MACD and both are plotted on a graph. If the MACD rallies (crosses from below) over the signal line, it can be taken as a signal that the market is oversold and long positions should be taken. Conversely if the MACD crosses the signal line from above it could be an indicator that the market is overbought and short positions should be taken. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 23 - Moving average convergence/divergence parameters

Moving average convergence/divergence oscillator					
Pair	**1**	**2**	**3**	**4**	**5**
Days of EMA1	12	24	36	48	60
Days of EMA2	26	52	78	104	130
Days of EMA of EMA1 - EMA2	9	18	27	36	45

The outcome of the back test was that over the 100 stocks and 5 parameter sets that five hundred price paths were generated and tested for both the buy signal and sell signal searches which equates to one thousand searches in total.

Of the one thousand price path searches 208 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 208 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 24 - Selected moving average convergence/divergence parameter sets

Parm1	Parm2	Parm3	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
24	52	18	Long		X		
12	26	9	Long				
60	130	45	Long	X		X	X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 25 - Moving average convergence/divergence first run results

Parameter1	24	12	60
Parameter2	52	26	130
Parameter3	18	9	45
Direction	Long	Long	Long
Net Profit	7 140	6 092	4 543
Sharp Ratio	0.4327	0.4269	0.4577
Profit trade %	57.04%	55.52%	67.31%
Profit Factor	2.15	1.93	27.99
Trades per strategy	15.88	20.63	7.40
Profitable price paths	17	24	30

3.4.8 Williams %R

The Williams %R is another oscillator. It ranges from 0 to -100 and any answer between 0 and -20 is thought to indicate overbought markets and any answers between -80 and -100 indicates oversold markets. Varying cut off levels was considered for the implementation of this strategy.

Strategies for each combination of values in the following two tables were back tested. A total of 30 trading strategies were back tested over 100 stocks for both buy and sell signals. In other words six thousand price path profitability tests were done. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 26 - Williams's %R parameter sets

Past number of days	Index cut off level
20	0.05
40	0.1
60	0.2
80	0.3
100	0.4
120	

The cut off level was multiplied by 100. This number was then equal to the bottom cut off number and the number was then also subtracted from 100 to create the top cut off value.

For example it 0.2 was selected then the bottom cut off value would be 20 and the top cut off value would be 80. If the index value is calculated to be more than 80 then a sell signal is generated and if the index value is less than the bottom cut off level a buy signal is generated.

Of the six thousand price path searches 50 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 50 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 27 - Selected Williams's %R parameter sets

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
100	0.05	Short	X	X	X	X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 28 - Williams's %R first run results

Parameter1	100
Parameter2	0.05
Direction	Short
Net Profit	4 080
Sharp Ratio	0.2846
Profit trade %	48.58%
Profit Factor	1.15
Trades per strategy	33.20
Profitable price paths	10

3.4.9 Volatility breakout trading strategy

The volatility break out rule was devised to take advantage of the fact that large stock moves are often preceded by other relatively large stock price moves. The volatility break out buy/sell signal is generated by using three measures. Firstly the Reference value, second the volatility multiplier, which is a decided upon integer, and lastly the volatility measure. In this case the reference value was taken as the exponential moving average of the stock price values according to the parameter days specified. The true range was calculated as the maximum of the following three daily values:

- Today's high minus today's low
- Today's high minus yesterday's close
- Yesterday's close minus today's low

The true range was then used to calculate the Average True Range (ATR) by calculation the exponential moving average of the chosen true range values according to the parameter days specified (The same parameter is used for both the reference value and the ATR). The ATR was then used as the volatility measure.

The strategy is implemented as follows, buy if today's close price is greater than the reference value plus the volatility multiplier times the volatility measure (ATR). Sell if today's close price is smaller than the reference value minus the volatility multiplier times the volatility measure.

Strategies for each combination of values in the following two tables were back tested. A total of 49 trading strategies were back tested over 100 stocks for both buy and sell signals. In other words nine thousand eight hundred price path profitability tests were done. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 29 - Volatility breakout parameters

Past number of days	Volatility multiplier
20	0.25
40	0.50
60	0.75
80	1.00
100	1.25
120	1.50
140	1.75

Of the eight thousand nine hundred price path searches 2 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 2 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 30 - Selected volatility breakout parameters sets

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
60	0.25	Short	X	X		X
20	1.75	Short			X	

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 31 - Volatility breakout first run results

Parameter1	60	20
Parameter2	0.25	1.75
Direction	Short	Short
Net Profit	359	105
Sharp Ratio	0.0697	-0.0568
Profit trade %	36.84%	66.67%
Profit Factor	1.06	1.03
Trades per strategy	19.00	12.00
Profitable price paths	1	1

