Identification and Performance Evaluation of Rand Hedge Stocks Listed on the JSE Securities Exchange

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Abstract

The historical volatility of the rand exchange rate has encouraged investors on the JSE Securities Exchange to invest in shares which are believed to have an inverse relationship to exchange rate movements of the rand, thus providing a buffer against rand weakness. As a result, the effective functioning of these shares in their role as "rand hedges" is of considerable economic importance for the many investors who rely on them to minimise exchange rate risk. However, the practice of identifying rand hedge stocks is complicated by the existence of long-term trends in share price and exchange rate time-series, which may falsely indicate hedging behaviour.

The objective of this research was to investigate whether removing the long-term trends in share price and exchange rate data could lead to the reliable identification of rand hedge stocks on the JSE. The underlying hypothesis was that by removing long-term trends in share-price time-series, the occurrence of spurious correlations between share price and exchange rate movements could be eliminated, thus facilitating the identification of shares possessing fundamental relationships with short-term movements in the rand exchange rate.

The results from the research indicate that the proposed methodology is effective in identifying the subset of hedge stocks which have underlying short-term positive (hedging) relationships with the exchange rate. However, there exist hedge stocks which do not exhibit this short-term positive relationship, and these will not be identified by the methodology.

Declaration

I, Anton Libero Paul Fatti, declare that this research report is my own, unaided work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Anton Libero Paul Fatti

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Table of Contents

List of Tables

List of Figures

List of Appendices

Glossary

ALSI, All share index

The JSE all-share index, a measure of the performance of the entire JSE

ARIMA Models

Statistical models of the underlying characteristics of time-series data

Autocorrelation

The existence of correlations between successive observations in a time series

Co-integration

A statistical tool for measuring the co-movement of economic time-series data

Correlation

A statistical measure of the nature of the relationship between two variables

Correlogram

A graph of the correlations of time-series observations a distance k apart plotted against k

Exchange Rate Exposure

A measure of a firm's risk exposure to fluctuations in the exchange rate

Futures Contract

A commitment to buy or sell a financial instrument, at a specified date and mutually agreed price

Hedging

Purchasing investments with the intention to reduce the risk of adverse price movements of an asset

JSE

The JSE Securities Exchange

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 characterised by a high level of trading activity. Liquidity can also be considered as the speed at which an asset can be converted to cash

Macroeconomic Variables

Economy-wide phenomena such as level of unemployment, national income, rate of growth, price levels, and interest rates

Market Capitalisation

The total value of all issued shares of a firm, calculated by multiplying the number of shares by the current market price

Market Risk Premium

The difference between the expected return on an investment and the risk-free rate, due to the risk inherent in the investment

Non-stationarity

The existence of trends or cycles in time-series data

Perpetuity

An annuity in which equal periodic payments continue indefinitely

Rand Hedge Share

A share which exhibits an inverse relationship to movements of the rand exchange rate, thus providing a buffer against weakness in the currency

Risk-free Rate

The rate of return on an asset that has virtually no risk, such as government bonds

Selling Short

The selling of a security that the seller does not own

Share Portfolio

A group of shares selected on specific characteristics in order to provide a desired aggregate behaviour

Stationarity

The absence of trends in time-series data

Time Series

Observations of a variable made over time

USD

United States dollar

ZAR

South African rand

1 Introduction

1.1 Context of Study

The historical volatility of the rand exchange rate has encouraged investors on the JSE Securities Exchange to invest in shares which are believed to have an inverse relationship to exchange rate movements of the rand, thereby buffering their portfolios against rand weakness. As a result, the effective functioning of these shares in their role as "rand hedges" is of considerable economic importance for the many investors who rely on them to minimise exchange rate risk.

The practice of identifying rand hedge stocks has been complicated by the existence of long-term trends in share prices and exchange rates which result from macroeconomic factors at a regional or global level. These macroeconomic trends may falsely indicate hedging behaviour by resulting in spurious correlations between share price and exchange rate time-series.

1.2 Purpose of the Study

This study set out to develop an empirical method for identifying rand hedge stocks on the JSE by eliminating the effect of macroeconomic influences on share prices and exchange rates which may falsely indicate a relationship between the two. It was postulated that the identification of shares which have a fundamental inverse relationship with short-term movements in the rand exchange rate would form a key step in constructing an effective rand hedging portfolio.

1.3 The Research Problem

The research problem was to develop a methodology to identify potential rand hedge stocks listed on the JSE based on their inverse correlation with short-term movements of the rand exchange rate, and then evaluate the effectiveness of such an approach by comparing the performance of the identified basket of stocks against that of the JSE all-share index during a period of devaluation of the rand.

1.3.1 Sub-problems

The first sub-problem was to develop a methodology to identify a basket of potential rand hedge stocks listed on the JSE based on their inverse relationship with short-term movements in the rand exchange rate.

The second sub-problem was to evaluate the identified basket of stocks as a hedging portfolio against rand-based exchange rate exposure by comparing its performance against that of the JSE all-share index during a period of rapid devaluation of the rand.

1.4 Delimitations

- The study was restricted to identifying and evaluating potential rand hedge stocks listed on the JSE. The underlying reasons for the rand hedge nature of the stocks were not investigated.
- The study considered only the rand/dollar exchange rate in identifying and evaluating rand hedge stocks. The dollar, being the currency of international commerce, has the strongest influence of all currencies on the performance of the South African market, and hence the rand/dollar exchange rate is the most important of the listed exchange rates to consider.

1.5 Structure of the Report

In order to set the stage for identifying and evaluating potential rand hedge stocks, the current literature on the topic is reviewed, including an examination of the theory of hedging and a discussion of potential methods for recognising rand hedge stocks. After stating the research hypotheses, the methodology for the study is described, including the nature of the data investigated, the analysis performed to identify the basket of potential rand hedge stocks, and the process followed to evaluate the basket of stocks as a hedging portfolio. Next, the results of the analysis are presented and interpreted, and the findings used to draw conclusions. Finally, a proposal for future research is outlined to provide a structure for the further development of this research.

2 Literature Review

2.1 Exchange Rate Exposure

Short-run financial risk, also known as transactions exposure, arises because firms must make transactions in the near future at uncertain prices or exchange rates. Short-term price or exchange rate changes can drive fundamentally sound firms into financial distress by creating a negative cash flow position which prevents firms from meeting their financial obligations (Firer, Jordan, Ross & Westerfield, 2003).

Operating exposure, or exchange exposure, is a measure of a firm's overall risk exposure to fluctuations in the exchange rate, including both transactions exposure and longer-term foreign exchange risk. Operating cash flows denominated in foreign currencies are a common source of operating exposure, and can have a considerable influence on firm value due to the importance of predictable cash flows to firm viability and profitability.

Eun & Resnick (2004) state that a firm's operating exposure is determined firstly by the market structure of inputs and products - in other words how competitive or monopolistic the market is - and secondly by the firm's ability to adjust its markets, product mix, and sourcing in response to exchange rate changes. Studies have shown that there are significant relationships between the operating exposure and market value of publicly traded shares.

Choi & Prasad (1995) found that the exchange exposure of individual firms is related to firm-specific operational variables, and that firms with significant exchange risk exposure tend to gain in value with a depreciation of the local currency. Their study identified a positive correlation between the scope of the firm's foreign operations (its foreign sales, assets, and operating profits) and its exchange rate sensitivity, and that the practice of aggregation of firm data into portfolios was responsible for the failure of prior studies in identifying a strong relationship between firm value and exchange risk sensitivity.

2.1.1 *Measuring Operating Exposure*

A variety of methods have been used to measure the operating exposure of firms. This section describes a selection of such methods.

Yücel & Kurt (2003) measured economic exposure by determining the slope of the share return on exchange rate changes. Donnely & Sheehy (1996) formed a portfolio of 39 companies and investigated the relationship between abnormal returns of the portfolio and exchange rate returns. Miller & Reuner (2000) estimated economic exposure using a multivariate modelling approach in which they combined a three-currency model with a selection of macroeconomic variables such as overall stock market return and interest rates.

Adler & Dumas (1984) liken exchange risk exposure to market risk exposure, and present an approach to measuring operating exposure as a regression coefficient. The rationale for this definition of exposure is that it considers the distribution of an asset's domestic currency price at a point in the future in two parts: one which is correlated with the exchange rate, and the other which is independent of it. The power of this approach is its ability to account for exposure derived from more than one foreign currency.

Pritamani, Shome & Singal (2004) define operating exposure as the slope of the univariate regression:

$$R_{i,t} = \alpha_i + \beta_i G_t + e_{i,t} \qquad [1]$$

Where:

$R_{i,t}$ is the return of stock i in period t;

G_t is the change in the exchange rate over the same period.

Eun & Resnick (2004) continue from this definition to calculate operating exposure for stock i as:

$$\beta_i = \frac{Cov(R_{i,t}, G_t)}{Var(G_t)} \qquad [2]$$

Where:

$Cov(R_{i,t}, G_t)$ is the covariance between the local currency value of the asset and the exchange rate;

$Var(G_t)$ is the variance of the exchange rate.

Thus there are two sources of operating exposure, namely (i) the variance of the exchange rate, and (ii) the covariance between the local currency value of the asset and the exchange rate.

2.2 Exchange Rates and Share Prices

The relationships between exchange rates and share prices have been the topic of much theoretical and practical research. Some of the pertinent findings in this field are discussed below.

2.2.1 Theory

Firer, Jordan, Ross & Westerfield (2003) describe an effective way to determine the intrinsic value of a share by calculating the present value of its future dividends, an approach referred to as the Dividend Growth Model. In the simplified case which assumes a constant dividend growth rate, known as the Gordon Growth Model, the share value is calculated by the following equation (based on the formula for a perpetuity):

$$P_0 = \frac{D_1}{k - g} \qquad [3]$$

Where:

P_0 is the intrinsic share value;

D_1 is the dividend paid out by the firm in year 1;

k is the rate of return demanded by investors;

g is the dividend growth rate (in perpetuity).

As an aside, it is worth noting that due to the Gordon Growth Model's assumption of a constant dividend growth rate, the model is best applied to mature companies or broad market indices with low to moderate growth rates (Investopedia.com, 2005).

In practice, the rate of return demanded by investors is the domestic interest rate plus some premium based on the perceived risk inherent in the share. To simplify the discussion, the domestic interest rate will be used as a proxy for *k*. Thus, [3] can be represented as:

$$P_0 = \frac{D_1}{r_d - g} \qquad [4]$$

Where:

r_d is the domestic interest rate.

In order to determine the theoretical effect of exchange rates on share prices, the relationship between exchange rates and interest rates is determined. The International Fisher Effect (IFE) states that the interest rate differential between two countries should be an unbiased predictor of the future change in the spot exchange rate (Trading Glossary, 2005). This statement can be represented as the following equation:

$$\Delta e = r_d - r_f \qquad [5]$$

Where:

Δe is the change in exchange rate;
r_d is the domestic interest rate;
r_f is the foreign interest rate.

Combining [4] and [5], the value of a share can be represented in terms of the change in exchange rate as follows:

$$P_0 = \frac{D_1}{\Delta e + r_f - g} \qquad [6]$$

A number of assumptions and simplifications are used in the formulation above, explaining to some degree the diversity of findings from prior studies of the relationship between exchange rates and share prices.

2.2.2 Prior Studies

Hau & Rey (2003) developed a model of integrated analysis of exchange rates, equity prices and equity portfolio flows, and found a negative correlation between equity excess returns (in the local currency) and the corresponding exchange rate returns, contradicting the conventional belief that currency appreciation accompanies strength in equity markets.

Moodley (2001) investigated the effectiveness of rand hedge shares on the JSE and found the existence of significant contemporaneous relationships between some of these shares and the exchange rate, but concluded that factors such as market structure, demand elasticity, hedging strategies, and the scale of foreign operations needed to be taken into account when assessing the sensitivity of companies' value to exchange rates.

2.3 Hedging Techniques

The practice of reducing a firm's operating exposure is known as hedging, and can take many different forms depending on the desired risk to be mitigated (Firer, Jordan, Ross & Westerfield, 2003).

Hedging is most frequently referred to in the context of financial derivatives, a field which has been the subject of comprehensive research. Adler & Dumas (1984:42) define hedges which mitigate currency risk as follows:

> *The amounts of the foreign-currency financial transactions (i.e. forward contracting or its equivalent) required to render the future, real, domestic currency market value of an exposed position statistically independent of*

unanticipated, random variations in the future domestic purchasing powers of these foreign currencies

An understanding of the basic principles of hedging via derivatives as well as the state of current research is useful for the purposes of contextualising this study. The practice of hedging with stocks is discussed thereafter.

2.3.1 Basic Principles of Hedging

Seminal work by Modigliani & Miller (1958) indicates that under perfect market conditions, firm value can not be altered by means of financial contracts. Only in the presence of market imperfections will hedging activities result in increased value for the firm. Berkman & Bradbury (1996) discuss four market imperfections that may give rise to the use of derivatives for hedging: (1) when there are costs associated with financial distress, (2) when a progressive tax environment exists, (3) when there are conflicts of interest between shareholders and holders of debt, and (4) when parties contracting with the firm, such as management, are unable to diversify their claim on the firm.

Hedging by means of futures instruments is one of the most popular forms of hedging because of its efficacy in mitigating the effects of portfolio devaluation. A futures contract represents a commitment to buy or sell a financial instrument, at a specified date and mutually agreed price. Bornman, Smit, & Gevers (2002) describe the standard technique of hedging by means of financial futures as follows. In order to hedge against a decline in the value of a share portfolio, the investor sells futures contracts short. By selling short, the risk of negative movements in share prices are offset through the corresponding profits obtained from the futures market. In the traditional futures hedging approach, the equivalent value of futures contracts is purchased as the value of the investment to be protected. On the last day of the contract period, the investor purchases back the equivalent number of contracts that were sold, thereby closing out the hedging position.

Considerable research has been done on optimising hedging strategies for futures instruments. Shaffer (2003) states that the Gini hedge ratio, based on the mean difference statistic developed by Gini (1912), provides an effective basis for constructing a futures hedging strategy. In contrast with the minimum-variance hedge framework developed by Ederington (1979), which can only be applied under conditions of normally distributed returns, the Gini hedge technique achieves expected utility maximisation under considerably more general conditions.

Nikolaos & Christos (2003) identify ways in which the Black-Scholes options pricing model described by Black & Scholes (1972) can be used to construct a hedging technique based on the model's ability for identifying overvalued and undervalued option contracts.

Foreign currency derivatives have been shown to be effective in hedging foreign exchange risk. Research by Allayannis & Ofek (2001) finds that US corporations are generally unaffected by exchange-rate movements, due to their extensive use of foreign currency derivatives and foreign debt for hedging.

