Evaluation of the performance of a pairs trading strategy of JSE listed firms

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ABSTRACT

A pairs trading strategy is a market neutral trading strategy that tries to make a profit by making use of inefficiencies in financial markets. In the equity pairs trading context, a market neutral strategy, is a strategy that hedges against both market and sector risk. According to the efficient market theory in its weak form, a pairs trading strategy should not produce positive returns since the actual stock price is reflected in its past trading data. The main objective of this paper is to examine the performance and risk of an equity pairs trading strategy in an emerging market context using daily, weekly and monthly prices on the Johannesburg Securities Exchange over the period 1994 to 2014. A bootstrap method is used determine whether returns from the strategy can be attributed to skill rather than luck.

Key Words: pairs trading, quantitative strategy, asset allocation

DECLARATION

I, Shreelin Naicker, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Shreelin Naicker

Signed at …………………………………………………….

On the …………………………….. Day of ………………………… 2015

DEDICATION

To Presodhini, Adara, Callan and Custard

ACKNOWLEDGEMENTS

Thank you to my wife Prissy for her continual support, to my work colleagues and class mates for their constant encouragement and to Prof Eric Schalling.

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1. CHAPTER 1: INTRODUCTION

1.1 Purpose of the study

This paper aims to investigate the profitability of a pairs trading strategy on the Johannesburg Securities Exchange using the distance approach. It builds on similar studies done by Perlin (2006).

This study will aim to prove whether or not a pairs trading strategy is profitable by using a model designed in MATLAB and based on information gained from literature and financial market practitioners.

The Johannesburg Securities Exchange (JSE) is the 16th largest in the world, and by far the largest of Africa's 22 stock exchanges. Market capitalisation of the JSE at the end of December 2003 stood at R4 029-billion, up from R1 160-billion five years earlier. In 2003 the JSE had an estimated 472 listed companies and a market capitalisation of US$182.6 billion (€158 billion), as well as an average monthly traded value of US$6.399 billion (€5.5 billion). As of 31 December 2012, the market capitalisation of the JSE was at US$903 billion. However, it is much less liquid than that found in the United States and parts of Europe and Asia.

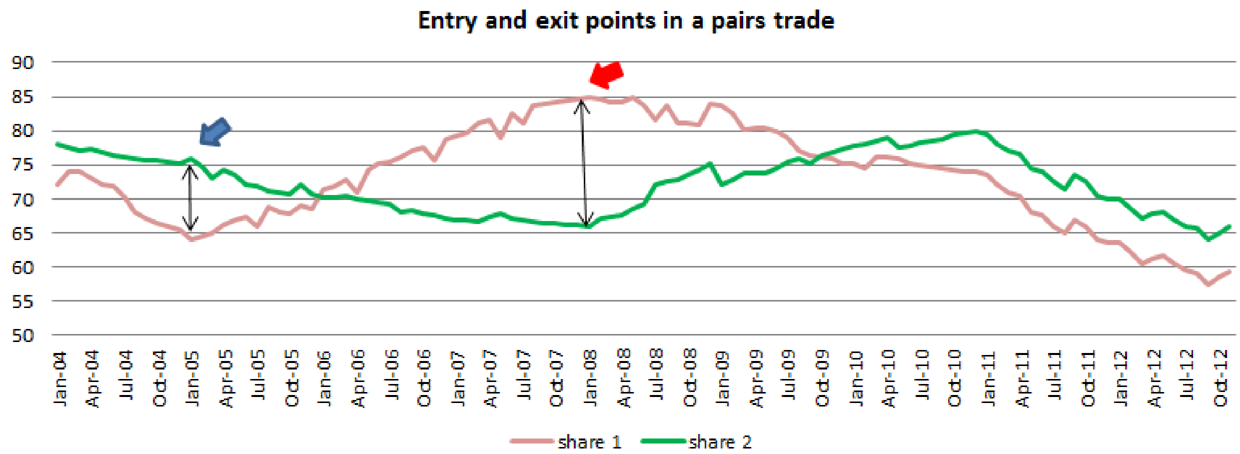
There are many studies on pairs trading strategies in the United States and Europe but very few have been done in the emerging markets context and even fewer done in stressed markets. Financial market stress occurs when there is a loss of liquidity, risk aversion, increased volatility and falling valuations in emerging as was as developed economies. As a result financial institutions find it difficult to secure funding to finance their short term liabilities.

Since a pairs trading strategy requires implementing two trades instead of one, evaluating performance in a less liquid market provides additional evidence regarding the strategy's global implementable efficacy. Pairs trading or statistical arbitrage as it is sometimes called, is based on the law of one price, but is not riskless as the word arbitrage suggests. There is embedded risk in the strategy which stems from different economic fundamentals like market liquidity.

1.2 Context of the study

Pairs trading is often referred to as a trading strategy that is market neutral, which attempts to identify financial instruments with similar characteristics. In order for pairs trading to be effective as a trading strategy the characteristics of these shares needs to be consistent over a period of time. A pairs trading strategy is easy to implement and has become very popular with traders throughout the world. Where a trader or fund manager finds two stocks whose prices move together over a window of time, the pairs trading strategy may be implemented when price relationship of the instruments differs from that obtained in their historical trading range, i.e. the two instruments prices are no longer consistent anymore. The undervalued instrument is bought, and an equally large short position is simultaneously instigated in the overvalued instrument. Pairs trading is based on the fact that long term historical price relationships outweigh short term price deviations over time which results in a trader making profit. Pairs trading has been used successfully by hedge funds and proprietary trading desks for many years. However, the pairs trading strategy or arbitrage trading as it is sometimes called, is not completely riskless. Once a trader has entered into a pairs trade, the trader will ultimately lose money should the gap between the two financial instruments widen, while the trader holds the position. Therefore, any trader would want to enter a pairs trade when the price gap between the trades is at its widest, and close his positions when the price gap between the two instruments is at its widest in the opposite direction. Pair trades are near market neutral and are based on relative valuation which can easily be automated. Pairs trading has become a popular investment strategy amongst investors as it promises to give substantial profits irrespective of market conditions. A pairs trading strategy removes systematic risk from portfolios and the investor is only subjected to asset specific risk. Pairs trading involve essentially constructing a portfolio of matching stocks in terms of systematic risks but with a long position in the stock perceived to be under-priced and a short position in the stock perceived to be over- priced. This would result in a portfolio where systematic risk is hedged.

Figure 1: An example of pairs trading



The largest gap between the 2 shares prices is indicated by the blue and red arrows, showing the entry and exit points of the trade. In order for a trader to earn a maximum profit, a trade will be instigated at the blue arrow, where a trader would short sell the green share and at the same time go long the pink share. The trader will exit the share at the red arrow but will make a profit on both the long and the short postion.

1.3 Problem statement

1.3.1 *Main problem*

Analyse the profitability and risk of a hedge fund trading strategy based on the distance approach to pairs trading. While pairs trading is a popular trading strategy used by hedge funds, it is not exclusively a hedge fund strategy and can be used across any asset class to hedge market risk. This analysis will cover daily, weekly and monthly frequencies for stocks traded on the JSE across different distance values. This research project extends the work of a number of researchers such as Gatev *et al* (1999) and Perlin (2006), who have conducted similar research in other markets. Many of the studies on Pairs Trading have been conducted on exchanges that are far more liquid than the JSE.

1.4 Significance of the study

Whereas there have been studies on pairs trading in the South African agricultural market and Pairs trading on the single stock futures market on the JSE, this research project aims to fill a gap in research by analysing a pairs trading strategy using the distance approach on single stock shares traded on the JSE. This research project will help researchers and practitioners obtain a better understanding of such a strategy in the context of an emerging market as well as gain an understanding of how the market has changed from 1994 to 2014.

1.5 Delimitations of the study

- Trading costs were estimated and based on the current trading costs on the JSE.
- Daily closing prices were used for all trading simulations. There is sometimes a difference between closing prices and trading prices

1.6 Definition of terms

Long Position: The buying of a security such as a stock, commodity or currency, with the expectation that the asset will rise in value.

Short Position: The sale of a borrowed security, commodity or currency with the expectation that the asset will fall in value.

Liquidity: The degree to which an asset or security can be bought or sold in the market without affecting the asset's price. Liquidity is characterized by a high level of trading activity. Assets that can be easily bought or sold are known as liquid assets.