3.4.10 Stochastic trading strategy

The Stochastic trading strategy is another type of oscillator as well as a mean reverting strategy, similar to the RSI. It also ranges from 0 to 100 with 20 indicating oversold markets and 80 indicating overbought markets. The stochastic consists of two moving lines called %k and %d. These move about one another in a similar manner that moving averages do, and it is thought that the crossings of %k and %d can also be used as buy and sell signals. This oscillator is calculated as follows:

$$\%k = 100*(C - Ll)/(Hh-Ll)$$

Where:

Ll = lowest low for the last *n* intervals

Hh = highest high for last *n* intervals

C = close of the latest

The %d is calculated in the following way:

$$\%d = 100*(HP/LP)$$

Where:

HP = *n* periods sum of (C - Ll)

LP = *n* periods sum of (Hh - Ll)

A buy or sell signal is generated when the %k signal line crosses the %d signal line from below or from above respectively. The number of days parameter indicates over how many past values the strategy searches for the highest high and the lowest low daily form the daily high and low stock price references. This parameter is also used to define n, as shown in the above mentioned formula to calculate HP and LP. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 32 - Stochastic parameters

Stochastic trading strategy							
Parameter	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Number of days	10	20	30	40	50	60	70

The outcome of the back test was that over the 100 stocks and 7 parameters that seven hundred price paths were generated and tested for both the buy signal and sell signal searches which equates to one thousand four hundred searches in total.

Of the one thousand four hundred price path searches 210 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 210 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 33 - Selected Stochastic parameter sets

Parameter	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
10	Short	X	X		
70	Short			X	X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 34 - Stochastic first run results

Parameter	10.00	70.00
Direction	Short	Short
Net Profit	2 893	1 652
Sharp Ratio	0.2378	0.1253
Profit trade %	51.54%	55.91%
Profit Factor	1.27	2.35
Trades per strategy	23.57	6.35
Profitable price paths	14	37

3.4.11 On balance volume trading strategy

On- balance volume is simply a cumulative graph of the daily volume of shares traded on the exchange. If the share price closed higher than the previous day's close the entire volume total for that day is added to the cumulative OBV. If the share price at close is lower than the previous close the volume amount is subtracted. This is indicator shows underlying strength or weakness in the share price and if limits are set at certain levels this indicator could be transformed into a trade entrée indicator.

In this case a channel breakout strategy was used on top of the data series generated by the OBV process. In other words a buy signal is generated if the OBV total for today is greater than the maximum of a set number of previous days and a sell signal is generated if today's OBV number is smaller than the minimum of a set number of past OBV days.

The following table lists the parameter sets which were back tested for. Each parameter gives the number of past days over which the minimum or maximum is taken. The same parameter set is used to find both the buy (long) or sell signals (short).

Table 35 - Channel break out parameters for on balance volume trading strategy

Channel breakout						
Parameter	**1**	**2**	**3**	**4**	**5**	**6**
Number of days	20	40	60	80	100	120

A buy signal is generated when the current OBV number is greater than the maximum over the set number of previous days and a sell signal is generated when the current OBV number is smaller than the minimum of the series. The outcome of the back test was that over the 100 stocks and 6 parameters that six hundred OBV paths were generated and tested for both the buy signal and sell signal searches which equates to one thousand two hundred searches in total.

Of the one thousand two hundred price path searches 297 proved to be more profitable than simply buying or selling the share they were calculated over in the time set considered. Of the 297 profitable price paths the best strategies in terms of Sharp ratio, net profits, profit factor and profitable trade percentage is given by the following table:

Table 36 - Selected channel break out parameter sets for on balance volume trading strategy

Parameter1	Parameter2	Direction	Sharp Ratio	Net Profit	P% Trades	Profit Factor
20	20.00	Long		X		
40	40.00	Long	X			
100	100.00	Short			X	X

The average performances of the strategies over all the profitable price paths are given below. The averages of the Sharp ratios, net profit, profitable trade percentage and profit factor were calculated for each parameter set. The bottom two measures shows the average number of trades done over the time period for each trading strategy as well as over how many profitable price paths the averages were calculated.

Table 37 - On balance volume first run results

Parameter1	20	40	100
Parameter2	20.00	40.00	100.00
Direction	Long	Long	Short
Net Profit	6 082	5 748	2 365
Sharp Ratio	0.3938	0.4062	0.1872
Profit trade %	56.07%	57.84%	60.34%
Profit Factor	2.19	2.49	9.06
Trades per strategy	19.82	14.89	6.48
Profitable price paths	67	57	33

3.5 Chapter summary and conclusion

In this chapter each of the trading strategies described in chapter two were applied to a data set in order to find the best parameter combinations according to the measurers specified over the first four years of the stock price data set. In the following chapter these strategies and the parameter sets identified will be applied to the last year of the test dataset and their performance will then be analyzed in more detail.