2.3.2 Hedging Currency Risk via Stocks

The practice of hedging against devaluation of the rand is an important consideration in South Africa, where the currency is prone to sudden, unanticipated periods of devaluation, as was the case during the last four months of 2001, where the rand depreciated by over 40 percent against the US dollar. Investors, ranging from private individuals to large institutions, who wish to invest on the JSE Securities Exchange need ways to identify shares which will perform well during such periods of currency devaluation.

Currency hedge stocks are chosen because of the negative relationship between their stock price and the exchange rate. In other words, these stocks tend to increase in value when the currency devaluates. Investors, depending on the degree to which they wish to mitigate the risk of currency depreciation, will construct a portfolio containing varying proportions of hedge stocks, taking into account that during periods of currency appreciation, these stocks will correspondingly tend to decrease in value.

2.3.3 Characteristics of Effective Hedge Stocks

In order for stocks to qualify as effective hedges, they must fulfil certain requirements, particularly requirements of market capitalisation and liquidity.

The Handbook of World Stock, Derivative and Commodity Exchanges (2005) defines a firm's market capitalisation (also known as market cap) as the total value of all issued shares, calculated by multiplying the number of shares by the current market price. In essence, market capitalisation is the price required to purchase the entire listed company.

Liquidity is the degree to which an asset or security can be bought or sold in the market without affecting the asset's price. Liquidity can also be considered as the ease by which an asset can be converted to cash, based on the number of players willing to buy and sell in a particular commodity market. High share liquidity can thus be identified by correspondingly high levels of trading activity (Charles Schwab, 2005).

Effective hedge stocks require large enough market capitalisation to enable institutional investors to build a portfolio out of them. Secondly, potential hedge stocks need sufficient liquidity in order for investors to buy and sell the shares when desired (Business Times, 2004).

2.4 Rand Hedge Stocks

Firer *et al* (2003) state that in an open economy, such as South Africa, where exports and imports form an important component of the country's financial activity, exchange rates play a correspondingly important role in determining economic performance. Swartz (2004) indicates that South African firms aim to mitigate their foreign exchange risk by investing in a portfolio of 'rand hedge' stocks which are considered to have a significant relationship with movements of the rand exchange rate.

The criteria for determining whether a specific stock is a rand hedge vary widely, ranging from targeting stocks with a large exposure to dollar earnings (Daily Dispatch, 1998) to searching for stocks whose price is correlated to the exchange rate.

This latter practice has a critical shortcoming: Bodnar (2003) identifies macroeconomic factors affecting the valuations of firms, such as changes in the risk-free rate, the market risk premium and investor sentiment that happen to be correlated to the exchange rate. These factors may falsely indicate correlations between stock price and the exchange rate leading to the conclusion that the stock is a potential rand hedge.

Bodnar (2003) adds that if the correlation of macroeconomic effects with exchange rates could be modelled, it would be possible to adjust exchange rate exposure estimates to remove this impact (a stock's exchange rate exposure is inversely related to its ability to act as a hedge to exchange rate fluctuations). However, previous research has had limited success in identifying a consistent relationship between exchange rates and observed proxies for these macroeconomic factors. Bodnar (2003) suggests an empirical approach that uses returns to market-capitalisation-based portfolios to adjust for macroeconomic factors, resulting in better estimates of firms' underlying exposure to the exchange rate. However, the definition of the market portfolio variable has a significant influence on the results, making the estimates of the exposures model dependent and difficult to interpret.

2.4.1 Shares Generally Considered to be Rand Hedges

South African investors frequently construct hedge portfolios by selecting firms with significant exports or foreign earnings. The rationale for this approach is that the performance of such firms should be directly related to the strength of the foreign currency, and should thus increase in strength during periods of weakness in the local currency.

Donnelly & Sheehy (1996), in a UK-based study of large exporters, found a negative relationship between the value of a share portfolio of exporter firms and the exchange rate. However, the explanatory power of the regression model used in their research was a relatively low 5.2%. Nonetheless, their findings provide some justification for the current practice of selecting exporter firms as currency hedges.

Absa Bank's Rand Protector Fund consists of 20 shares which are considered to be good hedges of rand weakness (Absa Bank, 2004). A selection of these shares is listed below:

- Anglo American Platinum
- BHP Billiton Plc.
- Goldfields
- Harmony Gold
- Iscor Ltd
- Naspers Ltd,
- Sappi Ltd.
- Steinhoff International Holdings

2.5 Potential Methods for Identifying Rand Hedge Stocks

The majority of studies on hedging and exchange rate exposure have used some form of statistical regression in order to determine the correlation between the stock price and the exchange rate. Bodnar (2003) describes how most research on the exchange rate exposure of firms has been obtained from a regression of stock returns on an exchange rate change, often with additional control variables such as a market portfolio return. However, the reliability of these estimates of exchange rate exposure are undermined by their low statistical significance.

The risks of incorrectly identifying relationships between pairs of time series data are discussed by Granger, Hyung & Jeon (2001), who caution that standard inference in an ordinary least squares regression may identify nonexistent relationships between pairs of independent series with strong time-related characteristics. In addition to this well-documented phenomenon, Granger *et al* (2001) found that similar 'spurious regressions' may be identified even in stationary series due to the misspecification of the statistical model to the series.

Chaudhry, Christie-David & Sackley (1998) investigated the long-run stochastic relationships between foreign currencies and various other assets so as to suggest a framework for managing long-term currency risk. After eliminating trends and auto-correlations in the time series evidence of co-integration between a number of assets (grains and oilseeds, energy, and precious metals) with foreign currencies was identified. Co-integration tests were used to adjust for non-stationarity in the time series data, with various heuristic methods being used to eliminate autocorrelations.

These findings suggest that the removal of non-stationarity and autocorrelations in commodity time series is a key step in classifying the relationships between financial instruments and the exchange rate, and should form part of the process of identifying rand-hedge stocks.

2.5.1 Techniques for Removing Long-Term Trends from Time Series Data

A variety of statistical techniques, including regression modelling, smoothing, and differencing, can be employed to remove non-stationarity from time series data.

One of the most straightforward ways to remove non-stationarity from time series is by fitting a regression model to the data. Draper & Smith (1980) give an example of how regression modelling can be performed on time series data. Once the validity of the regression model has been established, the time series of residuals forms the stationary version of the original data.

A second method for removing non-stationarity from time series data is by means of Holt's exponential smoothing method, a forecasting technique which explicitly accounts for non-stationarity in the data through the inclusion of a trend term (Albright, Winston, & Zappe, 2003). In order to optimise the fit of the model to the data, adjustments are made to smoothing parameters which determine the responsiveness of the model to changes in the trend or patterns in the data. Once an optimal fit has been obtained, the residuals from the fitted model should form a stationary series.

A third method for removing non-stationarity in time series mentioned above is a component of the Box-Jenkins forecasting methodology known as differencing. Chatfield (1989) presents one explanation of how the differencing technique is employed to ensure stationarity in the time series data, a central requirement for the Box-Jenkins methodology.

2.5.2 The Applicability of the Box-Jenkins Methodology to the Removal of Non-Stationarity in Time Series Data

The Box-Jenkins methodology's function as a forecasting tool has been employed in a broad range of financial research, an example of which is presented by Bornman, Smit, & Gevers (2002), where Box-Jenkins forecasting was central to the development of a hedging strategy using futures contracts.

In addition, the Box-Jenkins methodology has been employed in numerous non-forecasting applications of financial time-series analysis due to characteristics established in the time series during its execution.

One such non-forecasting application of the Box-Jenkins methodology is discussed in Van Druten (2005), where it was employed in conjunction with correlation analysis to determine the relationship between the rand/dollar and rand/euro rates, and the value of construction companies listed on the Johannesburg Stock Exchange. The Murray and Roberts share price was found to display significant rand hedge behaviour with respect to the rand/Euro exchange rate for weekly and monthly data.

The power of the Box-Jenkins methodology derives from its ability to eliminate not only non-stationarity but also autocorrelations in time series data, and thereby describe the underlying mechanism responsible for the behaviour of the observed series. This characteristic of the Box-Jenkins methodology makes it an attractive choice for the purposes of this research, which seeks to describe the underlying nature of time-series behaviour by eliminating extraneous time-related macroeconomic influences on the stock price and the exchange rate time series which could otherwise falsely indicate correlations between the series. An additional advantage of the Box-Jenkins methodology is that it is freely accessible in most statistical packages. The application of this methodology to the research analysis is described in detail in the *Project Theory* section.

2.6 A Recent Period of Rand Devaluation

The well-documented period of rapid depreciation of the rand during the last four months of 2001 is of interest to this research, since it may be used to investigate the efficacy of a rand hedge portfolio. It is important to ascertain the key dates of the period of depreciation for the purposes of this study. The end of the period of depreciation is easily defined, since the rand immediately started appreciating after reaching a low of USD1 = ZAR13.84 on 27 December 2001. However, since the sudden depreciation of the rand came after a long period of slow depreciation, pinpointing the exact date of the commencement of the rand's slide requires investigation into the causes of this behaviour.

Many reasons for the rand's period of rapid depreciation have been offered, but a recurring theme is a statement by the South African Reserve Bank on 14 October 2001 indicating that the bank would enforce exchange control rules on transactions between South African authorised dealers and non-residents. A number of South African banks, including Nedcor and Absa indicated during the commission of inquiry into the currency's depreciation that this October statement "played a crucial role in the currency's fall" (Shevel, 2002:1).

However, in response to these allegations, the South African Reserve Bank (2002:1) responded that "it should be borne in mind that by 14 October 2001 the rand had already started depreciating rapidly". The bank continues by discussing the investment flows by non-residents in South African bonds and equities during the 2001 calendar year, indicating the first business day of September 2001 as the commencement of the rand's slide (South African Reserve Bank, 2002:1):

> In calendar year 2001, non-residents purchased South African bonds and equities to the amount of ZAR4, 203 billion. These flows, however, and in particular purchases and sales of bonds, were quite volatile throughout the year. Notwithstanding this volatility, from the beginning of January 2001 to the end of August 2001, net purchases of equities and bonds by non-residents amounted to ZAR11,914 billion. In the remaining four months of the year this turned to net sales of ZAR7,710 billion. The big change occurred in September 2001 with net sales of South African equities and bonds by non-residents of ZAR5,510 billion. Thus non-resident portfolio investments in South Africa turned noticeably negative a month before the statement of 14 October 2001 and could hardly have been caused by it. These net sales occurred from the very first business day of

September 2001 and can also not necessarily be linked to the tragic events of 11 September 2001 or the decision by the Reserve Bank to decrease the repo rate by 50 basis points in September 2001.

In confirmation of this date, the commission of inquiry launched by the Department of Justice and Constitutional Development (2002:4) into the rapid depreciation of the rand focussed its investigation on the period of 1 September 2001 till 31 December 2001 for the following reasons:

> The reason for the focus on the last four months of the year is that over the period 1 January to 31 August 2001 the rand depreciated by 10.7% or an average of 1.3% per month, while from 1 September to 31 December 2001, the rand weakened by 42% - an average of 10.5% per month.

3 Propositions and Hypotheses

3.1 Proposition for Sub-problem 1

Sub-problem 1 of the research problem is formulated as the following research proposition:

> The calculation of correlations between share price and exchange rate time series data, after the removal of non-stationarity and autocorrelations, is an effective approach for identifying rand hedging behaviour in stocks listed on the JSE.

The efficacy of the identified potential rand hedge stocks as a hedging portfolio will be evaluated during the investigation of sub-problem 2, the hypothesis test of which is stated below.

3.2 Hypothesis for Sub-problem 2

Sub-problem 2 of the research problem will be tested by means of the following hypothesis.

> $\boldsymbol{H_0}$: The performance of the selected hedging portfolio is not different from that of the JSE All Share Index (ALSI) during a period of depreciation of the rand.
>
> $\boldsymbol{H_A}$: The performance of the selected hedging portfolio is better than that of the ALSI during a period of depreciation of the rand.

If the difference between the proportional increases of share *i* in the selected hedging portfolio and the proportional increase of the ALSI over the period of the rand's depreciation is denoted by X_i, then the hypotheses can be expressed as follows:

$\boldsymbol{H_0}$: $mean(X_i) \leq 0$

$\boldsymbol{H_A}$: $mean(X_i) > 0$

4 Project Theory

Before discussing the methodology for addressing the research problems, the statistical methodologies which were employed for the analysis are presented.

First, the Box-Jenkins methodology was used to eliminate extraneous influences on the share price and exchange rate time series. Then correlation analysis was used to determine the nature of the relationship between the share prices and the exchange rate. Finally, the performance of the identified portfolio of rand hedge shares was evaluated by visual analysis and by means of the Sign Test and the Wilcoxon Signed-Rank Test.

4.1 The Box-Jenkins Methodology

Autoregressive / Integrated / Moving Average (ARIMA) models were initially popularised by Box & Jenkins (1970), who comprehensively described the theory and methodology of ARIMA, and whose names are now used synonymously with the models. The forecasting power of ARIMA models is due to properties of the time series established during application of the Box-Jenkins method, namely stationarity in the mean and absence of patterns, or autocorrelations, in the residuals.

Chatfield (1989) describes the formulation of ARIMA processes, indicating that the general ARIMA(p,q,d) process can be written as:

$$W_t = \alpha_1 W_{t-1} + \ldots + \alpha_p W_{t-p} + Z_t + \ldots + \beta_q Z_{t-q} \qquad [7]$$

Where:

p denotes the autoregressive order;

d denotes the degree of differencing;

q denotes the moving average order.

[7] may be written in the form:

$$\Phi(B) W_t = \Theta(B) Z_t \qquad [8]$$

where $\Phi(B)$ and $\Theta(B)$ are polynomials of order p and q respectively, such that

$$\Phi(B) = 1-\alpha_1 B - \ldots - \alpha_p B^p$$

and

$$\Theta(B) = 1-\beta_1 B - \ldots -\beta_q B^q$$

Makridakis, Wheelwright & Hyndman (1998) explain the three phases of the Box-Jenkins methodology when defining an ARIMA model for a time series, namely: (1) *identification*, (2) *estimation*, and (3) *diagnostic checking*.

During the initial identification phase of the process the variance is stabilised, non-stationary patterns (trends) in the data are eliminated, and a tentative choice is made of the appropriate ARIMA model. The identification process is described by means of a decision diagram in Section 4.1.1.

In the second stage, the parameters of the model are estimated and iteratively refined, before the identification stage is revisited to select the best of the remaining candidate models.