S&P 500 Index: An index of 500 stocks chosen for market size, liquidity and industry grouping, among other factors. The S&P 500 is designed to be a leading indicator of U.S. equities and is meant to reflect the risk/return characteristics of the large cap universe. Companies included in the index are selected by the S&P Index Committee, a team of analysts and economists at Standard & Poor's. The S&P 500 is a market value weighted index in which - each stock's weight is proportionate to its market value.

Hedge fund: A hedge fund is a collective investment scheme, often structured as a limited partnership that invests private capital speculatively to maximize capital appreciation. Hedge funds tend to invest in a diverse range of markets, investment instruments, and strategies; today the term "hedge fund" refers more to the structure of the investment vehicle than the investment techniques. Though they are privately owned and operated, hedge funds are subject to the regulatory restrictions of their respective countries.

Market Neutral Strategy: A market neutral strategy is a strategy that hedges against both market and sector risk, i.e., the expected return from the strategy is uncorrelated with the market.

JSE: The Johannesburg Securities Exchange (JSE) is the 16th largest in the world, and by far the largest of Africa's 22 stock exchanges. Market capitalisation at the end of December 2003 stood at R4 029-billion, up from R1 160-billion five years earlier. In 2003 the JSE had an estimated 472 listed companies and a market capitalisation of US$182.6 billion (€158 billion), as well as an average monthly traded value of US$6.399 billion (€5.5 billion). As of 31 December 2012, the market capitalisation of the JSE was at US$903 billion.

MATLAB: MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN.

Bloomberg: The Bloomberg Terminal is a computer system provided by Bloomberg L.P. that enables professionals in finance and other industries to access the Bloomberg Professional service, through which users can monitor and analyse real-time financial market data and place trades on the electronic trading platform. The system also provides news, price quotes, and messaging across its proprietary secure network.

1.7 Assumptions

- It is assumed that the daily closing prices available from Bloomberg are accurate. The data was obtained using the historical data tool provided in excel. Data was analysed for improbable shocks and shares with improbable time series data were removed.
- Liquidity – it is assumed that there is a willing buyer and willing seller at any time, so that liquidity is guaranteed any time in the model. The pairs trading model designed in MATLAB relied heavily on this assumption. It is important to note that this model does not try to compensate for a lack of liquidity in the market.
- Trading costs - are constant over time – An analysis of JSE historical trading costs shows that the costs varied across the time period considered for this model. This model does not take into account variable trading costs across time but uses a constant 1% of the investment as trading costs. According to the latest cost tables provided by the JSE this is a reasonable assumption.
- It was assumed that capital for short positions was not required. This is consistent with research done by other researchers on this topic and is realistic in terms real market conditions. To accomplish short selling, you borrow shares of stock and then sell them in the open market, without ever owning the shares. Then you must buy identical shares back at a later date to return to the owner, your goal as a short seller is to purchase the shares back for less cost in the future and net a profit.

2. CHAPTER 2: LITERATURE REVIEW

2.1 The Law of One Price

The law of one price states that that if the returns from two investments are identical in every state then the current value of the two investments must be the same (Ingersoll 1987). Similarly, for markets to be perfectly integrated (which is commonly assumed), two portfolios created from two markets cannot exist with different prices if the pay offs are identical (Chen and Knez 1995). If these conditions are not satisfied, arbitrage opportunities exist thus giving investors opportunities to make risk-free profits by buying under-priced securities and short-selling the overpriced ones (Lamont and Thaler 2003). In a perfectly efficient market, the prices fully react to the available information at all times (Fama 1970). The market efficiency hypothesis reached its peak in 1970's, and at that time there was a consensus on the idea that as soon as any news reached the market it spreads quickly and immediately gets reacted to through stock prices changes.

2.2 History of Pairs Trading.

The increase in processing powers of computers led to more sophisticated trading models being developed and employed in investment banks. Teams were formed to use statistical methods, to develop computer based algorithms, which contained specific trading rules and where human subjectivity had no influence whatsoever in the process of trading. Many of these algorithms were successful for short periods of time but did not show great consistency. Nunzio Tartalia, a quant in Wall Street, assembled a team of mathematicians, physicists and computer scientists in the mid 1980's to design these algorithms to be used for trading the equity markets. This group of former academics used sophisticated statistical methods to develop high-tech trading programs. These programs used trading rules to replace the intellectual skill of traders with years of trading experience. A popular and successful trading rule or strategy that emerged was a program that identified pairs of securities whose prices tended to move together. It was reported that this group made a $50 million profit for the Morgan Stanley group based on the pairs trading strategy. Although the team had a few years of bad performance, the pairs trading strategy gained a good reputation in the financial markets and has since become an increasingly popular "market-neutral" investment strategy used by individuals and institutional traders as well as hedge funds. Pairs trading is now used across many asset classes and is used widely in both vanilla and derivative markets.

2.3 The CAPM and Pairs Trading

The CAPM model, essentially divides total risk, into two components namely systematic risk, which is the risk associated with holding a market portfolio, and asset specific risk which is the risk associated with the specific asset. The objective of a market neutral strategy is to remove systematic risk from a portfolio. According to the CAPM model the portfolio would then only be subjected to asset-specific risk. One of the market neutral strategies used to achieve this is to buy the undervalued asset and short selling the overvalued asset. When market forces affect the long asset, it is offset by the short position which results in an elimination of systematic risk. This is the basis of a pairs trading strategy which is a market neutral strategy as it involves taking a long and short position on relatively mispriced assets.

According to Vidyamurthy (2004) CAPM is an acronym for capital asset pricing model a formalisation of the notion of a market portfolio. A portfolio of assets that acts as a proxy for the market can be thought of as a market portfolio in CAPM terms. By using the ideas of beta and market portfolio, the CAPM model, attempts to explain asset returns as an aggregate sum of component returns.

The return on an asset can be broken up into two parts, the systematic component (sometimes referred to as the market component) and the non-systematic component. If

r_p is the return on the asset,

r_m is the return on the market portfolio,

beta of the asset is denoted as β,

then the formula showing the relationship that achieves the separation of the returns is given as

$$r_p = \beta r_m + \theta_p$$

, which is also often referred to as the security market line (SML).

βr_m is the market or systematic component of the return. β serves as a leverage number of the asset return over the market return. It may also be deduced from **Figure 2** that β is indeed the slope of the SML. θ_p in the CAPM equation is the residual component or residual return on the portfolio. It is the portion of the asset return that is not explained by the market return. The consensus expectation on the residual component is assumed to be zero.

If one was to separate the asset returns into its two components as described by the CAPM model, the model elaborates on a key assumption with respect to the relationship between them. This assertion of the CAPM model is that the market component and residual component are uncorrelated.

It was deduced earlier, that beta is the slope of the SML. By using the returns from the market and the returns from the asset, beta can be estimated as the slope of the regression line between the two. When the standard regression formula is applied to estimate the slope, one can conclude that the beta is the covariance between the asset and market returns divided by the variance in market returns.

$$\beta = \frac{\mathrm{cov}(r_p r_m)}{\mathrm{var}(r_{m)}}$$

A positive return for the market usually implies a positive return for the asset.

This implies that the sum of the market component and the residual component would then be positive. One can then deduce that if the residual component of the asset return is small then the positive return in the asset would be explained almost completely by its market component. A positive return in the market portfolio and the asset would imply a positive market component of the return. Thus beta would have a positive value. All assets would therefore be expected to have positive values for their betas.

A market neutral strategy is a strategy that hedges against both market and sector risk i.e. the return from the strategy is uncorrelated with the market. Thus the market neutral strategy does not concern itself with the state of the market (i.e. whether the market is going up or coming down) but rather, it is more focussed on producing profits in a steady manner, regardless of volatility.

We therefore would need a market neutral portfolio to trade? According to the CAPM model, a market neutral portfolio would have zero beta. By applying a zero value to the beta of the SML equation, one would find that the return on the portfolio would not have a market component and would completely be determined by θp which is the residual component of the equation. The component of the model that remains is uncorrelated with market returns, so that neutral returns are obtained and thus the criteria met of a market neutral strategy due to a zero beta. Since the mean of the residual return is zero, a strong mean reverting behaviour can be expected, of the residual time series. Unexpected market events and market forces that result in changes in supply and demand usually result in changes in asset prices away from their equilibrium price. Mean reversion can be described as the process of asset prices moving away from their normal levels and then reverting back. The exploitation in the process of return prediction of this mean reverting behaviour can lead to trading signals which can then be used to develop a trading strategy.