Chapter 4

Quantitative trading results

4.1 Introduction

In this chapter the strategies identified in the previous chapter will be applied to the last part of the dataset which has not been used by the selection process thus far. The original dataset covered 5 years worth of market data of the top 100 stocks on the JSE. The first 4 years were used to calibrate the best parameters for each strategy and these strategies will then be applied to the last year's worth of data. This section will report on the results of that analysis.

The results of the first study will also be used to choose the stock that the strategies will be applied to. For example if a single strategy did not make a profit at all on a specific stock in the first 4 years that stock will not be selected for that strategy in the last dataset. This is done to replicate the effects of back testing. If these strategies were done in practice a strategy would not be chosen for a specific stock if the strategy does not have a track record of being profitable on that stock.

Applicable stocks can be filtered in this way before the strategies are applied to them. The other previously defined measures can also be used in this way to find stock which presents a good and profitable fit to the strategies. The measures calculated for the strategies on the first four year's worth of market data will also be used to select the stocks for each strategy.

These measures will be used to filter the results of the previous section to such an extent that only a hand full of stocks will be considered for each strategy. This will allow for the construction of portfolio's of stocks and strategies which will enable the calculation of return figures if a suitable amount of capital was allocated to each strategy. Each strategy can then be evaluated on the return it would have generated if it was implemented in the markets.

4.2 Methodology

The following methodology was used for the generation of the trading strategy results over the last section of the data. Any reference to Sharp ratios, Profit factors, percent of profitable trades of net profit for filtering purposes will be made with regard to the answers obtained for these measures in the previous section as they were calculated with the first four years data. In real world application of quantitative trading strategies the past data sets of stocks are also known before hand and an investor or trader is able to calculate these measures from past data in order to aid the selection process. The measures of the first four years will be used to select strategies for the next year.

Basic trading rules for all strategies:

- Each individual trade will be held for a minimum of 20 trading days.
- Each individual trade will be held for a maximum of 40 trading days.
- Only strategies that made a profit will be considered.
- Only strategies with a Sharp ratio greater than 0 will be considered.
- If a trade makes a loss of 7.5% of the initial trade value, and the trade has been held for more than 20 trading days, the position will be closed out.
- All strategies are assumed to start with an available capital limit of R10, 000. This means that a buy signal is generated for a particular share the algorithm will buy as much stock as possible for R10, 000. (If a sell trigger is generated the algorithm will sell (short) as much stock as possible until it has reached a R10, 000 sell limit as well.)
- All profits/losses generated by a trade are added to the initial capital amount of R10, 000 and the additional profits/losses will be taken into account when the next trade is generated. This means that if the very first trade made a profit of R1,000 then the next trade of the same stock in the same strategy run

will have R11,000 available, which it will use in full, to buy or sell shares for the next buy/sell signal. This is done to reward or penalize consistently good or bad strategies.

- Brokerage or trading costs are not taken into consideration and are assumed to be zero.
- Dividends will not be taken into consideration and are assumed to be zero in all cases. The dividend's effect on the share price will still be seen in the share price and its effect will be implied in that way, but the dividend cash flow payments will be ignored.
- For each strategy the measures (Sharp ratios, Profit factors, percent of profitable trades of net profit) will be used to filter the results obtained in the previous section until around ten strategies will be applied to about then stocks. One strategy per stock. In each case the filters will be described.

4.3 Results

In order to replicate the results of a back testing procedure and to gauge the effectiveness of profitable trade selection prediction by back testing, the 5 year data set was split in into two parts. Five years worth of share price data was used and the last year was separated from out this data set. The first four years were used, as can be seen in the previous chapter, to derive the overall best (in terms of the measures derived in chapter two) strategies. These measures for the first four years will be used again in order to select the stocks over which the identified strategies did well (in terms of the measures defined).

The stocks over which the strategies did well will then be selected to be used by these strategies in the final separated year's share price data. The performance of the strategies will then be an indication of the applicability and profitability of quantitative trading. This is possible since the strategies and the measures they were selected on were created without taking the final year's data into consideration much in the same way that strategies and the measures used to select them are created and considered in the absence of future stock price performance when they are created in the present in practice.

The filters applied to the calculated measures of each identified strategy for the first four years are as follows. The first arrays of filters are applied to all strategies. If a strategy could not supply any qualifying measures for the first basic filter such a strategy will be deemed inferior by the measures defined and will be rejected for the remainder of this study. After the first filter each surviving set of strategies will be subjected to a second filter and will be refined down to a few select choices. The filters used will be described in each instance. The first ranges of filters are:

- Only choose stocks which showed a profit over the first four years for the identified strategies.
- Only choose stocks which resulted in a Sharp ratio greater than 0.5.
- Only choose stocks which resulted in 55% or more profitable trades when the selected strategy was applied to the stock.
- Only choose stocks which showed a profit factor of more than 2 when the strategies were applied to them.