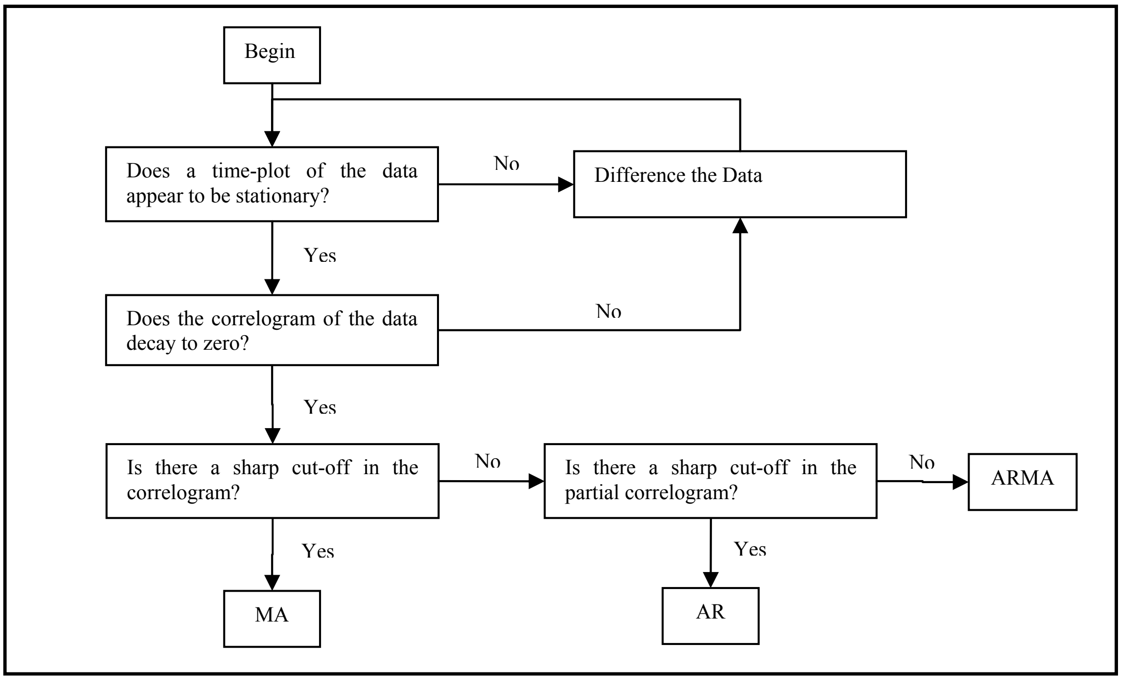
The third, and final, phase involves checking the selected model for adequacy by searching for patterns in the residuals when fitting the model to the existing data. Once these stages are completed, the model can be used for forecasting.

Further details of the Box-Jenkins methodology are presented in Appendix A.

4.1.1 Summary of the Identification Process

The model identification process is summarised in **Figure 1** below, and is described in detail in Appendix A.

Figure 1 - Flowchart of Box-Jenkins Model Identification Process



Source: Diggle (1990)

The importance of the correlogram as a tool to determine when stationarity has been achieved during the identification process is due to a characteristic of its graphical representation: a correlogram which fails to decay to zero is an indication of non-stationarity. The theory of the correlogram is described in Section 4.1.2.

4.1.2 The Correlogram of a Time Series

The correlogram of a time series can be understood in terms of *autocorrelation coefficients*, which measure the correlation between observations certain distances apart. Since these coefficients measure the correlation between observations within a time series, they are termed *autocorrelation* coefficients. Chatfield (1989) presents the equation for the correlation of observations a distance *k* apart, known as the autocorrelation coefficient at lag k:

$$r_k = \frac{\sum_{t=1}^{N-k}\left(x_t - \bar{x}\right)\left(x_{t+k} - \bar{x}\right)}{\sum_{t=1}^{N}\left(x_t - \bar{x}\right)^2} \qquad [9]$$

The correlogram is a graph of r_k plotted against the lag *k*. Under visual inspection, the correlograms of stationary series are generally characterised by relatively large values of r_1 (indicating short-term correlations) followed by progressively smaller values of

r_k tending towards zero. Non-stationary series are characterised by r_k values which do not decay to zero.

4.2 Correlation Analysis

Albright, Winston, & Zappe (2003) offer a description of correlations as numerical summary measures that indicate the strength of relationships between pairs of variables. The correlation coefficient, r_{XY}, between two variables, X and Y is calculated using the following formula:

$$r_{XY} = \frac{\sum \frac{(X_i - \overline{X})(Y_i - \overline{Y})}{(n-1)}}{s_X s_Y} \qquad [10]$$

The values of correlation coefficients fall in the inclusive range between -1 and +1. A positive sign on the correlation coefficient indicates a positive linear relationship between the two variables; likewise a negative sign indicates a negative linear relationship. The strength of the relationship between the two variables is given by the magnitude of the correlation coefficient, with values close to 0 indicating weak relationships and values close to 1 (and -1) indicating strong relationships. In addition to indicating the strengths of relationships between variables, correlation coefficients have the useful property of being unaffected by the units of measurement of the variables concerned (Albright, Winston, & Zappe, 2003).

A few important points should be made about correlation analysis. Firstly, it is important to note that correlations only measure the strength of *linear* relationships. If a nonlinear relationship exists, the correlation may incorrectly suggest that there is no relationship between the variables. Thus if the correlation is close to zero, the scatter plot of the two variables should be inspected visually to determine if the points cluster around some nonlinear function, before concluding that no relationship exists.

Secondly, correlation does not necessarily indicate causality. That is, the existence of a relationship between two variables can not be used to conclude that the behaviour of the one variable causally affects the behaviour of the other. It may be that a third (unmeasured) force is responsible for influencing both of the variables simultaneously.

Due to the usefulness of correlation analysis for determining linear relationships between variables, this functionality is available in most statistical software packages.

4.3 Cross-Correlation Analysis

Cross-correlation analysis is a development of correlation analysis and is a useful tool for determining the correlations at various lags between two time series variables. Given two time series, X_t and Y_t, the cross-correlation between X_t and Y_{t+k} is called the k^{th} order cross-correlation of X and Y, where the time index, k, is allowed to be either positive or negative (Hintz, 2001).

The sample estimate of this cross-correlation, is calculated using the following formula:

$$r_k = \frac{\sum_{t=1}^{N-k}\left(X_t - \overline{X}\right)\left(Y_{t+k} - \overline{Y}\right)}{\sqrt{\sum_{t=1}^{N}\left(X_t - \overline{X}\right)^2 \sum_{t=1}^{N}\left(Y_t - \overline{Y}\right)^2}} \qquad [11]$$

In effect, the 0^{th} order cross-correlation between X and Y is equivalent to the simple correlation between the two series. Autocorrelation coefficients, as described in Section 4.1 on the Box-Jenkins methodology, are simply cross-correlation coefficients between time series X and itself.

4.4 Sign Test

The Sign Test is a non-parametric method used to test a hypothesis about the location of the median of a population distribution. The test is based on the binomial distribution, since it assumes two mutually exclusive outcomes ("success" and "failure"), constant probability of success (i.e. p = 0.5), and n independent trials. When involving matched pairs, the Sign Test investigates the existence of a median difference of zero. The technique assumes that a random sample has been taken with independent, identically distributed observations. The data are converted into a series of pluses and minuses, with zero differences being discarded and the sample size reduced accordingly. The test is based on the number of pluses that occur (Hintz, 2001).

The total number of observations is denoted by *n* and the number of pluses by *m*. If the median difference between the paired populations was zero, and given that the probability of either outcome is equal (i.e. p = 0.5), then the expected value of m would be $n * p$ or $n/2$. For sample size n > 20 the Z statistic for the Sign Test is calculated as follows:

$$Z = \frac{m - n * p}{\sqrt{n(p)(1-p)}} \tag{12}$$

Given that p = 0.5, [12] can be represented as:

$$Z = \frac{2m - n}{\sqrt{n}} \tag{13}$$

This value is tested using the Standard Normal distribution to determine the outcome of the hypothesis test.

4.5 Wilcoxon Signed-Rank Test

In comparison to the Sign Test which is a simple but relatively weak test for the location of the median of a population distribution, the Wilcoxon Signed-rank Test is more powerful and correspondingly more complex. In addition to using the sign of the differences (original data minus hypothesised value for one-sample data or differences between the pairs of measurements for paired data) as the Sign Test does, this technique also uses magnitude of the rank of the differences in order to evaluate the null hypothesis. The Wilcoxon Signed-rank Test depends on four assumptions about the data under investigation: (1) the differences are continuous (not discrete); (2) the distributions of the differences are symmetric; (3) the differences are mutually independent; and (4) the differences have the same mean (Hintz, 2001).

5 Research Methodology

5.1 Data

The population of shares comprising the study, the period of the study, and the methods of data collection are presented in the sections below.

5.1.1 Population

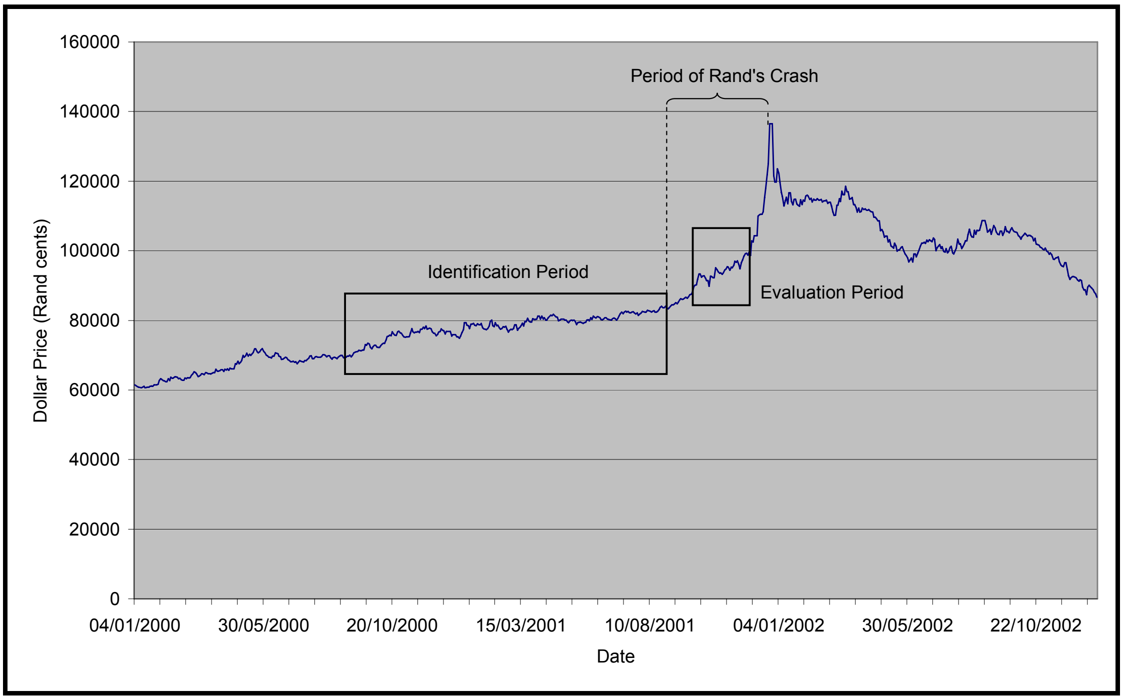
The population under investigation was all shares listed on the main board of the JSE, the ALSI and the rand/dollar exchange rate (the rand value of the dollar). Non-main board shares were excluded since they are characterised by small capitalisation and high degrees of illiquidity, features which would make them poor hedge stocks as explained in Section 2.3.3. The rand value of the dollar was selected to facilitate the comparison in performance between rand hedge shares and the exchange rate. Effective rand hedge shares would echo increases and decreases in the rand value of the dollar, strengthening when the dollar strengthens and vice versa.

5.1.2 Period of Research

For the purposes of the research, two periods of data were investigated. The first period, consisting of one year of daily data ending at the point just before the rand's crash during 2001, was used for the identification of the rand hedge stocks. The second set of data, covering a period during the rand's crash, was used to evaluate the hedging performance of the identified stocks.

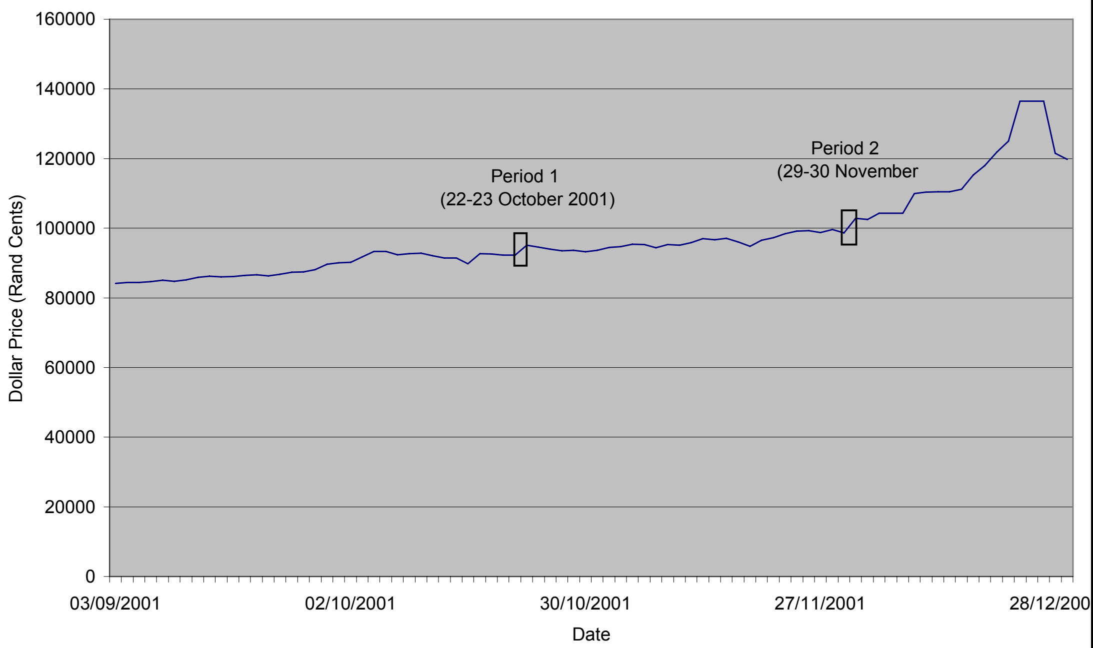
As discussed in Section 2.6, the period of the rand's rapid depreciation is generally considered to be between 1 September 2001 and 31 December 2001. Hence, the one year period immediately preceding the rand's crash, namely 1 September 2000 to 31 August 2001, was used for the identification of the rand hedge portfolio, and the central two month period of the rand's crash, namely 1 October 2001 to 30 November 2001, was used for the evaluation of the hedging performance of the identified portfolio. The one-month periods at the beginning and end of the rand's crash, on either side of the evaluation period (i.e. 1 September 2001 to 30 September 2001, and 1 December 2001 to 31 December 2001), were not included in the evaluation period since they were likely to contain volatile market behaviours which could influence the strength of the findings. The two periods are presented in **Figure 2**.