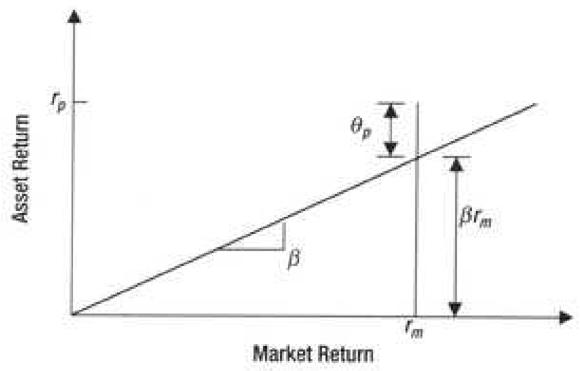
Using the definition of a market neutral strategy portfolio, we can construct a portfolio with a zero beta. A portfolio that only has long positions will have a positive beta and a portfolio with only short positions will have a negative beta. A negative beta means that an asset returns tends to move in the opposite direction to the markets returns i.e. there is a negative correlation between the assets returns and the market, and a positive beta means that the assets returns tend to move in the same direction as the markets returns i.e. there is a positive correlation between the assets returns and the market.

Therefore in order to construct a zero beta portfolio we cannot only use assets that have positive betas or assets that only have negative betas because this would not be possible. The only possibility would be to hold both long and short positions on different assets in a portfolio. Due to the fact that a zero beta portfolio has to comprise of both long and short positions these portfolios are often referred to as long-short portfolios.

Pairs trading is a market neutral portfolio that consists of just two securities and is a market neutral strategy in its most primitive form, which has one security as a long position and the other a short position. The spread of an asset is the difference between the bid and offer of a security or asset. The bid price is the maximum price that a buyer is willing to pay for a security and the offer price is the minimum a seller is willing to receive for a security. The spread is computed using the quoted prices of the securities. A portfolio is associated with the spread at any given time. In the CAPM equation the spread is related to the residual return component of the return. The spread represents the degree of mispricing of an asset or security and the higher the spread, the higher the mispricing and the greater the chance to capture a profit.

A pairs trade would be executed when the spread is substantially wide with the expectation that the spread will revert back to its mean. When this convergence occurs the positions would then be reversed and a profit would be made. Pairs Trading is based on the fact that in relative pricing, stocks with similar characteristics would be priced relatively the same.

Figure 2: CAPM and Pairs Trading



Source: Pairs Trading: Quantitative Methods and Analysis

2.4 Commonly used Pairs Trading methods

Nunzio Tatalia was a quantitative analyst who worked for Morgan Stanley in the 1980's and pioneered the pairs trading method. Since, the Nunzio Tartalia days of pairs trading many quantitative analysts and financial market practitioners have tried to replicate his team's work to come up with better methodologies in order to do achieve better results. The two main commonly used methods in pairs trading are called the distance method and the co-integration method, and recently the stochastic spread method has become popular. The distance method is used in Gatev *et al* (1999) and Nath (2003) for empirical testing whereas the cointegration method is detailed in Vidyamurthy (2004). Both of these are known to be widely adopted by practitioners. The stochastic spread approach was recently proposed in Elliot *et al* (2005).

2.4.1 The Distance Method

The distance method is used in Gatev *et al* (1999) and Nath (2003) for empirical testing. Under the distance method, the co-movement of a pair is measured by what is known as the distance, or the sum of squared differences between the two normalized price series.

$$D = \sum_{i=1}^{n} (P_{ai} + P_{bi})^2$$

P_{ai}, P_{bi} = normalised asset price.

The normalisation of prices for each security is done by subtracting the sample mean of the training period, and dividing by the sample standard deviation over the training period. A record is kept of the distribution of distances between each pair over the training period. One cannot use the original prices when using the minimum squared distance due to the fact that two securities can move together, but the squared distance between them could still be high. Therefore the normalization of prices is the technique to use in order to prevent this. After the normalization, stocks will be brought to the same standard unit and allows for a quantitatively fair formation of pairs.

In order to normalize the price data, the mean and standard deviation need to be calculated. A trade trigger can then be created by using the difference between the normalized prices, which is illustrated by the transformation below. A trade trigger is a market condition that results in an automated execution of a trade (either buying or selling).

$$P_{it}^{*} = \frac{P_{it} - E(P_{it})}{\sigma_i}$$

Where,

P_{it}^{*} = Normalised price of asset i at time t

$E(P_{it})$ = Expectation of P_{it} (in this case the average)

σ_i = Standard deviation of respective stock price

This is demonstrated below using the Anglo Gold and Goldfields daily closing prices, which are shares, traded on the JSE.