After these filters were applied a total of 64 separate stocks and 22 strategy parameter sets qualified. These were spread over 176 price paths which satisfied all the above mentioned criteria. The following sections show the breakdown of the results. The various strategies are identified by the following key set:

Table 38 - Quantitative trading strategies

Number	Strategy
1	Simple moving average
2	Channel breakout
3	Exponential moving average
4	Moving average convergence divergence oscillator (MACD)
5	Momentum
6	Bollinger bands
7	Trix oscillator
8	Relative strength index (RSI)
9	Williams %R
10	Volatility Breakout
11	Stochastic
12	On-Balance Volume

The results are separated into two phases. In phase one the strategies are selected over the stocks they were most profitable over by using the system of filters on the measures already defined. The strategies over these stocks were selected by their measures after all the measures for all combinations of strategies and stocks were calculated from the first four years of available data.

In the second phase only the strategy and stock combinations identified as profitable will be run over the final year's data in order to determine the predictive effect of selecting the "good" measures in the first phase. Profitable results in phase 2 would go some way to prove the effectiveness of these strategies once they have been selected and calibrated to past data. Unprofitable results would cast some doubt upon the validity of using quantitative trading strategies in practice.

Phase 1

The following two tables show the results of the first set of filters on all the strategies. The results have been divided into two tables. The first table shows the average return and Sharp ratio of each strategy over four years and the second shows the average profit factor and percentage of profitable trades over four years as well.

What can also be seen is that some of the strategies did not yield good enough results over the four year trial period to be included in the below seen set. These seemingly inferior strategies include Bollinger bands, the Williams %R and the volatility breakout strategy. These strategies are discarded from this point onwards. (It is entirely possible that under a different parameter set or if the strategies was changed in some small way that these strategies could yet prove to be effective in certain cases, but searching for the circumstances set in which these strategies work will have to be the subject of a different study.)

Table 39 - First run summarized results (i)

Strategy	Parm1	Parm2	Parm3	Long/short	Average return over 4 years	Average sharp ratio	Stock count
1	30	60		Short	58.81%	0.6226	3
1	40	80		Long	85.03%	0.8018	2
1	70	140		Short	48.83%	0.7657	1
2	60			Long	111.53%	0.7786	15
2	80			Long	91.62%	0.7251	12
2	100			Long	88.18%	0.7240	10
3	30	60		Long	61.21%	0.6932	5
3	70	140		Short	62.53%	0.7348	1
4	12	26	9	Long	105.06%	0.7238	9
4	24	52	18	Long	144.96%	0.8397	6
4	60	130	45	Long	72.15%	0.7698	25
5	60			Long	176.26%	0.9158	6
5	120			Long	125.17%	0.8433	16
7	20			Long	84.90%	0.7006	11
7	40			Long	48.22%	0.6246	11
7	60			Short	43.41%	0.8826	1
8	60	0.05		Long	139.59%	0.7808	5
8	100	0.05		Long	110.90%	0.6836	5
11	70			Short	45.71%	0.5529	1
12	20			Long	174.43%	0.9487	15
12	40			Long	134.63%	0.8219	14
12	100			Short	77.63%	0.8682	2

Surprisingly one of the two strategies with the highest return and Sharp ratios is one of the most simple namely the momentum strategy and the second is a strategy that relies more on volume than on actual stock prices. It will be interesting to see how these strategies perform in the test section of the dataset over the last year of the data.

Table 40 - First run summarized results (ii)

Strategy	Parm1	Parm2	Parm3	Long/short	Average profitable trades %	Average profit factor	Stock count
1	30	60		Short	62.10%	3.348	3
1	40	80		Long	77.50%	42.826	2
1	70	140		Short	66.67%	225.468	1
2	60			Long	70.49%	5.391	15
2	80			Long	69.58%	4.780	12
2	100			Long	70.74%	73.006	10
3	30	60		Long	71.95%	41.682	5
3	70	140		Short	75.00%	8.019	1
4	12	26	9	Long	63.17%	3.297	9
4	24	52	18	Long	70.32%	3.223	6
4	60	130	45	Long	74.01%	35.310	25
5	60			Long	61.01%	3.825	6
5	120			Long	67.05%	4.305	16
7	20			Long	68.91%	4.606	11
7	40			Long	75.06%	48.086	11
7	60			Short	75.00%	8.627	1
8	60	0.05		Long	65.91%	2.689	5
8	100	0.05		Long	63.35%	2.470	5
11	70			Short	57.14%	8.751	1
12	20			Long	66.36%	4.566	15
12	40			Long	66.97%	4.536	14
12	100			Short	72.92%	82.737	2

From this table it becomes apparent that the simple moving average strategy seems to be the most stable and yield the largest profits verses losses, as can be seen in the very high profitable trade percentage and average profit factor scores. However, as can be seen from the relatively small amount of stocks these strategies were traded over it could mean that these strategies are only applicable on a very small set of stocks. This concludes the first phase of the process.