Figure 2 - Rand/Dollar Exchange Rate Indicating Periods of Research



Within the four-month period of the rand's crash there are two-day periods in which the rand depreciated considerably more rapidly than the overall trend of the devaluation. Two such periods are shown in **Figure 3**, namely 22 to 23 October 2001, and 29 to 30 November 2001. These periods were used to evaluate the hedging performance of the identified portfolio during short term periods of rapid devaluation of the rand.

Figure 3 – Rand/Dollar Exchange Rate during Period of Rand's Crash Indicating Short Periods of Rapid Devaluation



5.1.3 Data Collection

Research data for the population and period described above were gathered as follows:

- The daily high, daily low, closing price, and volume of trades of research population described in Section 5.1.1 were downloaded from McGregor BFA to cover the period of research described in Section 5.1.2 (1 September 2000 to 31 August 2001 for the identification period, and 1 October 2001 to 30 November 2001 for the evaluation period).
- In order to ensure that only shares displaying suitable levels of liquidity for being rand hedges were used, all shares exhibiting more than 10% of days with a zero volume of trades during the pre-crash period (1 September 2000 to 31 August 2001) were excluded.
- Shares exhibiting a discontinuity in share price due to factors such as share splits were also excluded from the analysis.
- Shares from companies which de-listed or went bankrupt during the period of research were similarly excluded.

5.2 Data Reliability

In order to ensure that the share price and exchange rate data obtained from McGregor BFA were correct, data for the rand/dollar exchange rate and ten randomly selected shares were downloaded from I-Net-Bridge, an alternate source of share price data. For each of the ten shares and the rand/dollar exchange rate, the daily high, daily low, closing price, and volume of trade values obtained from McGregor BFA were compared against those obtained from I-Net-Bridge at the first day of each month. No discrepancies in these values were identified. This finding was taken to confirm the reliability of the data obtained from McGregor BFA.

5.3 Data Analysis and Interpretation

Details of the methodology used for identifying potential rand hedge shares and evaluating their performance are given in the following sections.

5.3.1 Identification of a Basket of JSE-listed Rand Hedge Stocks

The following steps were performed in addressing the first research sub-problem, namely to identify a basket of potential rand hedge stocks listed on the JSE based on their inverse relationship with short-term movements in the rand/dollar exchange rate.

For this portion of the analysis, data for the year preceding the rand's crash, comprising 1 September 2000 to 31 August 2001, were used. In order to investigate the sensitivity of the analysis to the movements in share prices and exchange rates, the identification process was performed twice, once for each of the following data sets:

- Daily closing prices
- Weekly averages of closing prices

First the Box-Jenkins methodology was applied to model the exchange rate and share price time series under investigation, and then the residuals were extracted from the resulting fitted ARIMA models. For illustrative purposes, the process is described with reference to the Anglogold share price. **Figure 4** shows the daily closing share price of Anglogold during the identification period.

Figure 4 - Anglogold Daily Closing Share Price during Identification Period

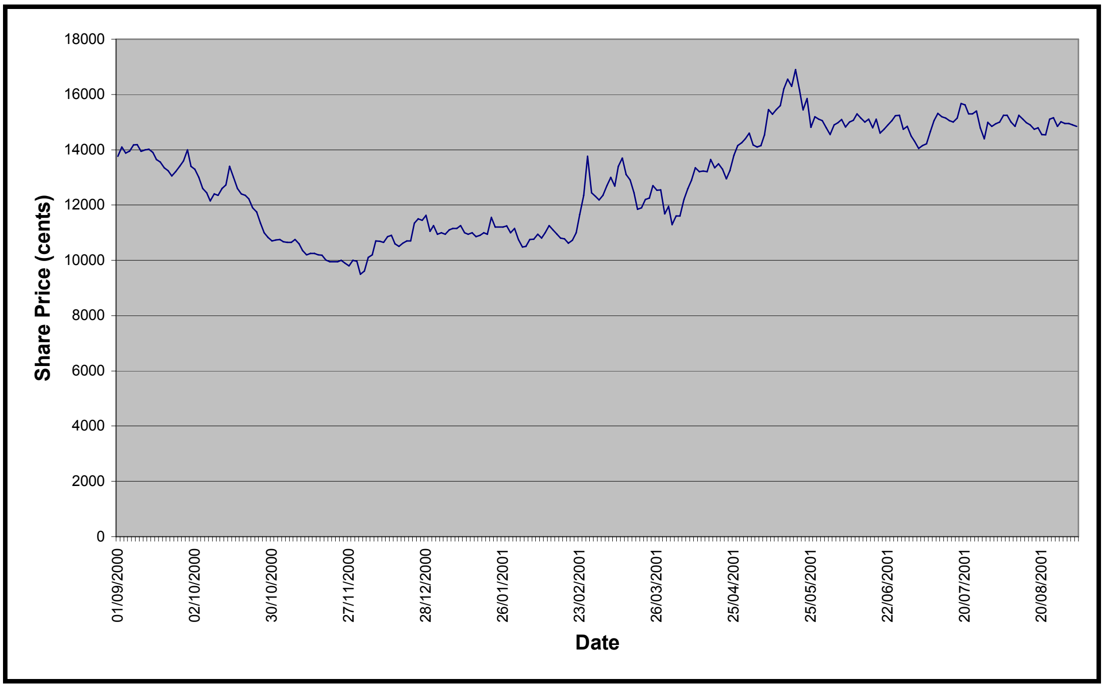
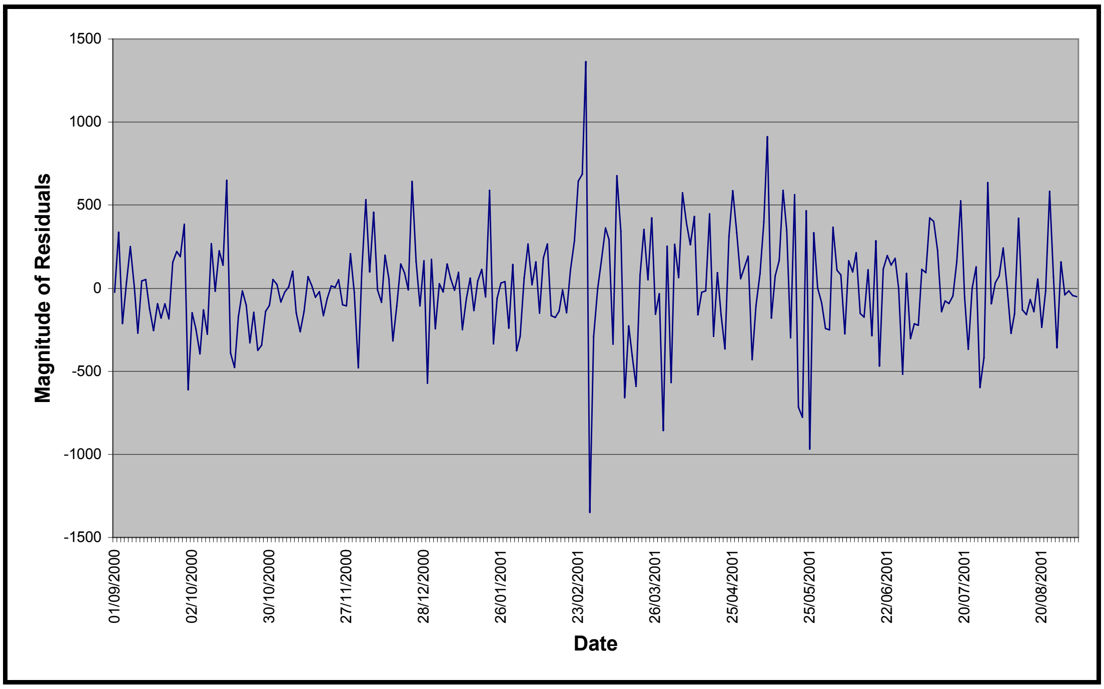


Figure 5 shows the residuals obtained after fitting an ARIMA (1,1,0) model to this data. Due to the application of the Box-Jenkins methodology, the residuals display the characteristics of a white noise series, namely stationarity in the mean of 0, constant variance, and the absence of serial correlations between data points.

Figure 5 - Residuals from Anglogold ARIMA Model during Identification Period



The distinct spikes between 27 February and 28 February in **Figure 5** correspond to the sudden change in the share price on the same dates visible in **Figure 4**. These spikes represent departures from the model, probably as a result of external factors, such as unexpected political or economic news.

Residuals from Box-Jenkins analysis of each of the shares were cross-correlated with the equivalent residuals from the rand/dollar exchange rate in order to quantify the nature of the relationship between the two series. The correlation coefficients obtained from this analysis indicate the strength and direction of the relationship between the variables at various lags. Since the exchange rate in this case referred to the value of the dollar in terms of rand cents, a weakening of the rand would be observed as an increase in the rand value of the dollar. Thus rand hedge shares, which are inversely related to the rand, in that they strengthen when the rand weakens, would display positive correlation coefficients. The strength of this relationship is measured by the significance of the correlation coefficients.

The significance of correlation coefficients is a function of the number of observations in the series under investigation. For the daily share price data series, there were 250 observations, and for the weekly average data series there were 50 observations. **Table 1** presents the critical values for correlation coefficients corresponding to populations of 50 and 250 observations as defined by Rohlf & Sokal (1969).

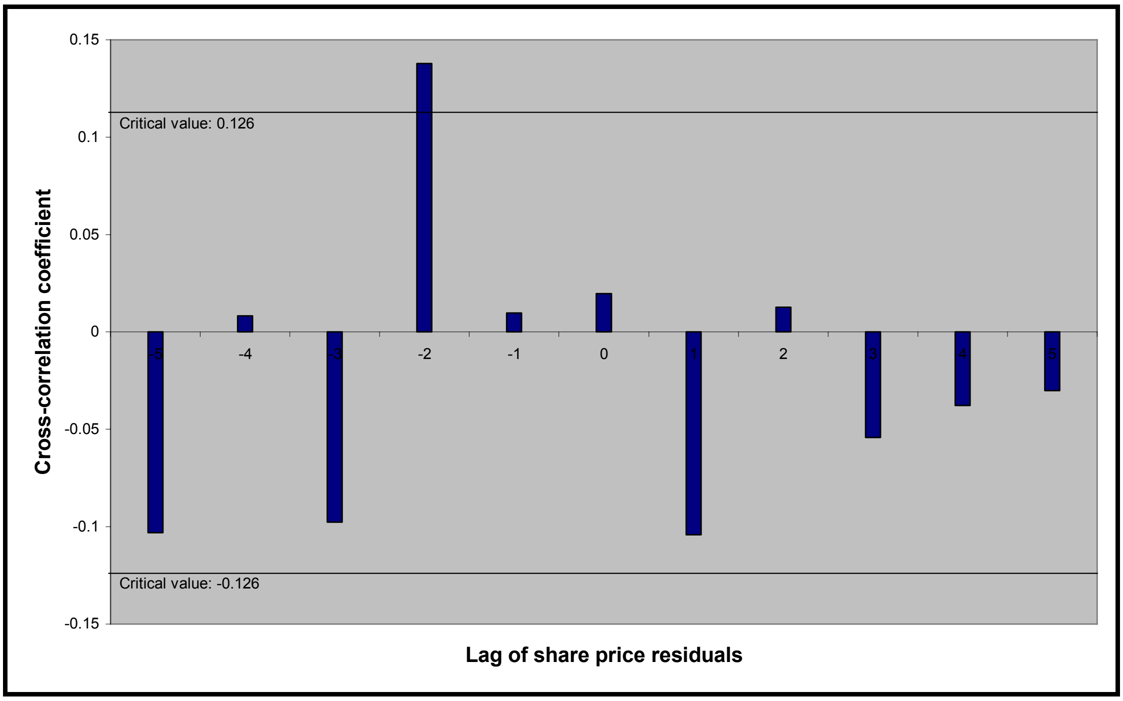
# of observations (n)	α = 5% significance level	α = 1% significance level
50	0.273	0.354
250	0.126	0.165

Table 1 - Selected Critical Values for Correlation Coefficients

For the purposes of this research, a significance level of α = 5% was used.

Figure 6 shows the cross-correlation coefficients between the residuals of the Anglogold share price and the residuals of the rand/dollar exchange rate.

Figure 6 - Cross-correlations of Anglogold Share Price Residuals with Rand/Dollar Exchange Rate Residuals obtained from analysis of daily data



Each cross-correlation coefficient obtained from this analysis is associated with a lag indicating the offset between the two time series at which the correlation coefficient has been calculated. In this case, positive lags indicate offsets at which movements in the share residuals precede those of the exchange rate, and negative lags indicate offsets at which movements in the share residuals follow movements of the rand. For daily data, such as used in this example, one lag corresponds to a day of trading.

The positive coefficient at lag -2 has a value of 0.138, which is greater than the 0.126 critical value for a correlation coefficient with 250 daily observations. This means that Anglogold shares exhibited a significant positive relationship with the dollar at lag -2 at the α = 5% level. In other words, the share price inversely followed movements of the rand, strengthening when the rand weakened, with a lag of 2 days.

For the purposes of identifying rand-hedge stocks, only lags smaller than or equal to zero were considered, since they measure movements of the share price that follow movements in the currency. All shares, such as Anglogold, which displayed a significant positive relationship with the dollar (in that the share price increases when the rand weakens) at a negative or zero lag were considered to be potential rand hedge stocks and were included in the hedging portfolio.

5.3.2 Evaluation of the Performance of the Identified Basket of Stocks

The long- and short-term rand-hedging performance of the selected portfolio of stocks was evaluated over corresponding periods of time:

- **Long-term**: During the central two months of the rand's decline in 2001, from 1 October 2001 to 30 November 2001.
- **Short-term**: During two-day periods of exceptional devaluation of the currency, namely 22 to 23 October 2001 and 29 to 30 November 2001.

Short-term hedging performance was evaluated by comparing the performance of the graphical representations of the identified hedging portfolios, the JSE all-share index, and the rand/dollar exchange rate.

Long-term hedging performance was evaluated by comparing the daily performance of the hedging portfolios against that of the ALSI in order to test the hypothesis defined in Section 3.2. Daily performance was measured by calculating the difference in the proportional daily increase in value of the hedging portfolio and the ALSI for each day in the evaluation period and analysing the resulting list of values by means of the Sign Test and the Wilcoxon Signed-rank Test. This calculation is described below.