Figure 3: Anglo Gold and Gold Fields closing price data

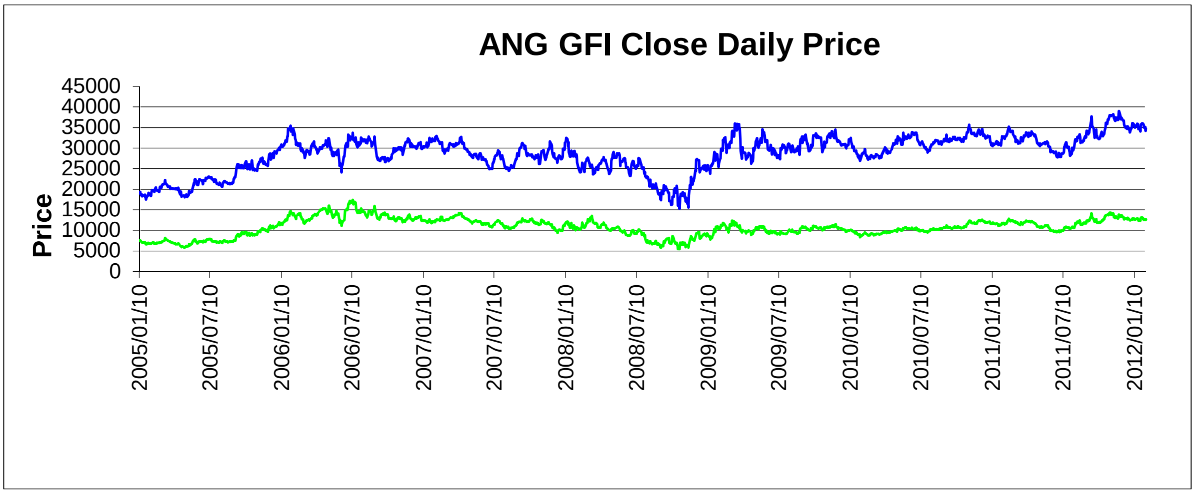


Figure 4: Normalized Anglo Gold closing price

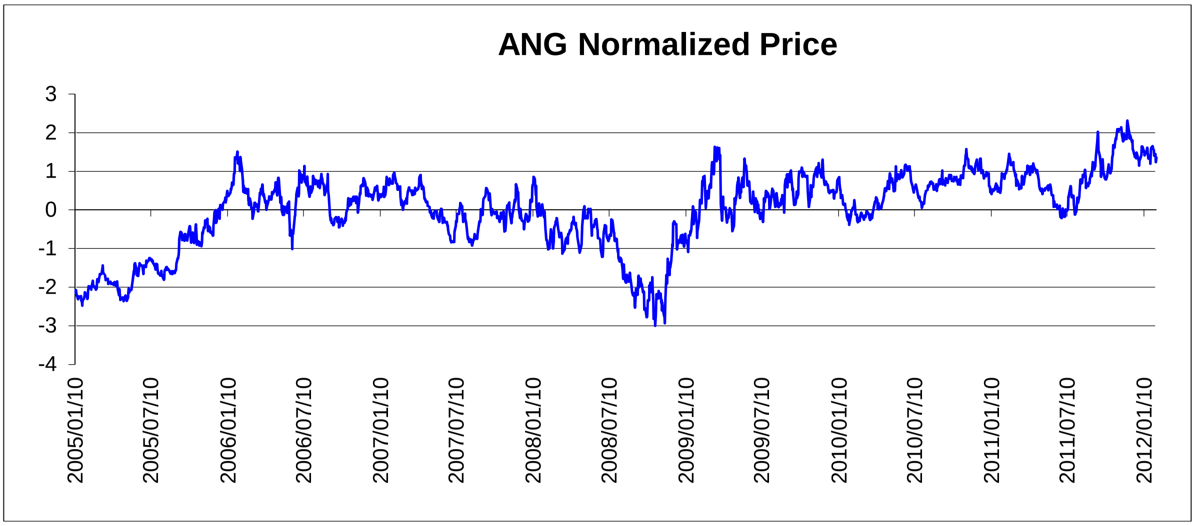


Figure 5: Normalized Gold Fields closing price

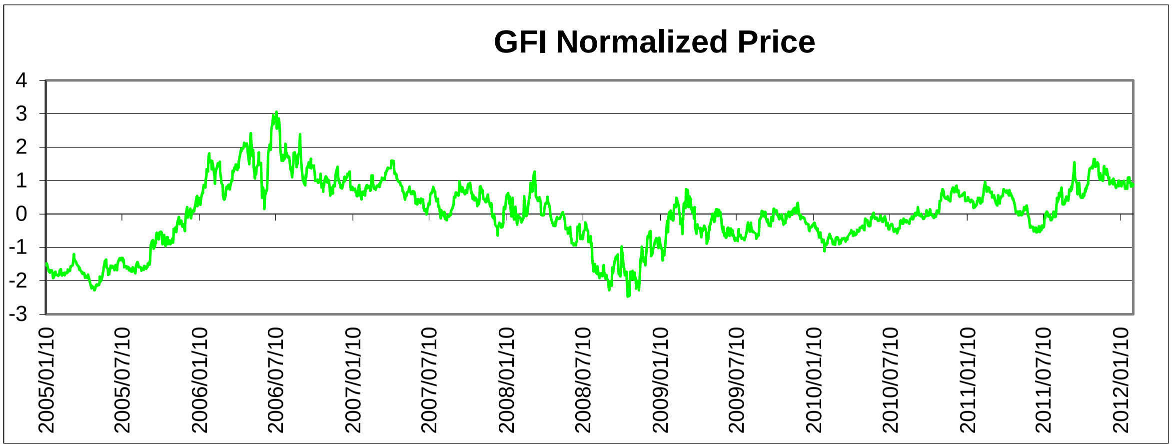
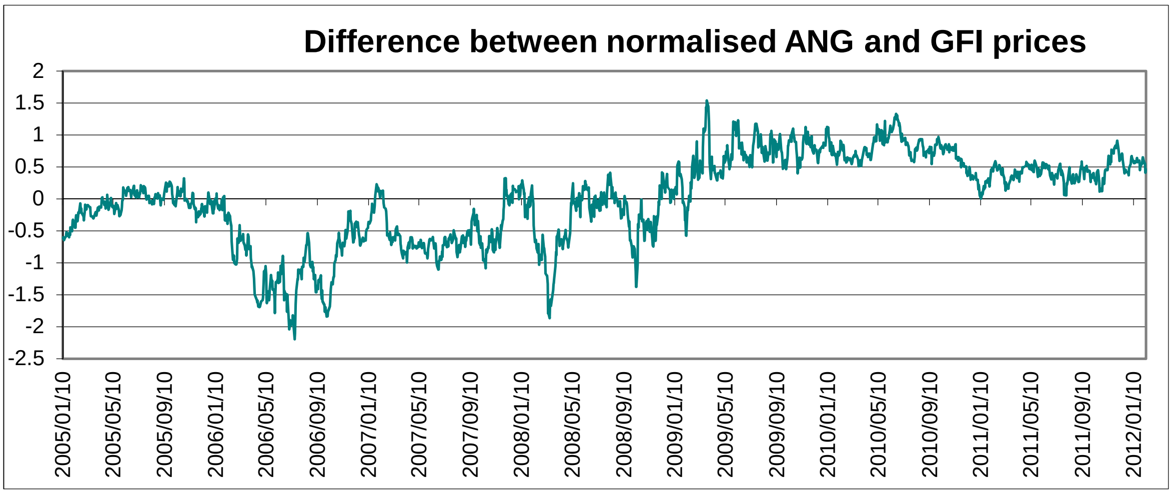


Figure 6: Difference between normalised Anglo Gold and Gold Fields share price.



One can trade by using the mean reverting bias demonstrated above. In normal daily trading activity, changes in supply and demand and unexpected news events can result in asset prices moving away from their equilibrium price. The process of asset prices moving away from the equilibrium price and reverting back again is a demonstration of what is known as a mean reversion process.

Another common practice amongst practitioners is to use the normalized difference between prices, sometimes referred to as the spread between market prices. In this approach, the equation above is still used, but with P_{it} replaced by d_{it} the difference between prices.

$$d_{it}^{*} = \frac{d_{it} - E(d_{it})}{\sigma_i}$$

Where $d_{it}^{*} = P_{ait} - P_{bit}$

Trading rules can be set up once more information about the spread and price behaviour is available. When a distance is above or below a threshold trading can commence. The threshold controls when a divergence is not considered normal i.e. as the threshold grows, fewer and fewer abnormal divergences are found, which results in the reduction in the number of transactions made by the strategy. This does not depend on transaction costs.

2.4.2 The Co-Integration method

The co-integration method is more complicated than the distance method and requires statistical analysis to implement through a pairs trading strategy. According to Vidyamurthy (2004) the co-integration method attempts to parametrize pairs trading strategies exploring the possibility of co-integration. Order of integration is a summary statistic for a time series that reports the minimum number of differences required to obtain a covariance stationary series and is denoted by $I(d)$ where d represents the order. In statistics co-integration is a property where two time series that are integrated of order 1 denoted by $I(1)$ can be linearly combined to produce a single time series which is order 0, or $I(0)$, and is stationary. According to Caldeira and Moura (2013), in general, linear combination of non-stationary time series are also non-stationary, thus not all possible pairs of stocks co-integrate.

A $(n \times 1)$ time series vector $\boldsymbol{y}_t$ is co-integrated if each of its elements individually are non-stationary and there exists a nonzero vector β such that $\beta \boldsymbol{y}_t$ is stationary.

Pairs trading involves investing equal amounts in asset A and asset B, which is achieved by short selling asset B and investing the amount in α shares of asset A where $\alpha p_t^A = \alpha p_t^B$ represents a cashless investment.

The idea of pairs trading is to invest an equal amount in asset A and asset B, $\alpha p_t^A = \alpha p_t^B$, making this a cashless investment.

Thus by taking the log of the equation:

$$0 = \log(\alpha) + \log(p_t^A) - \log(p_t^B) \tag{1}$$

The minus sign reflects the fact that asset B is sold short. The log-return on this investment over a small horizon $(t-1, t)$ is given by

$$\log\left(\frac{p_t^A}{p_{t-1}^A}\right) - \log\left(\frac{p_t^B}{p_{t-1}^B}\right) \tag{2}$$

In order to make a profit the investor would not need to predict the behaviour of p_t^A and p_t^B but only the difference

$$\log(p_t^A) - \log(p_t^B)$$

If we assume that $\{\log(p_t^A), \log(p_t^B)\}$ in equation (1) is a non-stationary $VAR(p)$ process, and there exists a value γ such that $\log(p_t^A) - \gamma\log(p_t^B)$ is stationary by our definition we have a co-integrated pair.

The investment equation will then become

$$0 = \log(\alpha) + \log(p_t^A) - \gamma \log(p_t^B) \quad (3)$$

The value of γ will be determined by the co-integration, and the long run equilibrium relationship between the assets determines α. The return on the investment will be

$$\log\left(\frac{p_t^A}{p_{t-1}^A}\right) - \gamma\log\left(\frac{p_t^B}{p_{t-1}^B}\right) \quad (4)$$

If γ = 1, the investor is able to profit from the trade, even though the investment has an initial value of 0. A γ close to zero requires funds to invest in A. A large γ exposes the investor to risk of going short on B.

2.5 Does a simple Pairs Trading strategy still work?

According to Binh Do *et al* (2009) a simple pairs trading strategy (equity convergence trading strategy) was found to be profitable over a long period of time although at a declining rate. The study showed that the mean return for the period 1989- 2002 was 60% less than the mean return for the period 1962-1988. By extending the work of Gatev *et al* (1999), Binh Do *et al* (2009) found no evidence to suggest that the profitability decline was due to increased competition in the hedge fund industry. The main reason for the decline was found to be a decreasing number of shares that did not converge within the trading period. This was attributed to a break down in the Law of One Price upon which this trading strategy is based. It is a requirement of the Law of One Price that two assets that are close economic substitutes in the training period continue to be so in the trading period.

It was also found that there was an increasing probability that close economic substitutes defined in the historical price space did not remain close substitutes in the trading period. The assertion was made that the increased fundamental risk was the reason that industry practitioners shied away from this strategy.