Phase 2

In this phase the strategies identified in the first phase as profitable will be applied to the same stocks with which they yielded profitable results with over the last year's data. The strategies have not been calibrated to the last year's data and no filters will be applied to the second set of results. This is to show what would have happened if an investor decided to use the strategies and stocks identified in phase 1 for one year. Profitable results in this phase would go some way to prove the effectiveness of the quantitative selection of trading strategies. Unprofitable results would cast some doubt upon the validity of using quantitative trading strategies in practice.

Table 41 - Second run summarized results

Strategy	Parm1	Parm2	Parm3	Long/short	Average return over 1 year	Average sharp ratio	Stock count
1	30	60		Short	7.16%	0.4036	3
1	40	80		Long	-3.27%	-0.6179	2
1	70	140		Short	-4.80%	-0.7411	1
2	60			Long	-1.85%	-4.1538	15
2	80			Long	-2.05%	-6.1962	12
2	100			Long	-0.79%	-7.8339	10
3	30	60		Long	4.85%	-11.1268	5
3	70	140		Short	0.00%	-13.9790	1
4	12	26	9	Long	15.95%	0.7613	9
4	24	52	18	Long	1.47%	0.0243	6
4	60	130	45	Long	5.82%	-1.5735	25
5	60			Long	12.64%	-4.1353	6
5	120			Long	8.63%	-1.5832	16
7	20			Long	5.78%	0.1295	11
7	40			Long	-1.42%	-6.3853	11
7	60			Short	-1.52%	-1.1079	1
8	60	0.05		Long	16.81%	0.7668	5
8	100	0.05		Long	12.91%	0.6737	5
11	70			Short	-11.90%	-2.9579	1
12	20			Long	-2.35%	-0.2178	15
12	40			Long	-1.25%	-0.1434	14
12	100			Short	-1.96%	-9.8956	2

From a profitability point of view it can be seen that some of the strategies performed consistently well, while other strategies had quite disappointing results. The most robust strategies which on average produced the highest returns were:

Table 42 - Robust quantitative trading strategies

Number	Strategy
3	Exponential moving average
4	Moving Average convergence divergence oscillator (MACD)
5	Momentum
8	Relative strength index (RSI)

Each of these strategies yielded a non-zero return. If these strategies were implemented during the final year in practice the investor using them would have yielded a profit. Of the strategies that did well, the RSI and MACD strategies were the strongest performers. The strategies which did not do well and did not yield positive returns were:

Table 43 - Less robust quantitative trading strategies

Number	Strategy
1	Simple moving average
2	Channel breakout
7	Trix oscillator
11	Stochastic
12	On-Balance Volume

These strategies did not yield consistent profitable results. The losses were not exceedingly large however, as can be seen from table 39. The losses were small relative to the gains of the strategies that did well and gave positive returns.

4.4 Chapter summary and conclusion

From the above analysis it can be seen that there is a practical use for the application of quantitative trading strategies in South African equity markets. A trader which uses quantitative measures to select robust trading strategies could conceivably use these strategies to trade for a profit. With the use of derivative instruments such a trader could conceivably increase his or her returns substantially. It must also be said that derivatives, like any type of gearing, also increase the risk of loss considerably and such instruments should only be applied with great care and constant proficient risk monitoring and management.

A table can be found below with the Bloomberg codes for the successful strategies as well as the returns they would have yielded if the described trading algorithm was implemented. It must also be said, again, that the strategies and stock combinations given below are no guarantee for future success. The following table only shows what would have happened in the past if these strategies were employed. In no way does it guarantee future returns.

Table 44 - Robust quantitative trading strategies

Number	Strategy
3	Exponential moving average
4	Moving Average convergence divergence oscillator (MACD)
5	Momentum
8	Relative strength index (RSI)