If X_i denotes the difference between the proportional increase in the selected hedging portfolio between day i – 1 and day i, and the corresponding increase of the ALSI, then X_i can be expressed as:

$$X_i = \left(\frac{p_i - p_{i-1}}{p_{i-1}}\right) - \left(\frac{a_i - a_{i-1}}{a_{i-1}}\right) \qquad [14]$$

Where:

p_i denotes the value of the hedging portfolio on day *i;*

a_i denotes the value of the ALSI on day i.

X_i is positive for days when the hedging portfolio outperformed the ALSI and negative for days when the hedging portfolio underperformed the index.

To support the results from the statistical analyses, graphical representations of exchange rate and share price movements during the period of the crash were used to give a visual indication of the hedging ability of the selected shares.

5.3.3 Further Analysis

In addition to selecting a portfolio of rand hedge shares, a portfolio of potential 'anti'-hedge shares was selected by identifying those shares displaying positive relationships with the exchange rate (in other words, shares which strengthened when the rand strengthened). The performance of this anti-hedge portfolio was compared to that of the ALSI, as well as against that of the selected hedging portfolio using the same methods described above for the hedging portfolio.

As a final step, the behaviour of known rand-hedge shares was evaluated in order to obtain a better understanding of the underlying behaviour of effective rand-hedge stocks. Once again, the performance of this known rand-hedge portfolio was evaluated using the statistical and graphical techniques described above.

6 Analysis of Results

The following sections present and interpret the results of the research. Section 6.1 presents the results of the identification component of the research in which a daily and a weekly potential hedge portfolio were identified. Sections 6.2 and 6.2.3 discuss, respectively, the evaluation of the identified hedge portfolios over the central two month period of the rand's decline as well as over short periods of rapid devaluation of the currency. Section 6.4 considers the identification and evaluation of potential anti-hedge portfolios. Finally, Section 6.5 presents the analysis of a basket of generally accepted rand hedge shares in order to understand the underlying reasons for their hedging ability. In all cases, the results are discussed from both a graphical and a statistical perspective.

6.1 Identification of Potential Rand Hedge Portfolios

The Box-Jenkins methodology was applied to the rand/dollar exchange rate and to all shares listed on the JSE securities exchange which fulfilled the requirements of effective currency hedge stocks specified in Section 5.1.1. ARIMA models could not be applied to some shares due to characteristics of their performance during the identification period, resulting in failure to meet the requirements of the evaluation step of the Box-Jenkins methodology. These shares were excluded from the study. Details of the ARIMA models fitted to the rand/dollar exchange rate and the remaining shares are presented in **Table 19** and **Table 20** in Appendix B.

Cross-correlation analysis was performed between the residuals obtained from the fitted ARIMA model of each of the shares and those obtained from the ARIMA model of the rand/dollar exchange rate. The results of the analysis are presented in Appendix B in **Table 21** for daily data and in **Table 22** for weekly data. Significant positive correlation coefficients are displayed in bold and significant negative correlation coefficients are displayed in bold italic. As described in Section 5.3.1, only correlation coefficients at negative or zero lags were considered for the identification of potential rand-hedge stocks.

All shares displaying significant positive cross-correlation coefficients were selected as part of potential hedge portfolios classified as daily or weekly according to the nature of the analysed data. The correlation coefficients for the shares comprising the selected daily and weekly portfolios are presented in **Table 2** and **Table 3** respectively. Significant positive correlation coefficients are shown in bold and significant negative correlation coefficients are shown in bold italic. The portfolios constructed from the analysis of daily and weekly data will be referred to hereafter as the 'daily hedge portfolio' and the 'weekly hedge portfolio' respectively.

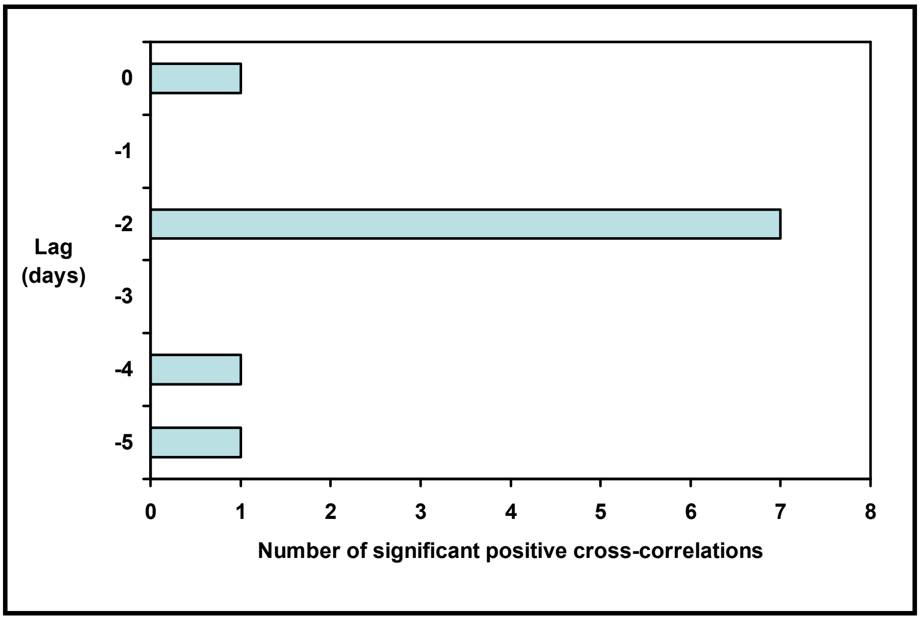
Table 2 – Cross-Correlation Coefficients of Daily Rand-Hedge Stocks

Lag	-5	-4	-3	-2	-1	0
ABSA	-0.062715	-0.082157	0.075658	**0.187322**	***-0.136500***	-0.036958
ANGGOLD	-0.102991	0.008244	-0.097707	**0.137772**	0.009689	0.019621
ARI	**0.172746**	-0.001601	0.019060	0.003935	0.029763	-0.047164
CADIZ	-0.062784	0.120114	0.075798	**0.157028**	-0.106588	0.001603
DIDATA	-0.012248	-0.004411	-0.013473	**0.142264**	-0.020024	0.022772
HARMONY	-0.043157	0.051137	-0.001650	**0.149422**	-0.008312	-0.041608
MUSTEK	0.029473	**0.153759**	0.035661	0.083483	-0.016701	-0.036799
PERGRIN	-0.052726	0.044844	0.034969	**0.159197**	-0.057655	0.038193
RICHEMONT	0.038920	-0.016434	0.010129	0.099948	0.080954	**0.142564**
SAPPI	-0.081539	-0.009456	0.050084	**0.131359**	***-0.146506***	-0.072105

A number of the identified shares display significant negative correlation coefficients in addition to the significant positive correlation coefficients for which they were selected. For instance, Sappi has a positive correlation coefficient of 0.131 at lag -2, as well as a negative correlation coefficient of -0.147 at lag -1. For the purposes of this research, all shares displaying significant positive correlation coefficients were selected, regardless of their having significant negative correlation coefficients or not.

It should be mentioned that when running multiple hypothesis tests on a sample set, it can be expected that a number of spurious results (where significant results are falsely indicated, known as type I errors), corresponding to the selected significance level, will be identified. In this case, where 6 cross-correlations are performed on each of 85 shares at a 5% significance level, approximately 26 spurious results would be expected had hypothesis tests been performed. However, for the purposes of this step in the methodology the significance level of the results is only used to identify and rank shares with strong correlations with exchange rate movements, and not to perform hypothesis testing. As a result, the existence of spuriously significant results in this step does not invalidate the methodology.

Figure 7 - Distribution of Significant Positive Cross-Correlations from Daily Data



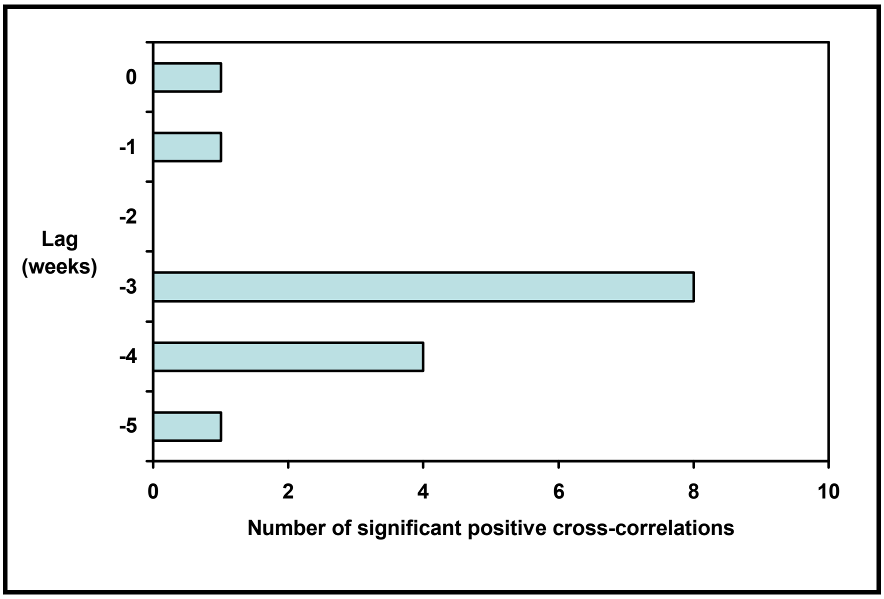
The distribution of significant positive values shown in Figure 7 displays a concentration of seven observations at lag -2 (indicating relatively rapid market adjustments to changes in the exchange rate with a 2-day delay), in contrast with at most one observation at the other lags. This concentration of observations indicates some significant underlying behaviour which can not simply be discounted by Type I errors. Investigations into the reasons for this behaviour could form part of future research.

Interestingly, none of the shares identified as potential hedges using daily data were also identified as potential hedges using weekly data. A possible explanation is that some of the shares showing a significant positive correlation coefficient at a certain lag have large, and sometimes significant negative correlation coefficients at other lags. In the case of Anglogold discussed earlier, and shown graphically in **Figure 6** on page 30, a significant positive correlation coefficient at lag -2 is followed by two large non-significant negative correlation coefficients at lags -3 and -5. The effect of these negative correlations appears to cancel out the effect of the positive correlation at lag -2 when a weekly average is taken, which could explain why no significant positive correlation is obtained when performing the identification step using weekly data. Further research would be required to validate this proposition.

Table 3 - Cross-Correlation Coefficients of Weekly Rand-Hedge Stocks

Lag	-5	-4	-3	-2	-1	0
ABI	-0.075707	**0.275420**	-0.156437	-0.032897	-0.169849	0.048269
ALEXFBS	-0.148147	**0.308884**	0.027112	-0.129685	-0.185742	-0.091976
ANGLO	0.050343	0.056949	**0.285072**	-0.137805	0.032676	-0.202385
BARPLAT	0.003426	0.179479	**0.274940**	0.091482	-0.125152	-0.116618
BTG	0.194886	-0.102794	0.049407	0.032759	0.033797	**0.279643**
DELTA	**0.344289**	-0.070796	-0.082477	0.066864	**0.430556**	-0.093756
FIRSTRAND	-0.105904	0.012686	**0.301217**	0.019650	-0.188140	***-0.354075***
GRAYPROP	***-0.298463***	0.041587	**0.355676**	0.238554	-0.170040	-0.196601
ISPATISC	***-0.318934***	***-0.355250***	**0.388276**	-0.019418	-0.178498	-0.179945
METOREX	0.069415	**0.274119**	-0.009020	0.121613	0.131785	0.029139
MVELA_RES	-0.052556	**0.335089**	-0.006244	-0.176139	0.027342	0.206670
NORTHAM	-0.112639	0.232558	**0.376877**	-0.083022	-0.124199	0.026163
OLD_MUTUAL	***-0.337794***	0.021870	**0.399856**	0.047008	-0.111784	***-0.274759***
STANBANK	-0.203118	-0.042374	**0.306219**	-0.000169	***-0.284251***	-0.234511

Figure 8 - Distribution of Significant Positive Cross-Correlations from Weekly Data



The distribution of significant positive cross-correlations shown in **Figure 8** displays a concentration of observations at lag -3, in other words following movements of the rand by three weeks. The underlying reason for this behaviour is not immediately clear, and investigation into this phenomenon could form part of future research.

6.2 Evaluation of Long-Term Performance of Potential Hedge Portfolios

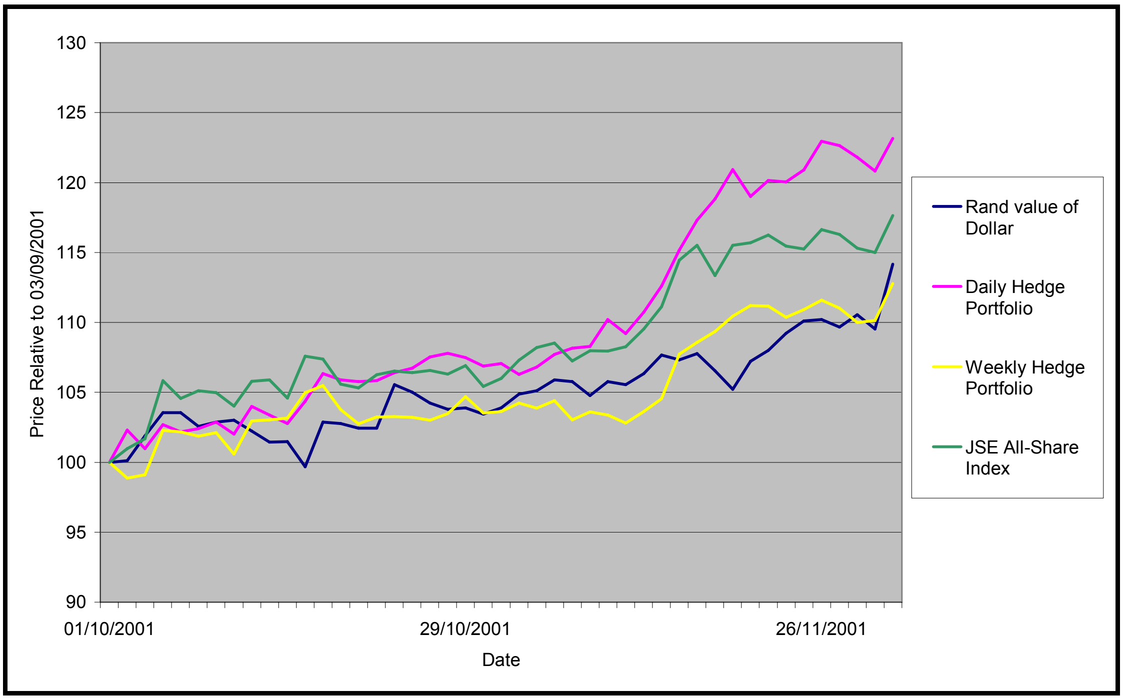
6.2.1 Graphical Performance

Figure 9 charts the performance of the rand/dollar exchange rate, the ALSI, and the potential hedge portfolios which were identified in Section 6.1 over the period 1

October 2001 to 30 November 2001. For the purposes of comparison, the data series have been scaled to a value of 100 on 1 October in this and subsequent graphs. This is equivalent to purchasing 100 rands worth of each share in the portfolio. The 'value' of the hedge portfolio over time is then calculated to be the mean value of the holdings in each of the shares.