It was suggested in Binh Do *et al* (2009) that one should form pairs of fundamental similarity which not only avoids unnecessary costs but would also reduce non-convergence risks. In practice trading algorithms should contain risk mitigating tools like stop loss which will minimize the impact of divergent trades. One of the drawbacks of the simple pairs trading strategy is that a pair may have a high historical spread but is still used a recognised pair due to the fact that it has one of the lowest spreads for the training period i.e. the pair are close economic substitutes in the training period but in the trading period the pair have a higher spread. It was suggested that a superior method would be to form pairs based on a number of criteria and the best strategy sometimes is to do nothing.

It was found in Binh Do *et al* (2009) that periods of high market volatility could result in divergence being driven further. The divergence rate was regressed against the market volatility proxied by the relevant six month return standard deviation of the S&P 500 index[1] . Thus a positive

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[1] The S&P 500, or the Standard & Poor's 500, is a stock market index based on the market capitalizations of 500 leading companies publicly traded in the U.S. stock market, as determined by Standard & Poor's. It differs from other U.S. stock market indices such as the Dow Jones Industrial Average and the Nasdaq due to its diverse constituency and weighting methodology. It is one of the most commonly followed equity indices and many consider it the best representation of the market. It is usually used as a benchmark for common stocks in the United States.

relation would support this proposition. A negative relationship between the divergence rate and market volatility held true for the overall. Thus, while volatility might have had a small part to play, it cannot be seen as a major driver.

2.6 New directions in Pairs Trading

An increase in technology and processing power of computers has led researchers into various new directions in pairs trading. The pairs trading method discussed in this research paper can be described as a classical approach. Some of the new methods are described below.

- With the use of Bollinger bands, shares that were not previously thought of as a pair can now be used for pairs trading; Bollinger bands are a technical analysis tool developed by John Bollinger by using a moving average with two trading bands above and below it and simply adds and subtracts a standard deviation calculation. Bollinger bands adjust themselves to market conditions by measuring price volatility.

- By looking for correlations between securities across asset classes;

- Exploiting new technology, such as the use of trading algorithms and advanced execution systems;

- Using various time horizons e.g. Intra-day trading or less exploited time horizons;

- Using multiple stocks instead of one to one pairs; the multiple stocks would have to meet all the requirements of the training period in order to form multiple pairs which would be traded over some trading period.

- New or alternative statistical methods, of which co-integration is perhaps the most well-known (if not the most well-understood); other areas of research include the use of new distance measures, the assimilation of technical analysis within rigorous statistical frameworks, Kalman filtering and a myriad of other;

2.7 Practical Issues when Pairs Trading

Below is a list of some of the main features to be considered when implementing Pairs trading. In the most generic sense, the pairs trader will:

Look over some (recent) historical “training period” at some subset of the universe of available securities to decide how to form pairs, which she will then trade over some future “trading period. The “training period” is a preselected period where the parameters of the experiment are computed.

Thus, the decision variables to consider are:

- The length of the "training period";
- The subset of securities, within an asset class, to choose from;
- The metric for measuring which is the best partner for a security;
- The cut-off for the metric when deciding which pairs are too unstable to even bother with; A threshold that is too small can result an unreasonably high number of pair formations over the historical data provide in the training period.
- The length of the "trading period"; Immediately after the training period, the trading period follows, where we run the experiments using the parameters computed in the "training period".
- The trigger point at which a spread trade is opened;
- The trigger point at which a spread trade is closed;
- Steps for risk control; Stop loss orders and diversification are examples of common risk controls. Stop losses however can result to pre-mature termination of trades. If we enter a position as soon as there is a deviation and this widens before reverting back then pre-mature termination can occur resulting in losses. Diversification is also another common risk control and can be implemented by having positions in several pairs and limiting how much we invest in each of these pairs.

3. CHAPTER 3: RESEARCH METHODOLOGY

3.1 Database

The data that was considered was all the shares listed on the JSE Mainboard for the period 1994 - 2014. The time period chosen, provides a dataset that covers both bullish and bearish markets. Initially the entire data set of shares was considered for use in the pairs trading model. After using basic dataset analysis tools, shares that had jumps in the data, which could not be explained by market events, was removed from the dataset. The total number of shares considered for the pairs trading was 154.

3.2 Methodology

3.2.1 Pairs Selection

It was essential that the trading strategy be carried out only on shares that meet the criteria as suitable candidates for a pair trading strategy. The technique chosen for the purposes of this research was the minimum squared distance rule. In order to use the minimum squared distance rule, however, the original price series required normalising, in order to bring all stocks to a standard unit.

The formula used in the normalisation process is as follows.

$$P_{it}^{*} = \frac{P_{it} - E(P_{it})}{\sigma_i}$$

Where,

P_{it}^{*} = Normalised price of asset i at time t

$E(P_{it})$ = Expectation of P_{it}, (in this case the average)

σ_i = Standard deviation of respective stock price

All prices will be transformed to the same normalised unit, which will permit the use of the minimum squared distance rule.

The next step is to choose, for each stock, a pair that has the minimum squared distance between the normalized prices. This is a simple search on the database, using only past information up to time t. The normalized price for the pair of asset i is now addressed as P_{it}^{*}. After the pair of each stock is identified, the trading rule is going to create a trading signal every time that the absolute distance between P_{it}^{*} and p_{it}^{*} is higher than d. The value of d is arbitrary and does not depend on trading costs; it represents the filter for the creation of a trading signal. It can't be very high, otherwise only a few trading signal are going to be created and it can't be too low or the rule is going to be too flexible and it will result in too many trades and, consequently, high value of transaction costs. According to the pairs trading strategy, if the value P_{it}^{*} is higher than p_{it}^{*} then a short position is kept for asset i and a long position is made for the pair of asset i.

3.2.2 Assessing performance of the Pairs Trading strategy

In order to assess the effectiveness of the pairs trading strategy it is proposed that it should be compared to the returns of a bootstrapping method for evaluating the performance of the trading rule against the use of random pairs for each stock.

The Inputs for the pairs trading strategy is as follows:

x - A matrix containing the closing prices of all trades used for Pairs Trading, with time on the rows and share prices on the columns.

Capital – The amount invested in each trade done in the Pair Trading.

d – The first trading day for Pair Trading.

Window – This is a window that is the training period to find suitable pairs.

t - The threshold parameter which determines what is unusual behaviour.

ut - The period that the function will update the pairs of stocks i.e. the periodicity of recalculation of the pairs of each stock.

C - Transaction Cost (Cost of making a single trade). This model assumes a constant 1% transaction cost which is a consistent with similar research projects done on this subject.

maxPeriod - Maximum time period to hold any of the positions otherwise referred to as the holding period.

Once all liquid stocks have been paired up in the formation period, a trading rule is created whereby a position is opened every time the absolute distance between P_{it}^{*} and p_{it}^{*} is higher than a predetermined threshold value (measured by normalised price) which is called d. The value of this threshold value, d, is subjective and represents a rule for the creation of a trading signal. Intuitively, the value of d should not be very high, otherwise no trades will take place, nor should it be too low, as this will result in too many trades and hence high transaction costs.

The subjectivity in the selection of d and the intuitive knowledge that it should not be too high or too low, give rise to a range of normalised prices based on threshold values that are required to be tested. This gives the study flexibility by not imposing restrictive assumptions, and also allows the testing of the impact of different threshold values on the strategy's performance. A position in a pair is opened when the assets normalised prices diverge by more than d and close when the prices converge.

3.3.1 Bootstrap Method for Assessing Pairs Trading Performance

Using the idea of Perlin (2006), the bootstrap method is used to test the trading strategy against pure chance. The cumulative total returns for every simulation of the bootstrap method are saved and compared to the pairs trading strategy. One then has to count the percentage number of times, that the returns from the random process were less than those from the pairs trading strategy. For the comparison, one needs to calculate the median number of days and the median number of assets that that the pairs trading strategy used. Then, using the median number of days and median number of assets, one will set up random entries in the market, for long and short trading. The cumulative raw returns are then saved for each simulation which is repeated a number of times.

- Use the median number of days and the median numbers of assets that the pairs trading strategy has been trading in the market split by long and short positions
- Define a variable for number of days in the market and number of assets, which represents random entries in the market. This needs to be for both long and short positions.
- Steps 1 and 2 will be repeated by a random number of steps, where the accumulated return is saved after each loop.