Table 45 - Detailed results of robust quantitative trading strategies

Strategy	Parm1	Parm2	Parm3	Long/short	Row Labels	Return
3	30	60		Long	MRF SJ Equity	0.00%
3	30	60		Long	MVG SJ Equity	0.63%
3	30	60		Long	NHM SJ Equity	0.00%
3	30	60		Long	TFG SJ Equity	23.60%
3	30	60		Long	WBO SJ Equity	0.05%
3	70	140		Short	HAR SJ Equity	0.00%
4	12	26	9	Long	APN SJ Equity	5.99%
4	12	26	9	Long	AVI SJ Equity	24.95%
4	12	26	9	Long	BAW SJ Equity	2.95%
4	12	26	9	Long	CML SJ Equity	15.80%
4	12	26	9	Long	CMP SJ Equity	2.54%
4	12	26	9	Long	MPC SJ Equity	17.16%
4	12	26	9	Long	SHP SJ Equity	44.64%
4	12	26	9	Long	SOL SJ Equity	5.24%
4	12	26	9	Long	SPP SJ Equity	24.26%
4	24	52	18	Long	APN SJ Equity	7.14%
4	24	52	18	Long	BAW SJ Equity	-6.59%
4	24	52	18	Long	BIL SJ Equity	-12.33%
4	24	52	18	Long	CFR SJ Equity	9.19%
4	24	52	18	Long	CML SJ Equity	12.04%
4	24	52	18	Long	EXX SJ Equity	-0.63%
4	60	130	45	Long	ACP SJ Equity	8.88%

4	60	130	45	Long	CFR SJ Equity	7.71%
4	60	130	45	Long	CLS SJ Equity	9.37%
4	60	130	45	Long	CPL SJ Equity	7.93%
4	60	130	45	Long	DRD SJ Equity	0.00%
4	60	130	45	Long	EMI SJ Equity	1.12%
4	60	130	45	Long	GFI SJ Equity	0.18%
4	60	130	45	Long	GRT SJ Equity	5.42%
4	60	130	45	Long	HYP SJ Equity	-4.51%
4	60	130	45	Long	KIO SJ Equity	-1.96%
4	60	130	45	Long	MPC SJ Equity	21.23%
4	60	130	45	Long	MSM SJ Equity	19.20%
4	60	130	45	Long	NTC SJ Equity	7.67%
4	60	130	45	Long	REM SJ Equity	6.56%
4	60	130	45	Long	RES SJ Equity	9.01%
4	60	130	45	Long	RMH SJ Equity	-2.24%
4	60	130	45	Long	SHP SJ Equity	0.00%
4	60	130	45	Long	SNT SJ Equity	2.53%
4	60	130	45	Long	SPP SJ Equity	0.00%
4	60	130	45	Long	SYC SJ Equity	5.82%
4	60	130	45	Long	TBS SJ Equity	12.44%
4	60	130	45	Long	TFG SJ Equity	19.42%
4	60	130	45	Long	TRU SJ Equity	5.22%
4	60	130	45	Long	VKE SJ Equity	6.14%
4	60	130	45	Long	WHL SJ Equity	-1.52%
5	60			Long	CML SJ Equity	14.85%
5	60			Long	KIO SJ Equity	-5.76%
5	60			Long	MPC SJ Equity	11.81%
5	60			Long	NHM SJ Equity	0.00%
5	60			Long	SHP SJ Equity	27.49%
5	60			Long	SPG SJ Equity	27.42%
5	120			Long	CFR SJ Equity	-2.47%
5	120			Long	CML SJ Equity	10.09%
5	120			Long	CPL SJ Equity	4.58%
5	120			Long	JDG SJ Equity	2.00%
5	120			Long	JSE SJ Equity	-0.97%
5	120			Long	KIO SJ Equity	5.25%
5	120			Long	LEW SJ Equity	2.19%
5	120			Long	MPC SJ Equity	17.57%
5	120			Long	MVG SJ Equity	-4.95%
5	120			Long	NTC SJ Equity	0.00%
5	120			Long	PET SJ Equity	0.00%
5	120			Long	PSG SJ Equity	1.74%
5	120			Long	SHP SJ Equity	35.17%
5	120			Long	SPG SJ Equity	31.72%
5	120			Long	SPP SJ Equity	8.92%
5	120			Long	WHL SJ Equity	27.25%

8	60	0.05		Long	CFR SJ Equity	11.30%
8	60	0.05		Long	CML SJ Equity	23.11%
8	60	0.05		Long	REM SJ Equity	-0.58%
8	60	0.05		Long	SHP SJ Equity	34.08%
8	60	0.05		Long	SPP SJ Equity	16.12%
8	100	0.05		Long	CFR SJ Equity	-1.96%
8	100	0.05		Long	CML SJ Equity	8.20%
8	100	0.05		Long	REM SJ Equity	5.22%
8	100	0.05		Long	SHP SJ Equity	36.45%
8	100	0.05		Long	SPP SJ Equity	16.66%

Appendix I

Table of stocks to be included in study sorted by the Cap times liquidity calculation. This table is also followed by an alphabetically sorted table of the same set of stocks. The market cap amounts are in millions of Rands. The cap times liquidity calc measure is equal to:

Cap times liquidity calc = (2010 Average volume * Market Cap on 2010/12/31) / 1 000 000

Sorted by stock ranking.