Additionally, the rand value of the dollar has in all cases been used as the measure of exchange rate in order to facilitate the visual evaluation of the hedging performance of the series under investigation. Since the rand value of the dollar increases as the rand devaluates, rand-hedge shares would be expected to move in tandem with movements of this measure of exchange rate.

Figure 9 - Performance of Rand/Dollar Exchange Rate, Potential Hedge Portfolios, and ALSI over Period 1 October 2001 to 30 November 2001



During the initial period of the analysis, until 18 October, the ALSI outperformed the potential hedging portfolios and the exchange rate. However, from this point onwards (with the exception of 5 days in early November), the daily hedge portfolio consistently outperformed the ALSI and ended the period considerably higher than the ALSI. The weekly hedge portfolio, in contrast, consistently underperformed the

ALSI, remaining in a range close to the rand value of the dollar until the end of the period.

The graphical performance of the individual shares making up the daily and weekly hedging portfolios is shown, respectively, in **Figure 21** and **Figure 22** in Appendix B. In both cases there is a large variation in the performance between the individual shares over the period of the rand's crash, with most shares showing lower performance than that of the rand value of the dollar, which increased by 42.4% over the period under investigation.

6.2.2 Statistical Evaluation

The results of statistical analyses of the performance of the potential hedge portfolios are presented below. First, the normal-based confidence intervals of the portfolios are presented for comparison against the performance of the ALSI after which the results of the Sign Test and Wilcoxon Signed-rank Test are discussed.

Confidence Interval Analysis

Table 4 presents 95% confidence intervals for the performance of the potential hedge portfolios over the period of the rand's crash.

Table 4 –Confidence Interval Analysis of Potential Hedge Portfolios

Statistic	Daily hedge portfolio	Weekly hedge portfolio
Mean % change	23.2%	12.8%
Standard Deviation % change	16.6%	16.4%
n (portfolio size)	10	14
2-sided t-statistic (n-1, α = 0.05)	2.262	2.160
Lower Confidence Interval of Mean % Change	-14.4%	-22.7%
Upper Confidence Interval of Mean % Change	60.8%	48.3%
% Change of ALSI	17.6%	17.6%

The large variation in performance between the shares in the portfolios is demonstrated in the magnitude of their standard deviations. The confidence intervals for the mean percentage change of both the daily hedge portfolio [-14.4%; 60.8%] and weekly hedge portfolio [-22.7%; 48.3%] are wide, and in both cases include the value of the percentage change of the ALSI. By this metric there is no significant difference in performance between the ALSI and the potential hedging portfolios.

Sign Test

The performance of the potential rand hedge portfolios was tested with the following hypothesis test, as presented in Section 3.2:

> $\boldsymbol{H_0}$: The performance of the selected hedging portfolio is not different from that of the ALSI during a period of depreciation of the rand.
>
> $\boldsymbol{H_A}$: The performance of the selected hedging portfolio is better than that of the ALSI during a period of depreciation of the rand.

The hypothesis test is expressed statistically as follows:

> $\boldsymbol{H_0}$: $median(X_i) = 0$
>
> $\boldsymbol{H_A}$: $median(X_i) > 0$

The formulation of X_i is presented in Section 5.3.2. Details of the calculations for the daily and weekly hedge portfolios are presented in **Table 23** of Appendix A. The theoretical background of the Sign Test is presented in Section 4.4

The results of the Sign Test analysis are presented in **Table 5**. For the purposes of evaluating the null hypothesis, a one-sided critical value from the normal distribution with a significance level of α = 5% was used.

Table 5 – Sign Test Results for Potential Hedge Portfolios

Statistic	Daily Hedge Portfolio	Weekly Hedge Portfolio
m (number of observations > 0)	27	17
n (total number of observations)	44	44
Critical value (α=0.05)	1.645	1.645
Critical value (α=0.1)	1.282	1.282
Z	1.508	-1.508
Decision	**Reject H_0 at α=0.1 level**	**Fail to reject H_0**

The Z-value for the daily hedge portfolio (1.508) lies below the critical value at a significance level of α = 5% (1.645), but above the critical value at a significance level of α = 10% (1.282), indicating that the null hypothesis can be rejected at the 10% significance level. The results of the Sign Test thus bear out the interpretation of the graphical analysis concluding that the daily hedge portfolio outperformed the ALSI during the period of the rand's crash.

In contrast, the weekly hedge portfolio performed significantly worse than the ALSI, with a Z-value of -1.069, which is considerably lower than the critical values at either the α = 5% or 10% levels. As was the case for the daily hedge portfolio, the results of the Sign Test confirm the interpretation of the graphical depiction of the portfolio performance in **Figure 9**: the weekly hedge portfolio clearly performed worse than the ALSI.

Wilcoxon Signed-Rank Test

The Wilcoxon Signed-Rank Test was performed to test the same null hypothesis presented above. The results of the test are given in **Table 6**.

Table 6 – Wilcoxon Signed-Rank Test Results for Potential Hedge Portfolios

Portfolio	Alternative Hypothesis	P-value	Decision (5%)
Daily	Median>0	0.221	Fail to reject H_0
Weekly	Median>0	0.894	Fail to reject H_0

The p-value for the daily hedge portfolio (0.221) is considerably greater than 0.05, which means that the null hypothesis can be rejected at the 5% level. In other words, according to this test there is no significant statistical evidence that the performance of the daily hedge portfolio was better than that of the ALSI over the evaluation period.

Echoing the finding for the daily hedge portfolio, the p-value for the weekly hedge portfolio (0.894) indicates that the null hypothesis can not be rejected at the 5% level. There is thus no statistical evidence, from either the Sign Test or the Wilcoxon Signed-Rank Test, that the weekly potential hedge portfolio outperformed the ALSI over the evaluation period.

6.2.3 Further Statistical Analysis of Individual Potential Hedge Shares

In the statistical tests described above, the daily change in value of the potential hedge portfolios was compared against that of the ALSI. In order to determine the longer-term nature of the relationship between the portfolios and the ALSI, a further piece of analysis was performed on the daily hedge portfolio.

In this analysis, the change in value was performed with four-day intervals during the period of the rand's crash. A four-day interval was chosen for two reasons: first, the lag of k=4 days is the first non-significant point on the correlogram; second, a four-day interval ensures that subsequent observations do not fall on the same day of the week (as would have been the case for a five-day interval), thus minimising the effect of cyclical factors on the values. The proportional change between each observation and the following observation was then calculated using the following formula as before,:

$$C_i = \frac{x_{i+1} - x_i}{x_i} \qquad [15]$$

Where

C_i is the proportional change at period i

x_i is the share price at period i

x_{i+1} is four days after x_i

The equivalent set of proportional change values was calculated for the ALSI and these values subtracted from the corresponding values for each share. The results of applying the Sign Test to the resulting set of values are presented in **Table 7**.

Table 7 – Sign Test Result for Daily Hedge Portfolio and Individual Shares in

Share	m (no. of values > 0)	N	Critical value (α=0.1)	Z	Decision
Portfolio	7	11	1.282	**0.905**	**Fail to reject H_0**
ABSA	3	11	1.282	**-1.508**	**Fail to reject H_0**
ANGLOGOLD	6	11	1.282	**0.302**	**Fail to reject H_0**
ARI	4	11	1.282	**-0.905**	**Fail to reject H_0**
CADIZ	7	11	1.282	**0.905**	**Fail to reject H_0**
DIDATA	6	11	1.282	**0.302**	**Fail to reject H_0**
HARMONY	6	11	1.282	**0.302**	**Fail to reject H_0**
MUSTEK	6	11	1.282	**0.302**	**Fail to reject H_0**
PERGRIN	7	11	1.282	**0.905**	**Fail to reject H_0**
RICHEMONT	4	11	1.282	**-0.905**	**Fail to reject H_0**
SAPPI	7	11	1.282	**0.905**	**Fail to reject H_0**

In all cases the null hypothesis (that there was no significant difference between the performance of the shares and the JSE all-share index) could not be rejected. In other words, none of the sets of four-day movements of the shares in the daily hedge portfolio significantly outperformed those of the JSE all-share index during the evaluation period.

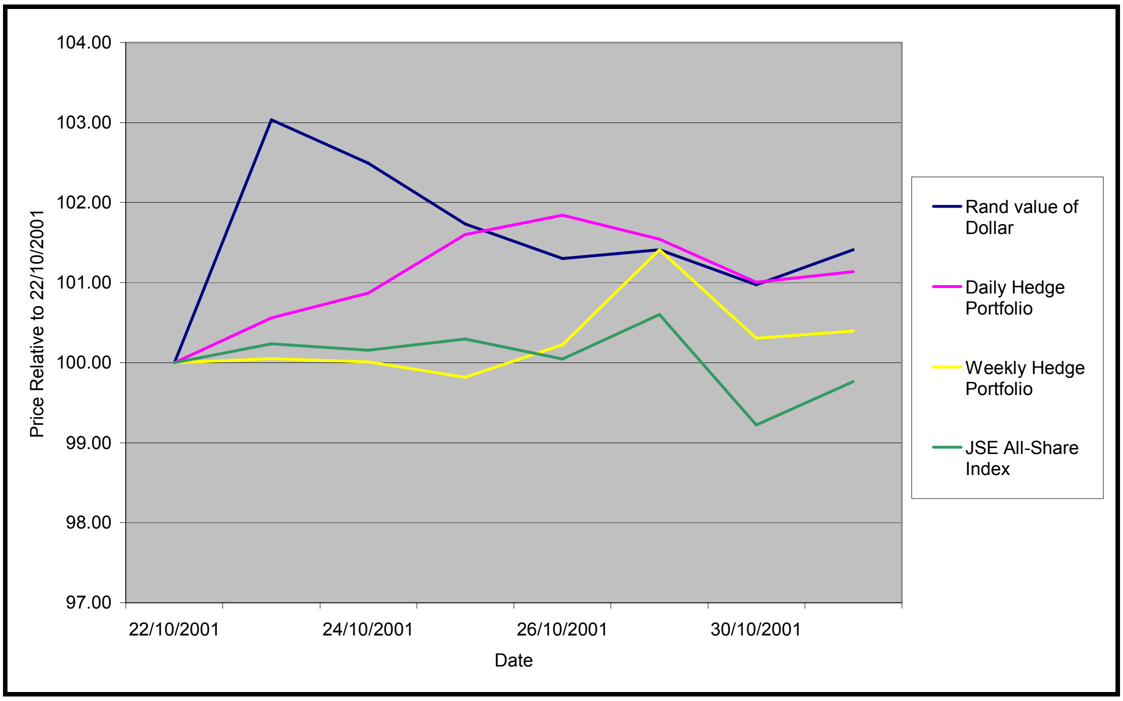
6.3 Evaluation of Short-Term Performance of Potential Hedge Portfolios

Since the methodology applied for identifying the hedge stocks used short-term (daily and weekly) metrics, the performance of the potential hedge portfolios was also evaluated over short-term periods of rand devaluation. In order to determine whether the selected portfolios would perform as short-term hedges in periods during and directly after sudden currency devaluations, their performance was graphically evaluated over the periods 22 to 31 October 2001 and 29 November to 6 December 2001. Both of these periods commence with a sudden devaluation of the rand from one day to the next, as indicated in **Figure 3** on page 26.

6.3.1 Portfolio Performance between 22 and 31 October 2001

The performance of the selected hedging portfolios after the first period of short-term devaluation of 22 to 23 October is displayed in **Figure 10**.

Figure 10 – Performance of Potential Hedge Portfolios between 22 and 31 October 2001



The initial devaluation of the rand can clearly be seen in the initial sharp increase in the rand value of the dollar on the left of the graph, with a somewhat slower decrease thereafter. The ALSI remains relatively constant during the period with an increase and subsequent decrease in value starting on 26 October which echoes the earlier movement of the exchange rate.

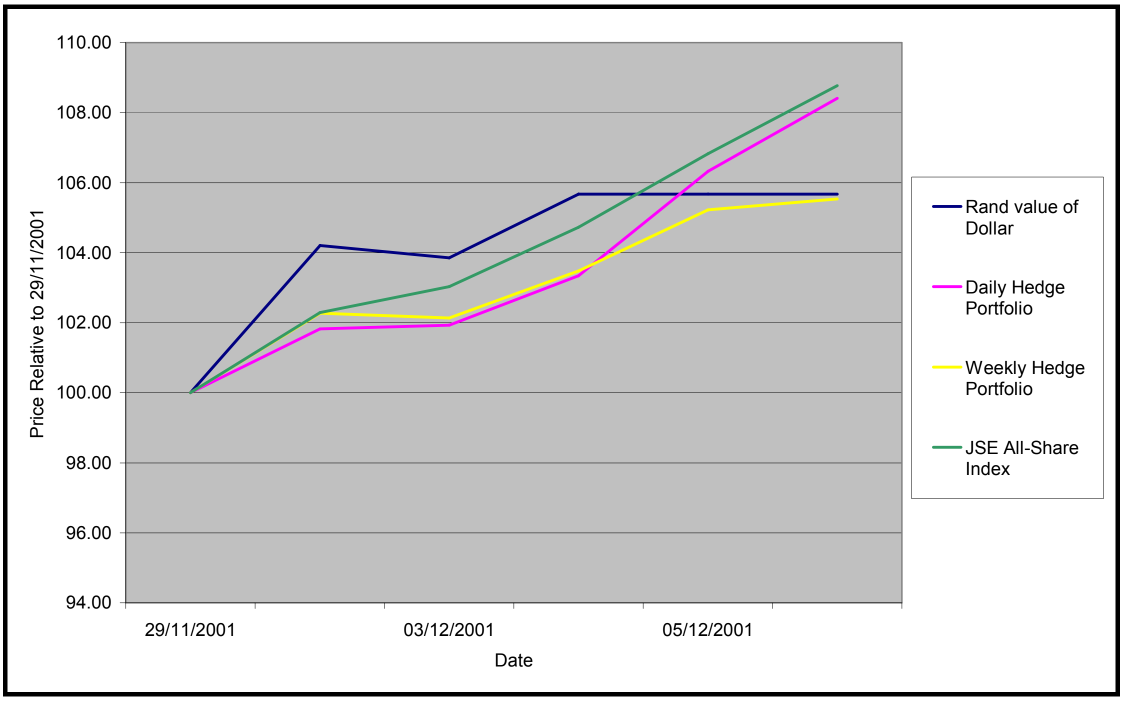
The daily hedge portfolio, in contrast, shows a strong increase corresponding to the dollar's strengthening, reaching a peak of 1.84% above its 22 October value on 26 October, and then following the weakening of the dollar, decreases again from 29 to 30 October. The weekly hedge portfolio shows a later increase, starting on 26 October, reaching a peak growth of 1.41% which matches the relative value of the dollar on 29 October, before dropping back below the dollar's value thereafter.