Example

x - A matrix with the prices of all assets that was available to trade in the tested period.
n - Number of simulations.
Number of periods - Number of periods trading in the market
Number of assets - Number of assets traded for each day.
C - Trading cost per trade.
tfactor - The time factor, i.e., how many units of time within one year

n = 2500, Number of Periods =200, Number of assets =20, C=0

The result is a distribution of returns which is tested against the pairs trading strategy, to verify the percentage of returns that the pairs trading strategy is better than the bootstrapping model. The number of times the cumulative returns from the pairs trading strategy beats the cumulative return from random trading, is divided by the number of simulations to obtain the percentage beaten.

CHAPTER 4: PRESENTATION OF RESULTS

4.1 Returns Analysis

Table 1: Pairs Trading Raw Returns

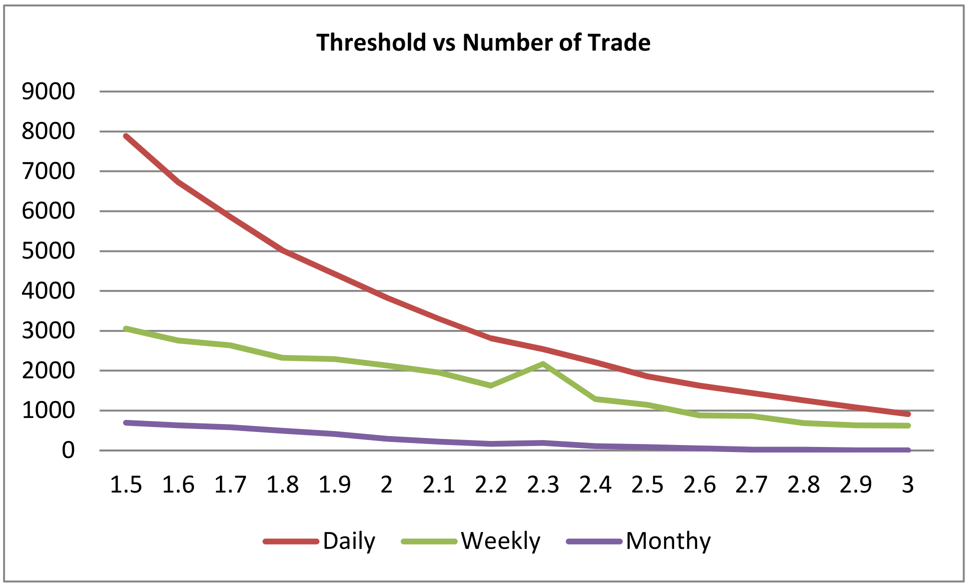
Threshold Value	Total Raw Return (No Transaction Costs)			Total Raw Retun (With transaction costs)		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
1.5	9.23%	9.65%	5.24%	-4.16%	5.47%	3.45%
1.6	11.21%	9.12%	5.19%	-3.38%	8.52%	2.87%
1.7	8.32%	10.14%	4.25%	-2.42%	10.27%	0.45%
1.8	7.53%	11.13%	4.26%	-1.25%	11.18%	2.16%
1.9	8.12%	12.34%	3.98%	1.78%	12.05%	1.31%
2	6.98%	13.28%	2.18%	1.32%	10.64%	0.78%
2.1	7.24%	14.38%	2.47%	2.94%	12.93%	1.34%
2.2	6.41%	12.64%	2.05%	3.82%	11.93%	0.85%
2.3	6.12%	13.54%	1.75%	3.15%	11.86%	-0.95%
2.4	5.31%	14.39%	1.70%	2.89%	13.76%	-0.59%
2.5	5.87%	12.96%	2.76%	4.08%	11.37%	-1.08%
2.6	4.96%	11.94%	2.84%	5.32%	9.86%	0.68%
2.7	5.16%	8.29%	1.34%	4.38%	9.38%	0.23%
2.8	4.34%	8.17%	0.49%	3.73%	8.37%	-0.14%
2.9	4.75%	7.25%	1.28%	5.96%	7.98%	0.31%
3	3.68%	7.87%	1.59%	3.87%	7.49%	0.17%

The strategy's raw returned proved to be profitable with and without transaction costs. This was evident in the daily, weekly and monthly scenarios with no transaction costs and mostly in the daily (threshold greater than 1.9) and weekly scenarios with transaction costs. The raw returns were calculated as the sum of payoffs during the trading period of the strategy which was then annualised.

The results shows that the annualized returns for the daily scenario ranged between 3.68% and 11.21% (between -4.16% and 5.96% with transaction costs) and between 14.39% and 7.25% (between 5.47% and 13.76% with transaction costs) for the weekly scenario. Whilst the strategy remained profitable for the monthly scenario with transaction costs the strategy only remained profitable for the monthly strategy with threshold values less than 2.3.

The raw returns with transaction action costs suggest that the trading costs have the greatest impact on the lower thresholds (Between 1.5 and 2). Returns for high frequency data are more sensitive to transaction costs which can be clearly seen between the daily and monthly returns.

Figure 7: Threshold vs Number of Trades



The results show a negative correlation between the threshold and the number of trades. This is because the threshold value represents an abnormal behaviour. As the threshold value increases, it is expected that the number of abnormal divergences will decrease and hence the number of pairs decrease. This is an expected result. As the threshold increases, the number of trades decreases due to the fact that less pairs will make the criteria for pair formation.

Table 2 :Pairs Trading Long and Short Postions

Threshold Value	Daily		Weekly		Monthly	
	Long	Short	Long	Short	Long	Short
1.5	12.13%	5.26%	9.23%	7.46%	8.59%	1.96%
1.6	13.41%	8.14%	12.03%	10.82%	8.46%	1.64%
1.7	12.04%	8.51%	14.06%	10.52%	6.93%	-2.64%
1.8	10.48%	8.42%	14.27%	10.73%	8.39%	-3.36%
1.9	9.20%	8.12%	15.02%	11.73%	9.47%	-5.35%
2	8.21%	7.23%	14.93%	10.52%	9.58%	-3.58%
2.1	8.45%	5.82%	15.93%	12.82%	4.94%	-3.78%
2.2	9.36%	6.34%	16.32%	13.92%	3.85%	-4.85%
2.3	7.42%	4.21%	15.32%	14.24%	2.84%	-3.84%
2.4	7.38%	6.32%	16.92%	13.73%	3.27%	-3.74%
2.5	7.25%	5.21%	16.42%	13.63%	2.47%	0.24%
2.6	6.91%	4.72%	14.85%	10.54%	4.83%	1.65%
2.7	3.59%	2.43%	12.75%	9.34%	1.83%	2.63%
2.8	3.42%	2.32%	11.75%	7.27%	1.31%	0.67%
2.9	4.72%	2.19%	9.35%	2.62%	1.63%	0.54%
3	4.30%	1.56%	8.34%	4.26%	0.16%	0.32%

It is evident from Table 2 that the long positions are more profitable than the short positions for daily, weekly and monthly periods. In addition, it can be seen that the time period chosen was representative of a bull market. This suggests that a long only fund would have been a suitable strategy over the chosen time period. The returns were also positive in the short positions for all thresholds in the daily and weekly frequencies but lower than all the returns for the long positions across all its corresponding thresholds in the daily and weekly frequencies. At the monthly frequency the returns for the long positions were significantly larger than the returns for the short positions with negative returns for short positions between thresholds 1.7 and 2.4.