Table 46 - Stocks selected for this study

Ranking	Stock	2010 Average volume	Market Cap on 2010/12/31	Cap times liquidity calc
1	BIL	3 544 183	1 606 282	5 692 957
2	CFR	9 774 189	224 110	2 190 496
3	MTN	7 861 506	253 123	1 989 930
4	AGL	4 219 406	452 762	1 910 386
5	FSR	13 690 182	109 996	1 505 869
6	OML	12 602 794	70 869	893 148
7	SBK	4 632 100	170 471	789 638
8	SAB	1 553 124	373 595	580 239
9	SOL	1 911 316	222 064	424 433
10	IMP	2 281 373	147 164	335 736
11	NPN	2 045 456	157 541	322 243
12	SLM	4 315 938	58 632	253 052
13	GFI	2 317 383	86 840	201 242
14	SHF	5 012 662	37 614	188 546
15	ASA	1 457 615	100 549	146 562
16	ANG	1 097 787	124 613	136 798
17	SHP	2 221 676	54 158	120 321
18	ABL	3 469 313	31 162	108 110
19	WHL	4 330 148	22 863	99 002
20	GRT	3 203 219	28 806	92 272
21	RMH	1 952 477	46 551	90 889
22	RDF	3 996 497	21 494	85 903
23	NED	1 100 921	67 064	73 832
24	INP	1 573 125	44 656	70 249
25	AMS	371 580	182 828	67 935
26	NTC	2 723 592	22 129	60 270
27	REM	1 028 253	58 351	60 000
28	TRU	1 746 049	32 680	57 061
29	KIO	410 394	136 652	56 081

30	MMI	2 238 352	24 989	55 934
31	HAR	1 546 147	35 649	55 119
32	BVT	1 048 306	51 312	53 791
33	APN	1 194 366	39 835	47 578
34	CSO	1 503 601	29 439	44 264
35	TKG	2 030 558	19 790	40 184
36	INL	880 672	44 650	39 322
37	EXX	805 680	48 781	39 302
38	PPC	1 806 536	20 487	37 010
39	AEG	2 137 159	17 127	36 604
40	SAP	1 792 805	18 262	32 740
41	ACL	927 053	35 312	32 737
42	IPL	990 301	29 898	29 608
43	MSM	966 261	29 846	28 839
44	TFG	1 247 775	21 645	27 008
45	TBS	719 350	36 826	26 491
46	PIK	1 133 586	23 251	26 357
47	DSY	980 982	23 335	22 891
48	ARI	508 246	44 722	22 730
49	MUR	1 699 348	13 332	22 656
50	CLS	1 698 513	12 309	20 907
51	NPK	1 295 660	15 190	19 681
52	MPC	1 060 318	17 681	18 747
53	BAW	1 139 408	15 440	17 593
54	MRF	3 959 269	4 087	16 180
55	SAC	1 928 951	6 600	12 730
56	NHM	777 681	16 360	12 723
57	FPT	1 670 938	6 972	11 650
58	JDG	1 061 685	9 889	10 499
59	GND	1 113 809	8 811	9 814
60	SPP	570 700	16 739	9 553
61	LON	214 196	41 268	8 839
62	LBH	402 326	20 737	8 343
63	MDC	365 449	19 048	6 961
64	RLO	508 894	13 288	6 762
65	AVI	613 096	10 513	6 446
66	EMI	702 620	7 026	4 936
67	CPL	830 150	5 891	4 891
68	ILV	376 552	12 681	4 775
69	DTC	431 931	6 172	2 666
70	LEW	299 422	7 971	2 387
71	RES	271 963	8 369	2 276
72	CML	385 210	5 903	2 274
73	TON	192 219	11 372	2 186

74	SUI	167 788	11 717	1 966
75	UUU	102 996	19 052	1 962
76	AFX	256 345	7 080	1 815
77	CMP	545 963	3 216	1 756
78	SNU	1 015 435	1 701	1 727
79	AFE	162 678	9 829	1 599
80	ZED	614 724	2 543	1 563
81	VKE	290 514	5 125	1 489
82	JSE	218 562	6 726	1 470
83	SPG	471 530	2 717	1 281
84	WBO	136 115	9 174	1 249
85	HYP	129 163	9 468	1 223
86	PET	721 492	1 673	1 207
87	GRF	257 574	4 413	1 137
88	SNT	72 420	15 575	1 128
89	TSH	190 177	5 715	1 087
90	ACP	182 963	5 841	1 069
91	MVG	590 331	1 744	1 030
92	SYC	208 147	4 463	929
93	AFR	324 648	2 854	926
94	BDM	1 468 414	586	860
95	AQP	49 207	17 232	848
96	DRD	631 044	1 309	826
97	WEZ	422 362	1 915	809
98	PSG	104 848	7 496	786
99	CZA	147 666	5 082	750
100	GIJ	1 020 701	726	741

Sorted by share name.