In this example, the daily hedge portfolio appears to follow movements of the rand with a lag corresponding to the 2-day significant lagged correlation, with the weekly hedge portfolio and the ALSI appearing to follow the movements of the rand some two days later.

6.3.2 Portfolio Performance between 29 November and 6 December 2001

Figure 11 shows the performance of the hedge portfolios during and after the sudden depreciation of the rand from 29 to 30 November.

Figure 11 – Performance of Potential Hedge Portfolios between 29 November and 6 December 2001



In this case the ALSI outperforms both the potential hedge portfolios, with an overall growth of 8.6%, which is also greater than the 5.7% increase of the rand value of the dollar over the period 29 November to 6 December.

The daily hedge portfolio grew by 8.4% by 6 December, which is fractionally less than the 8.6% growth of the ALSI but still greater than the 5.7% strengthening of the dollar, and the 5.5% growth of the weekly hedge portfolio. Both potential hedge portfolios, despite lower performance than the ALSI, nonetheless show movements which follow the exchange rate. In this case, the portfolios move concurrently with the exchange rate: increasing and decreasing on the same day as the exchange rate does.

6.4 Identification and Evaluation of Potential Anti-Hedging Portfolios

A second set of portfolios was constructed from shares exhibiting positive relationships with the strength of the rand during the identification stage of the research methodology. These portfolios were evaluated for their performance as anti-hedge shares. Investors hedge via anti-hedge shares by selling short before an anticipated drop in the rand's value, and then purchasing the shares back once the currency, and thus the shares, have decreased in value.

6.4.1 Identification of Potential Anti-Hedging Portfolios

The identification of the potential anti-hedging portfolios was performed in the same way as for the potential hedging portfolios, except that only shares whose ARIMA residuals displayed significant negative cross-correlation coefficients with the ARIMA residuals of the exchange rate were chosen. These negative correlation coefficients indicate that the shares increase and decrease in concert with the value of the rand, and thus would potentially behave as anti-hedge stocks. Shares which had been selected for the potential hedge portfolios in Section 6.1 were excluded from the selection.

The cross-correlations of the selected daily and weekly potential anti-hedge stocks are presented in **Table 8** and **Table 9**. The two portfolios will hereafter be referred to as the 'daily anti-hedge portfolio' and the 'weekly anti-hedge portfolio'.

Table 8 – Potential Daily Anti-Rand-Hedge Stocks

Lag	-5	-4	-3	-2	-1	0
ADCORP	-0.0444	-0.0243	-0.0181	-0.1103	0.0040	***-0.1297***
CAPTALL	0.0418	0.0455	-0.0109	-0.0246	***-0.1933***	0.0833
ELLERINE	-0.1002	-0.0242	0.1224	0.0582	-0.0694	***-0.1424***
FRONTRNGE	-0.0005	-0.0174	0.0605	-0.0537	0.0515	***-0.1273***
MARTPROP	-0.1217	-0.0567	***-0.1608***	0.0108	0.0734	-0.0752
MERCANTIL	0.0428	***-0.1303***	0.0535	-0.0679	0.0567	-0.0301
PIKWIK	-0.0671	-0.0441	-0.0365	-0.0975	0.0953	***-0.2092***
PRISM	0.0223	0.0000	-0.0035	0.0161	-0.0921	***-0.1351***
SAB	0.0170	0.0016	0.0198	-0.0584	0.0262	***-0.1445***
STANBANK	0.0892	0.0558	-0.0390	-0.0850	***-0.1439***	-0.0968
VENFIN	-0.0169	-0.0323	-0.0638	-0.0093	***-0.1292***	-0.0337

The significant negative cross-correlations identified using daily data shown in **Table 8** display more of a pattern than was observed with in the positive correlation coefficients. As shown in **Figure 12**, the majority of significant values lie at lag 0 and lag 1, with single observations at lag -3 and lag -4. The existence of such a pattern in the observations suggests consistent underlying market behaviour which rapidly (within two days of currency movements) adjusts the value of anti-hedging shares in response to changes in the exchange rate.

Figure 12 - Distribution of Significant Negative Cross-Correlations from Daily Data

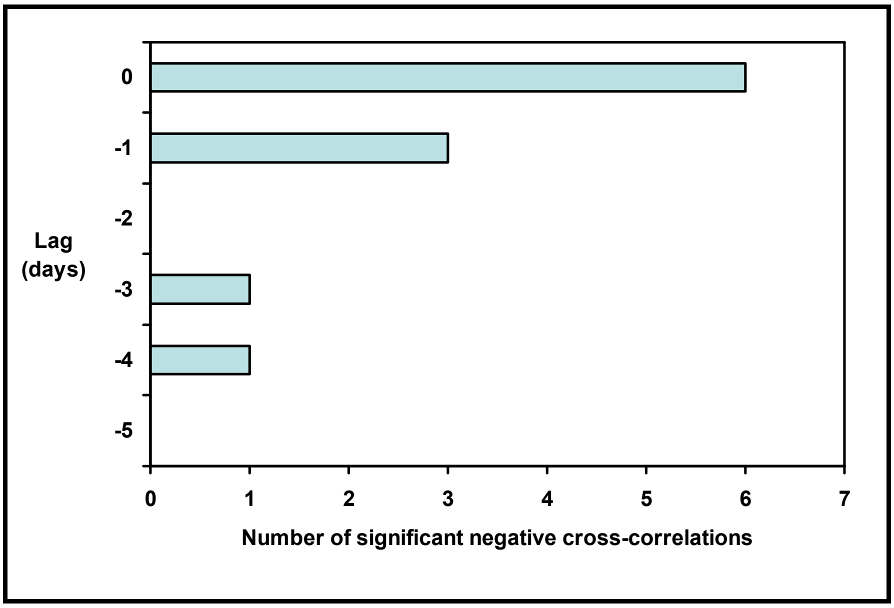
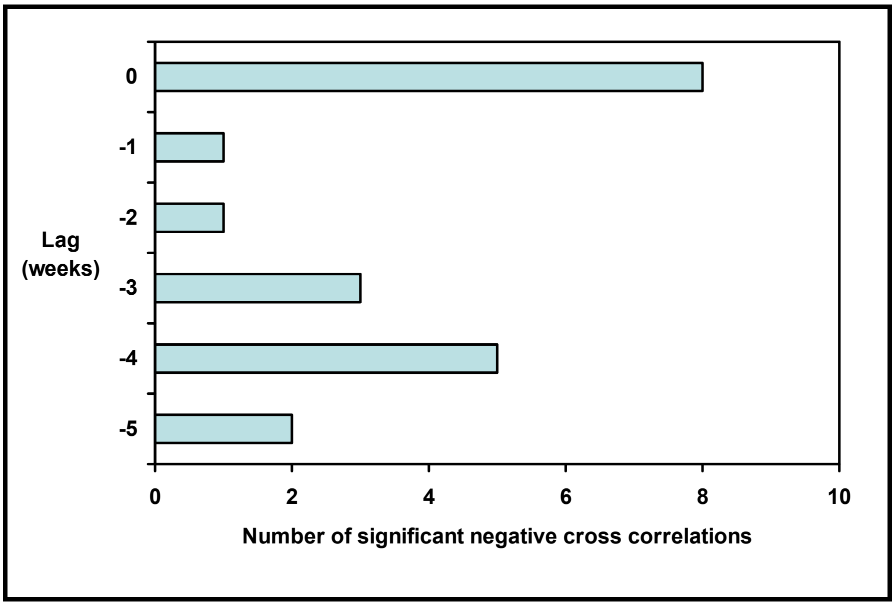


Table 9 – Potential Weekly Anti-Rand-Hedge Stocks

Lag	-5	-4	-3	-2	-1	0
ABIL	-0.2105	***-0.3027***	0.0462	0.1367	-0.0881	***-0.3359***
BIDVEST	***-0.4285***	0.0163	0.0055	0.1933	***-0.4188***	0.1776
CONNECT	-0.0472	***-0.2940***	-0.0943	0.0753	0.0343	-0.0306
DATATEC	0.0903	-0.2242	-0.0251	0.0752	0.2362	**-0.3098**
DAWN	-0.2567	***-0.2999***	-0.0037	-0.0071	0.0044	-0.0991
ERM	-0.2225	0.0245	0.0039	0.0533	0.1335	***-0.3048***
GFIELDS	-0.1714	-0.0615	***-0.2734***	0.0276	-0.0322	***-0.3774***
LIB-HOLD	0.0166	0.0510	-0.0510	***-0.2847***	0.0283	-0.1070
MR_PRICE	-0.1793	-0.1024	***-0.3999***	0.1818	-0.0210	0.0725
NASPERS	-0.1692	***-0.2993***	0.1245	0.1359	0.0173	-0.1809
NETCARE	0.1996	***-0.3716***	-0.1708	-0.0827	0.1710	-0.0809
PSG	-0.0667	-0.1323	0.1946	0.0041	0.0032	***-0.3548***
RAINBOW	-0.1312	-0.1267	0.1745	0.0120	0.0468	***-0.4181***
REUNERT	-0.0480	0.0428	***-0.2822***	0.1603	0.0864	-0.0288
SANLAM	***-0.2845***	-0.0917	-0.0545	0.0447	0.1541	-0.1387
TRUWRTHS	-0.1349	0.0758	0.0915	0.0260	-0.0964	***-0.2747***
WBHO	-0.2579	0.0495	0.1394	0.0709	-0.1403	***-0.3144***

The distribution of significant negative coefficients for weekly data shown in **Figure 13** once again shows a concentration of values at lag 0, indicating, as before, rapid market reactions to exchange rate movements. However, the reason for a second grouping of values around lag -4 (one month after movements of the currency) is less clear. Further research would be required to determine the reasons for this behaviour.

Figure 13 - Distribution of Significant Negative Cross-Correlations from Weekly Data

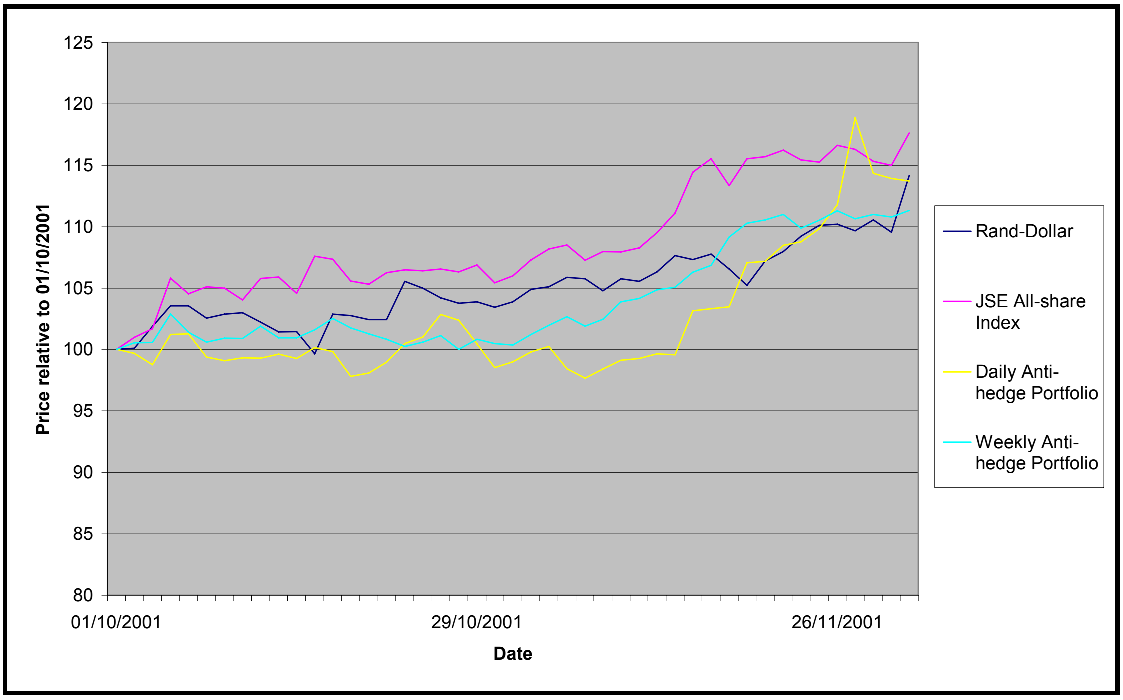


The analysis in this case aims to test whether the potential anti-hedge portfolios significantly under-perform the ALSI over the period of the rand's crash. First, the graphical performance of the portfolios is evaluated, and then statistical tests are used to identify the significance of the results.

6.4.2 Graphical Evaluation of Potential Anti-Hedge Portfolios

The graphical performance of the anti-hedge portfolios in relation to the exchange rate and the ALSI is presented in **Figure 14**.

Figure 14 - Performance of Anti-Hedging Portfolios vs. Rand/Dollar Exchange Rate



The performance of both the daily and weekly anti-hedge portfolios is visibly worse than that of the ALSI over the majority of the evaluation period, with the performance of the daily anti-hedge portfolio being below that of the weekly anti-hedge portfolio for all but two short periods. The daily anti-hedge portfolio shows considerably more variability than the weekly anti-hedge portfolio which echoes movements in the ALSI, albeit at a lower value. The statistical tests of the next section will determine whether either of these portfolios significantly under-performed the ALSI.

6.4.3 Statistical Evaluation of Potential Anti-Hedge Portfolios

The same statistical tests that were performed on the potential hedge portfolios were applied to the potential anti-hedge portfolios. These comprised normal-based confidence interval analysis, the Sign Test, and the Wilcoxon Signed-rank Test. The results of these analyses are presented and discussed below.

Confidence Interval Analysis

Table 10 presents 95% confidence intervals for the performance of the potential anti-hedge portfolios over the period of the rand's crash.