4.2 Risk Analysis

Table 3: Pairs Trading Jensen's Alpha and Beta

Panel A : Pairs Trading - Daily Frequency				
Threshold Value	Alpha	Prob	Beta	Prob
1.5	0.00598276	0.0000006	0.024543	0.840887
1.6	0.00431922	0.0000009	0.009721	0.594389
1.7	0.00456808	0.0000001	0.043016	0.756629
1.8	0.00285896	0.0000001	0.063359	0.886225
1.9	0.00400581	0.0000003	0.09359	0.956756
2	0.0018178	0.0000004	0.080462	0.89827
2.1	0.00986827	0.0000004	0.056984	0.256394
2.2	0.00258262	0.0000007	0.068454	0.893334
2.3	0.00576429	0.0000008	0.004136	0.638737
2.4	0.00152687	0.0000005	0.060365	0.348256
2.5	0.00307732	0.0000002	0.006265	0.49264
2.6	0.00396551	0.0000006	0.084489	0.035023
2.7	0.00263836	0.0000008	0.023824	0.342221
2.8	0.00472492	0.0000004	0.011724	0.396056
2.9	0.00680388	0.0000005	0.014944	0.682803
3	0.00927326	0.0000004	0.094731	0.886258

Panel B : Pairs Trading - Weekly Frequency				
Threshold Value	Alpha	Prob	Beta	Prob
1.5	0.00435544	0.0000000	0.005442	0.663084
1.6	0.00910521	0.0000006	0.008942	0.691234
1.7	0.00560497	0.0000009	0.092881	0.433955
1.8	0.00686081	0.0000004	0.048165	0.957822
1.9	0.00863861	0.0000006	0.062692	0.18623
2	0.00158439	0.0000008	0.023081	0.14327
2.1	0.00990205	0.0000001	0.046503	0.465326
2.2	0.00453413	0.0000006	0.028264	0.668153
2.3	0.00673998	0.0000008	0.058292	0.696617
2.4	0.002313	0.0000001	0.001649	0.810589
2.5	0.00810588	0.0000006	0.045037	0.489013
2.6	0.00447477	0.0000006	0.065259	0.44614
2.7	0.00989766	0.0000009	0.046936	0.915255
2.8	0.00986877	0.0000003	0.08855	0.687477
2.9	0.00776677	0.0000001	0.097703	0.815616
3	0.00321902	0.0000009	0.064059	0.698721

Panel C : Pairs Trading - Monthly Frequency				
Threshold Value	Alpha	Prob	Beta	Prob
1.5	0.00686644	0.0000002	0.079836	0.023528
1.6	0.00884066	0.0000000	0.090844	0.095266
1.7	0.00125636	0.0000006	0.001287	0.042588
1.8	0.00668062	0.0000008	0.004715	0.061135
1.9	0.00063486	0.0000007	0.098179	0.078838
2	0.0082859	0.0000003	0.034018	0.077986
2.1	0.00813866	0.0000001	0.0752	0.041399
2.2	0.00706795	0.0000004	0.009386	0.012606
2.3	0.0088033	0.0000007	0.091665	0.071903
2.4	0.00692759	0.0000002	0.090935	0.082947
2.5	0.00664396	0.0000001	0.052744	0.01378
2.6	0.00286175	0.0000007	0.096037	0.014073
2.7	0.00003491	0.0000009	0.084469	0.032925
2.8	0.00505924	0.0000006	0.012447	0.08558
2.9	0.0021893	0.0000002	0.017106	0.055185
3	0.00373908	0.0000005	0.045204	0.068724

In order to obtain the alpha and beta coefficients, which is representative of the risks associated with pairs trading, the portfolio returns were regressed on the weighted index of the Top 40. Jenson's alpha or alpha as it is commonly called is a performance measure that represents the average return on a portfolio over and above that predicted by the CAPM model, given the portfolio's beta and average market return. If one has to choose between two trading strategies with the same return, one would want to invest in the strategy that is less risky. Jensen's alpha can help one determine if they are earning the right return for the level of risk for the strategy. Jensen's alpha should be positive and statistically significant if the strategy has performance which cannot be explained by the market. Then the strategy would be earning excessive returns.

From panels A, B and C we can see that the daily, weekly and monthly returns have positive and significant alphas at all threshold values. We can conclude that the pairs trading strategy has a positive abnormal return after considering market factors.

The second coefficient in Table 2 is the pairs trading strategy's Beta. Beta is a measure of the volatility or systematic risk of a trading strategy in comparison to the market as a whole. Beta can be thought of as measure of a securities response to swings in the market. The higher the beta of an asset the more correlated with the market it is i.e. the greater its market risk and the more exposed it is to changes in the market.

From Table 2, we can see that all the beta coefficients are small and close to zero with none of them significant at daily, weekly and monthly frequencies. This is an expected result and supports the concept of pairs trading being a market neutral strategy i.e. its returns is not dependent on market movements. Pairs trading involves the execution of a long and short position at the same time which creates a natural hedge against market movements.

4.3 Skill vs. Luck

The bootstrapping technique has become a standard when determining the performance of investment strategies and the skill of investment managers. The bootstrapping technique allows for a comparison of the actual returns from a strategy or investment product against a series of randomly generated returns. The idea is to test whether the returns which are attributable to a strategy are due to skill or whether they were arrived at by random chance or luck. By creating a synthetic portfolio using random market entries and then saving the performance for each simulation, the results can be tested against the performance of the actual values. If the measures of performance that are attributed to the strategy are not significantly different from those generated by random signals (luck) then one may come to the conclusion that the strategies return is not profitable.

According to Perlin (2006) , a percentage close to 90% would mean a valuable strategy, 50% represents a case of chance and 10% means the pairs trading strategy presents no value i.e. one can get more value from random trading. At daily and weekly frequencies the returns due to pairs trading are far superior to those which could be attributed to luck with the strategy beating between 91% and 100% of the random portfolios for each threshold value.

At the monthly frequency the evidence was not as conclusive for all thresholds when taking into consideration transaction costs with most thresholds above 50% (between 41% and 97%). It is reasonable to conclude that random trading only beats the pairs trading strategy in a few cases and thus a pairs trading strategy is superior to random trading.

In the monthly frequency much fewer trades are created using the pairs trading strategy and might not be entirely conclusive in assessing the strategies performance.

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Table 4: Pairs Trading Returns vesus Bootstrap

Panel A - Daily Frequency						
Threshold	% Days in market	No Trade	Raw Ret	% Randon Portfolio Beaten	Raw Return TC	% Random Portfolio Beaten
1.5	82.13%	7888	9.23%	100.00%	-4.16%	100.00%
1.6	74.23%	6730	11.21%	100.00%	-3.38%	100.00%
1.7	71.82%	5858	8.32%	100.00%	-2.42%	100.00%
1.8	68.36%	5020	7.53%	100.00%	-1.25%	100.00%
1.9	63.36%	4426	8.12%	100.00%	1.78%	100.00%
2	58.48%	3830	6.98%	100.00%	1.32%	100.00%
2.1	53.84%	3304	7.24%	100.00%	2.94%	100.00%
2.2	47.47%	2810	6.41%	100.00%	3.82%	100.00%
2.3	42.84%	2538	6.12%	100.00%	3.15%	100.00%
2.4	36.39%	2210	5.31%	100.00%	2.89%	100.00%
2.5	32.39%	1858	5.87%	100.00%	4.08%	100.00%
2.6	29.38%	1626	4.96%	100.00%	5.32%	96.00%
2.7	26.04%	1438	5.16%	100.00%	4.38%	94.30%
2.8	22.70%	1258	4.34%	100.00%	3.73%	100.00%
2.9	17.94%	1076	4.75%	100.00%	5.96%	100.00%
3	13.85%	912	3.68%	100.00%	3.87%	100.00%

Panel B - Weekly Frequency						
Threshold	% Days in market	No Trade	Raw Ret	% Randon Portfolio Beaten	Raw Return TC	% Random Portfolio Beaten
1.5	82.39%	3056	9.65%	100.00%	5.47%	100.00%
1.6	76.48%	2758	9.12%	100.00%	8.52%	100.00%
1.7	72.48%	2635	10.14%	100.00%	10.27%	100.00%
1.8	71.49%	2320	11.13%	100.00%	11.18%	100.00%
1.9	68.38%	2290	12.34%	100.00%	12.05%	100.00%
2	63.94%	2135	13.28%	100.00%	10.64%	100.00%
2.1	59.18%	1959	14.38%	100.00%	12.93%	100.00%
2.2	54.56%	1627	12.64%	100.00%	11.93%	100.00%
2.3	51.44%	2175	13.54%	100.00%	11.86%	98.90%
2.4	48.27%	1290	14.39%	100.00%	13.76%	93.60%
2.5	43.39%	1142	12.96%	100.00%	11.37%	100.00%
2.6	39.59%	876	11.94%	100.00%	9.86%	100.00%
2.7	32.39%	867	8.29%	98.50%	9.38%	92.20%
2.8	27.39%	691	8.17%	97.20%	8.37%	95.30%
2.9	24.25%	627	7.25%	95.20%	7.98%	91.60%
3	19.32%	621	7.87%	100.00%	7.49%	100.00%