Table 47 - Stocks selected for this study sorted alphabetically

Ranking	Stock	2010 Average volume	Market Cap on 2010/12/31	Cap times liquidity calc
18	ABL	3 469 313	31 162	108 110
41	ACL	927 053	35 312	32 737
90	ACP	182 963	5 841	1 069
39	AEG	2 137 159	17 127	36 604
79	AFE	162 678	9 829	1 599
93	AFR	324 648	2 854	926
76	AFX	256 345	7 080	1 815
4	AGL	4 219 406	452 762	1 910 386
25	AMS	371 580	182 828	67 935
16	ANG	1 097 787	124 613	136 798

33	APN	1 194 366	39 835	47 578
95	AQP	49 207	17 232	848
48	ARI	508 246	44 722	22 730
15	ASA	1 457 615	100 549	146 562
65	AVI	613 096	10 513	6 446
53	BAW	1 139 408	15 440	17 593
94	BDM	1 468 414	586	860
1	BIL	3 544 183	1 606 282	5 692 957
32	BVT	1 048 306	51 312	53 791
2	CFR	9 774 189	224 110	2 190 496
50	CLS	1 698 513	12 309	20 907
72	CML	385 210	5 903	2 274
77	CMP	545 963	3 216	1 756
67	CPL	830 150	5 891	4 891
34	CSO	1 503 601	29 439	44 264
99	CZA	147 666	5 082	750
96	DRD	631 044	1 309	826
47	DSY	980 982	23 335	22 891
69	DTC	431 931	6 172	2 666
66	EMI	702 620	7 026	4 936
37	EXX	805 680	48 781	39 302
57	FPT	1 670 938	6 972	11 650
5	FSR	13 690 182	109 996	1 505 869
13	GFI	2 317 383	86 840	201 242
100	GIJ	1 020 701	726	741
59	GND	1 113 809	8 811	9 814
87	GRF	257 574	4 413	1 137
20	GRT	3 203 219	28 806	92 272
31	HAR	1 546 147	35 649	55 119
85	HYP	129 163	9 468	1 223
68	ILV	376 552	12 681	4 775
10	IMP	2 281 373	147 164	335 736
36	INL	880 672	44 650	39 322
24	INP	1 573 125	44 656	70 249
42	IPL	990 301	29 898	29 608
58	JDG	1 061 685	9 889	10 499
82	JSE	218 562	6 726	1 470
29	KIO	410 394	136 652	56 081
62	LBH	402 326	20 737	8 343
70	LEW	299 422	7 971	2 387
61	LON	214 196	41 268	8 839
63	MDC	365 449	19 048	6 961
30	MMI	2 238 352	24 989	55 934
52	MPC	1 060 318	17 681	18 747

54	MRF	3 959 269	4 087	16 180
43	MSM	966 261	29 846	28 839
3	MTN	7 861 506	253 123	1 989 930
49	MUR	1 699 348	13 332	22 656
91	MVG	590 331	1 744	1 030
23	NED	1 100 921	67 064	73 832
56	NHM	777 681	16 360	12 723
51	NPK	1 295 660	15 190	19 681
11	NPN	2 045 456	157 541	322 243
26	NTC	2 723 592	22 129	60 270
6	OML	12 602 794	70 869	893 148
86	PET	721 492	1 673	1 207
46	PIK	1 133 586	23 251	26 357
38	PPC	1 806 536	20 487	37 010
98	PSG	104 848	7 496	786
22	RDF	3 996 497	21 494	85 903
27	REM	1 028 253	58 351	60 000
71	RES	271 963	8 369	2 276
64	RLO	508 894	13 288	6 762
21	RMH	1 952 477	46 551	90 889
8	SAB	1 553 124	373 595	580 239
55	SAC	1 928 951	6 600	12 730
40	SAP	1 792 805	18 262	32 740
7	SBK	4 632 100	170 471	789 638
14	SHF	5 012 662	37 614	188 546
17	SHP	2 221 676	54 158	120 321
12	SLM	4 315 938	58 632	253 052
88	SNT	72 420	15 575	1 128
78	SNU	1 015 435	1 701	1 727
9	SOL	1 911 316	222 064	424 433
83	SPG	471 530	2 717	1 281
60	SPP	570 700	16 739	9 553
74	SUI	167 788	11 717	1 966
92	SYC	208 147	4 463	929
45	TBS	719 350	36 826	26 491
44	TFG	1 247 775	21 645	27 008
35	TKG	2 030 558	19 790	40 184
73	TON	192 219	11 372	2 186
28	TRU	1 746 049	32 680	57 061
89	TSH	190 177	5 715	1 087
75	UUU	102 996	19 052	1 962
81	VKE	290 514	5 125	1 489
84	WBO	136 115	9 174	1 249
97	WEZ	422 362	1 915	809

19	WHL	4 330 148	22 863	99 002
80	ZED	614 724	2 543	1 563

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