Panel C - Weekly Frequency						
Threshold	% Days in market	No Trade	Raw Ret	% Randon Portfolio Beaten	Raw Return TC	% Random Portfolio Beaten
1.5	82.47%	697	5.24%	100.00%	3.45%	90.60%
1.6	78.23%	628	5.19%	100.00%	2.87%	90.80%
1.7	68.62%	581	4.25%	100.00%	0.45%	80.60%
1.8	65.29%	495	4.26%	100.00%	2.16%	72.80%
1.9	62.18%	413	3.98%	100.00%	1.31%	65.80%
2	58.28%	295	2.18%	100.00%	0.78%	40.60%
2.1	41.39%	223	2.47%	82.60%	1.34%	78.60%
2.2	34.29%	167	2.05%	78.50%	0.85%	72.50%
2.3	26.48%	186	1.75%	98.60%	-0.95%	74.80%
2.4	21.48%	107	1.70%	100.00%	-0.59%	79.50%
2.5	15.85%	88	2.76%	100.00%	-1.08%	54.30%
2.6	13.35%	50	2.84%	87.20%	0.68%	40.90%
2.7	10.58%	21	1.34%	79.40%	0.23%	65.40%
2.8	7.49%	21	0.49%	82.50%	-0.14%	70.40%
2.9	6.37%	7	1.28%	100.00%	0.31%	97.40%
3	2.52%	8	1.59%	90.30%	0.17%	67.30%

5. CHAPTER 5: Conclusions and Recommendations

The best raw returns were found to be at the weekly frequency whilst the daily and monthly frequency was also profitable before taking into transaction costs. Frequency refers to how often trading occurs i.e. either on a daily, weekly or monthly basis. After taking into account transaction costs, the weekly raw returns were still positive for all thresholds whilst the daily returns were positive for thresholds greater than 1.8 and for monthly returns with transaction costs all the returns were positive for thresholds less than 2.3. For the daily raw returns with transaction costs, the high transaction costs for emerging market equity exchanges, could explain the negative returns for thresholds less than 1.9.

The evidence of a bull market is clearly visible as the returns from the long positions are greater than the short positions for all the frequencies and for almost all the thresholds.

The results also shows that the intellectual capital used in the trading strategy would outperform random trading as illustrated by the comparison against the bootstrap method.

The time period for the data also took into consideration the financial crisis period of 2008-2009. The results also shows that the pairs trading strategy remained profitable through the financial crisis and that the notion that a pairs trading strategy is market neutral is sound.

Interesting further studies using pairs trading could be done across asset classes in South Africa, especially with commodity instruments. It would also be interesting to conduct this research on South Africa's highly developed derivatives market.

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APPENDIX A – Share codes used for pairs trading

Table 5: List of share codes used

JSE Share Code	Company
ABL	African Bank Inv Ltd
ACL	ArcelorMittal SA Limited
ACT	AfroCentric Inv Corp Ltd
ADH	ADvTECH Ltd
ADR	Adcorp Holdings Limited
AFE	AECI Limited
AFR	Afrgri LTD
AFX	African Oxygen Limited
AGL	Anglo American plc
ALT	Allied Technologies LTD
AMA	Home of Living Brands holding Limited
AME	African Media Ent Ltd
AMS	Anglo American Plat Ltd
AND	Andulela Inv Hldgs Ltd
AOO	African & Over Ent Ltd
APK	Astrapak Limited
APN	Aspen Pharmacare Hldgs Ltd
ARI	African Rainbow Min Ltd
ART	Argent Industrial Ltd
ASA	ABSA GROUP LTD
ASR	Assore Ltd
ATN	Allied Electronics Corp LTD
AVI	AVI Ltd
AWT	Awethu Breweries Ltd
BAT	Brait SE
BAU	Bauba Platinum Limited
BAW	Barloworld Ltd
BCF	Bowler Metcalf Ltd
BDM	Buildmax Ltd
BEG	Beige Holdings LTD
BEL	Bell Equipment Ltd
BIL	BHP Billiton plc
BSR	Basil Read Holdings Ltd

JSE Share Code	Company
BVT	Bidvest Ltd
CAP	Cape empowerment LTD
CAT	Caxton CTP Publish Print
CFR	Compagnie Fin Richemont
CKS	Crookes Brothers Ltd
CLH	City Lodge Hotels Ltd
CLS	Clicks Group Ltd
CMH	Combined Motor Hldgs Ltd
CNL	Control Investments Group Limited
CPL	Capital Property Fund
CRG	Cargo Carriers Ltd
CRM	Ceramic Industries LTD
CSB	Cashbuild Ltd
CUL	Cullinan Holdings Ltd
CVI	Capevin Investments LTD
DAW	Distr and Warehousing
DLV	Dorbyl Limited
DON	The Don Group Limited
DRD	DRD Gold Ltd
DST	Distell Group Ltd
DTA	Delta EMD Ltd
DTC	Datatec Ltd
EHS	Evraz Highveld Steel & Van
ELR	ELB Group Ltd
FBR	Famous Brands Ltd
FPT	Fountainhead Property Trust
FSR	Firstrand Ltd
GFI	Gold Fields Ltd
GGM	Goliath Gold Mining Ltd
GND	Grindrod Ltd
GRF	Group Five Ltd
GRT	Growthpoint Prop Ltd
HAR	Harmony GM Co Ltd
HDC	Hudaco Industries Ltd
HWN	Howden Africa Hldgs Ltd
HYP	Hyprop Inv Ltd
IFH	IFA Hotels & Resorts Limited
ILV	Illovo Sugar Ltd
IMP	Impala Platinum Hlgs Ltd
INL	Investec Ltd
IPL	Imperial Holdings Ltd
ITE	Italtile Ltd
IVT	Invicta Holdings Ltd

JSE Share Code	Company
JDG	JD GROUP LIMITED
JSC	Jasco Electron Hldgs Ltd
KAP	KAP Industrial Hldgs Ltd
KGM	Kagiso Media Limited
LAB	Labat Africa Limited
LBH	Liberty Holdings Ltd
LNF	London Fin Inv Group plc
LON	Lonmin plc
MAS	Masonite Africa Ltd
MDC	Mediclinic Internat Ltd
MFL	Metrofile Holdings Ltd
MPC	MR PRICE GROUP LIMITED
MRF	Merafe Resources Ltd
MST	Mustek Ltd
MTA	Metair Investments Ltd
MTN	MTN Group Ltd
MUR	Murray & Roberts Hldgs
MVG	Mvelaphanda Group Limited
NCS	Nictus Ltd
NED	Nedbank Group Ltd
NHM	Northam Platinum Ltd
NPK	Nampak Ltd
NPN	Naspers Ltd -N-
NTC	Netcare Limited
NWL	Nu-world Holdings Limited
OCE	Oceana Group Ltd
OCT	Octodec Invest Ltd
OMN	Omnia Holdings Ltd
PBT	PBT group Limited
PET	Petmin Ltd
PIK	Pick n Pay Stores Ltd
PMM	Premium Properties Limited
PNC	Pinnacle Hldgs Ltd
PPC	PPC Limited
PPR	Putprop Ltd
PSG	PSG Group Ltd
PWK	Pick N Pay Holdings Ltd
QPG	Quantum Property Group
RBW	Rainbow Chicken Limited
RLO	Reunert Ltd
RMH	RMB Holdings Ltd

JSE Share Code	Company
RNG	Randgold & Expl Co Ltd
RTN	Rex Trueform Cl Co -N-
RTO	Rex Trueform Cloth Co Ld
SAB	SABMiller plc
SAC	SA Corp Real Estate Ltd
SAP	Sappi Ltd
SBK	Standard Bank Group Ltd
SBL	Sable Holdings Limited
SBV	Sabvest Ltd
SCL	Sacoil Holdings Ltd
SER	Seardel Inv Corp Ltd
SHP	Shoprite Holdings Ltd
SIM	Simmer and Jack Mines Limited
SLO	Southern Electricity Company Limited
SNT	Santam Limited
SNU	Sentula Mining Ltd
SOL	Sasol Limited
SOV	Sovereign Food Inv Ltd
SPA	Spanjaard Limited
SUI	Sun International Ltd
SYC	Sycom Property Fund
TBS	Tiger Brands Ltd
TFG	The Foschini Group Limited
TMT	Trematon Capital Inv Ltd
TON	Tongaat Hulett Ltd
TON	Tongaat Hulett Ltd
TPC	Transpaco Ltd
TRE	Trencor Ltd
TSH	Tsogo Sun Holdings Ltd
TSX	Trans Hex Group Ltd
VIL	Village Main Reef Ltd
WBO	Wilson Bayly Hlm-Ovc Ltd
WHL	Woolworths Holdings Ltd
WNH	Winhold Ltd
YRK	York Timber Holdings Ltd
ZCI	ZCI Limited
ZSA	Zurich Insurance Company SA