Table 10 –Confidence Interval Analysis of Potential Anti-Hedge Portfolios

Statistic	Daily anti-hedge portfolio	Weekly anti-hedge portfolio
Mean % change	13.7%	11.3%
Standard Deviation % change	52.7%	17.8%
n (portfolio size)	12	17
2-sided t-statistic (n-1, α = 0.05)	2.201	2.120
Lower Confidence Interval of Mean	-102.3%	-26.4%
Upper Confidence Interval of Mean	129.7%	49.1%
% Change of ALSI	17.6%	17.6%

The low performance of the daily and weekly anti-hedging portfolios is visible in the mean percentage change figures, which at 13.7% and 11.3% respectively are considerably lower than the 17.6% increase in the ALSI. The large values for the standard deviation of the percentage change figures result from the large variation in performance between the shares in both portfolios as can be seen in **Figure 24** and **Figure 25** of Appendix B. The confidence intervals for the mean percentage change of both the daily [-102.3%, 129.7%] and the weekly [-26.4%; 49.1%] anti-hedge portfolios are wide, and in both cases include the value of the percentage change of the ALSI. As was the case for the potential hedge portfolios, this metric indicates no significant difference in performance between the potential anti-hedging portfolios and the ALSI.

Sign Test

The evaluation of the potential anti-rand hedge portfolios was tested with the following hypothesis test, the inverse of the one presented in Section 3.2:

> ***H_0***: The performance of the selected anti-hedging portfolio is not different from that of the ALSI during a period of depreciation of the rand.
>
> ***H_A***: The performance of the selected hedging portfolio is worse than that of the ALSI during a period of depreciation of the rand.

The hypothesis test is expressed statistically as follows:

H_0: $median(X_i) = 0$

H_A: $median(X_i) < 0$

The formulation of X_i is presented in Section 5.3.2. Details of the calculations for the daily and weekly anti-hedge portfolios are presented in **Table 24** of Appendix A.

The results of the Sign Test analysis are presented in **Table 11**. For the purposes of evaluating the null hypothesis, a one-sided critical value from the normal distribution with a significance level of α = 5% was used.

Table 11 – Sign Test Results for Potential Anti-Hedge Portfolios

Statistic	Daily Anti-hedge Portfolio	Weekly Anti-hedge Portfolio
m (number of values > 0)	20	17
N	44	44
Critical value (α=0.05)	-1.645	-1.645
Critical value (α=0.1)	-1.282	-1.282
Z	-0.603	-1.508
Decision	**Fail to reject H_0**	**Reject H_0 at α=0.1 level**

The Z-value for the daily anti-hedge portfolio lies within the critical values at both α=5% and α=10%, meaning that the null hypothesis can not be rejected. In this case the graphical analysis of the performance of the daily anti-hedge portfolio showing under-performance relative to the ALSI is not confirmed by the Sign Test.

However, for the weekly anti-hedge portfolio, the value of Z lies outside the critical value at the α=10% level, allowing the null hypothesis to be rejected. This confirms the graphical interpretation indicating that the ALSI performed significantly better than the weekly anti-hedge portfolios during the period of the rand's crash.

Wilcoxon Signed-Rank Test

The Wilcoxon Signed-Rank Test was performed to test the same null hypothesis presented above. The results of the test are given in **Table 12**.

Table 12 – Wilcoxon Signed-Rank Test Results for Potential Anti-Hedge Portfolios

Portfolio	Alternative Hypothesis	P-value	Decision
Daily	Median<0	0.280	**Fail to reject H_0 at α=0.05 and 0.1 level**
Weekly	Median<0	0.117	**Fail to reject H_0 at α=0.05 and 0.1 level**

The p-values of 0.280 and 0.117 for the daily and weekly hedge portfolios respectively are considerably larger than 0.1, indicating that in both cases the null hypothesis can not be rejected at either the 5% or 10% levels. According to this metric there is thus no significant statistical evidence that the performance of either of the potential anti-hedge portfolios was worse than that of the ALSI over the period of the rand's crash.

6.5 Analysis of Known Rand Hedge Stocks

In order to obtain a better understanding of the underlying behaviour of effective rand-hedge stocks, a portfolio of the generally acknowledged rand-hedge stocks presented in Section 2.4.1 was analysed using similar techniques to those used for the identification and evaluation of the potential hedge portfolios.

6.5.1 Cross-Correlation Analysis

First, the cross-correlations between the residuals of ARIMA models fitted to the stocks during the identification period and those of the rand/dollar exchange rate were calculated and significant values identified. The cross-correlations using daily and weekly data are presented in **Table 13** and **Table 14** with significant values displayed in bold. In this case correlation coefficients at negative and zero lags are presented as before, as well as coefficients at positive lags which indicate share price movements preceding movements in the currency. As discussed in Section 6.1, the existence of spuriously significant results (type I errors) can be expected when performing a large number of statistical tests, as is the case here. However, as discussed before, the significance level of the results is only used to determine the strength of the correlations with exchange rate movements, and not to perform hypothesis testing. Hence the existence of spuriously significant results in this step does not invalidate the methodology.

Table 13 – Daily Cross-Correlation Analysis of Known Hedge Stocks

Lag	-4	-3	-2	-1	0	1	2	3
ANGLOPLAT	0.0661	-0.0121	0.0212	-0.0656	-0.0369	-0.0141	-0.0344	-0.0215
BHPBILL	-0.0220	-0.0488	-0.0552	0.0116	-0.0381	-0.0058	0.0013	0.0937
GFIELDS	0.0812	-0.0260	0.0867	-0.0058	0.0063	***-0.1887***	-0.0245	0.0053
HARMONY	0.0511	-0.0017	**0.1494**	-0.0083	-0.0416	***-0.2090***	-0.0756	0.0416
NASPERS	-0.0569	-0.0400	0.1066	-0.0739	-0.0011	***-0.1519***	-0.0194	-0.0376
SAPPI	-0.0095	0.0501	**0.1314**	***-0.1465***	-0.0721	-0.0222	-0.0621	0.0313
STEINHOFF	-0.0519	-0.0041	0.0143	-0.0033	0.1128	0.0495	-0.0901	-0.1075

Table 14 – Weekly Cross-Correlation Analysis of Known Hedge Stocks

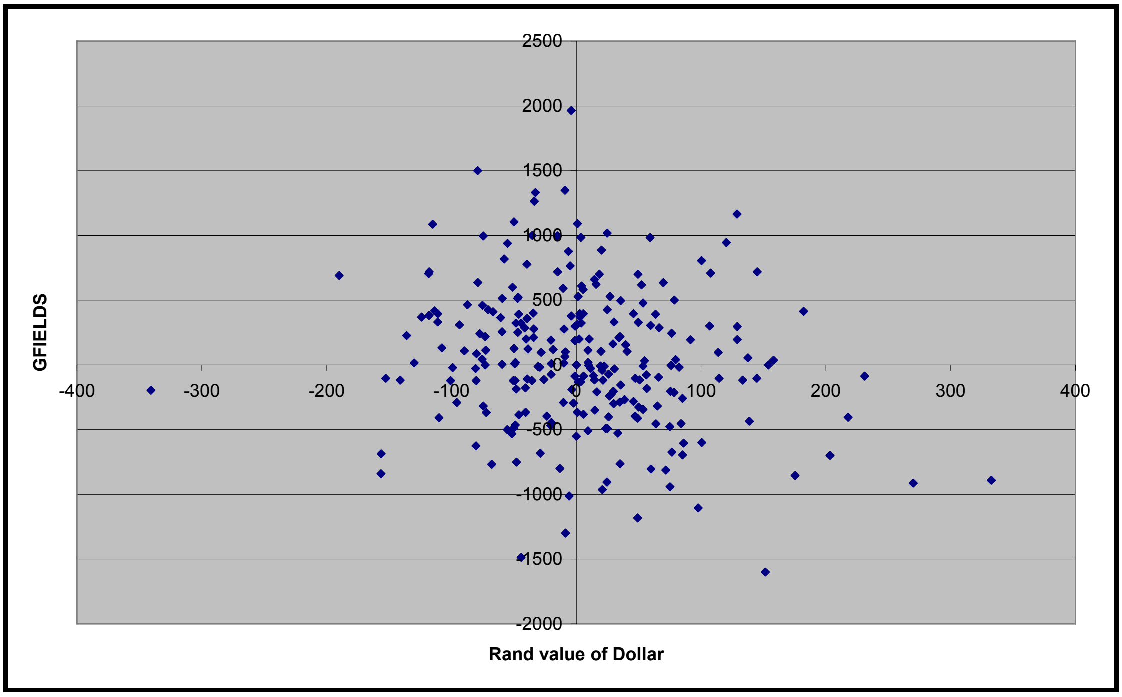
Lag	-4	-3	-2	-1	0	1	2	3
ANGLOPLAT	-0.0058	0.2369	0.2327	-0.1392	-0.1265	-0.0483	0.1384	-0.1709
BHPBILL	-0.1000	**0.2622**	-0.1010	-0.0614	-0.1154	0.0543	-0.0523	-0.0582
GFIELDS	0.0245	0.0039	0.0533	0.1335	***-0.3048***	-0.1236	-0.1570	0.1202
HARMONY	-0.0615	***-0.2734***	0.0276	-0.0322	***-0.3774***	-0.0951	0.0013	**0.2732**
NASPERS	***-0.2993***	0.1245	0.1359	0.0173	-0.1809	0.0149	0.1394	-0.0231
SAPPI	-0.1329	0.1585	-0.0040	0.0057	-0.2288	-0.2503	0.1306	-0.0092
STEINHOFF	-0.0165	0.1058	-0.1107	-0.0702	-0.0712	-0.0165	0.2475	***-0.3100***

It should be noted that there is no clear pattern to the significant cross-correlations either with the daily or the weekly data. In fact, in the daily data shown in **Table 13**, only two of the shares, namely Harmony and Sappi, show the significant positive correlations with the strength of the dollar (in that they strengthen when the rand weakens) that would be expected of rand-hedge shares. In both cases this significant correlation is at lag -2: that is, following movements in the rand by 2 trading days.

In addition, both of these shares display significant negative correlations with the strength of the dollar (in that they weaken when the rand weakens). In the case of Harmony, this negative correlation is at lag 1, indicating that the share weakens one day in advance of the weakening of the rand. Sappi, on the other hand, shows a negative correlation at lag -1, indicating that the share tends to weaken one day after a weakening of the rand, and then strengthen the following day. Despite this combination of positive and negative correlations at different lags both shares are generally considered as effective rand hedge shares.

Two shares in **Table 13**, Goldfields and Naspers, show significant negative correlations with the exchange rate at lag 1, without displaying significant positive correlation coefficients at any lag. The weak negative relationship between the residuals of Goldfields and the exchange rate can be seen in the trend from top left to bottom right in the scatter plot of **Figure 15.**

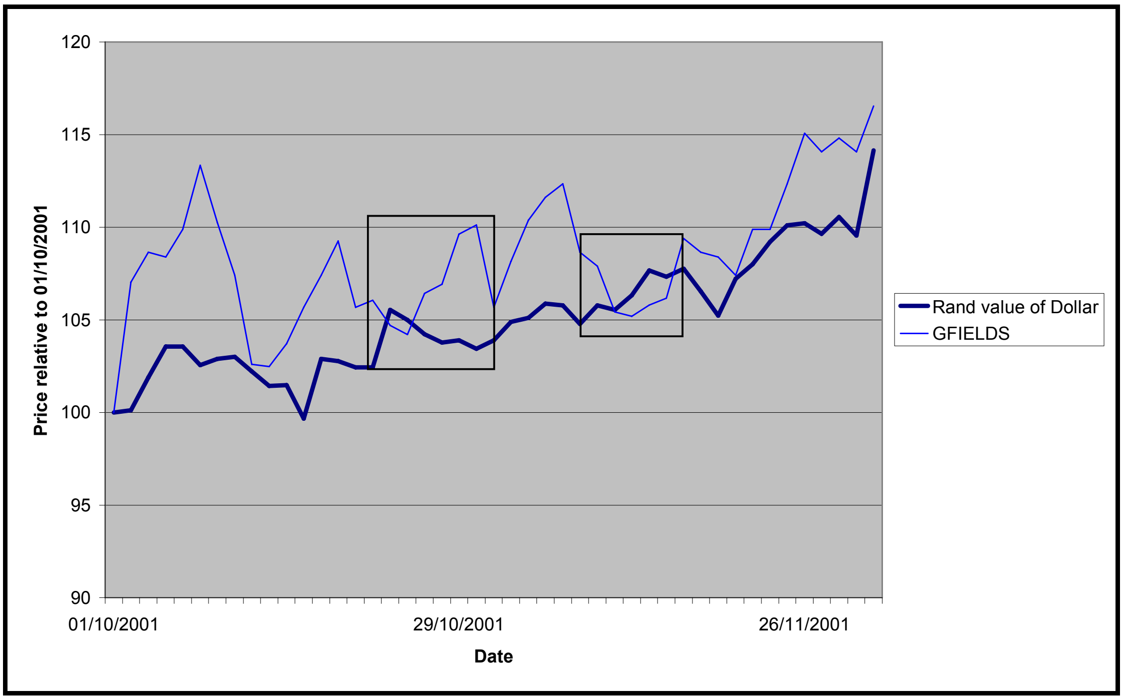
Figure 15 - Plot of ARIMA residuals of Goldfields and Rand/Dollar Exchange Rate at Lag 1 over Identification Period



Both Goldfields and Naspers also display significant negative correlations with the exchange rate for weekly data, at lag 0 and lag -4 respectively. Although such negative correlations would tend to prevent the shares from acting in a rand-hedging fashion in the short term, long term hedging behaviour is still possible, as the performance of Goldfields over the period of the rand's crash demonstrates. In contrast, Naspers underperformed the ALSI over the entire period of the rand's crash.

Figure 16 shows the performance of Goldfields relative to the rand/dollar exchange rate. Despite its negative correlations with the exchange rate discussed above, the overall long-term trend of the share tracks the trend of the exchange rate.

Figure 16 – Performance of Goldfields and Rand/Dollar Exchange Rate over Period of Rand's Crash



The share's negative short term relationship with the strength of the dollar (in that the share weakens in conjunction with the rand) can be seen in **Figure 16**. Increases and decreases in the rand value of the dollar are freqently accompanied by opposite movements in the share price, as highlighted in the rectangular areas. However, the overall movement of the share price and exchange rate follow a similar long term trend, as is confirmed by the plot of daily percentage change values shown in **Figure 17**, and by the associated 0.132 correlation coefficient. In effect, the long-term trend of the share 'overwhelms' the short-term anti-hedging behaviour of the share. In this example Goldfields performs as an anti-hedge in the short term, but a hedge in the long term.

Figure 17 – Plot of Daily Percentage Change Values for Goldfields and Rand/Dollar Exchange Rate over Period of Rand's Crash

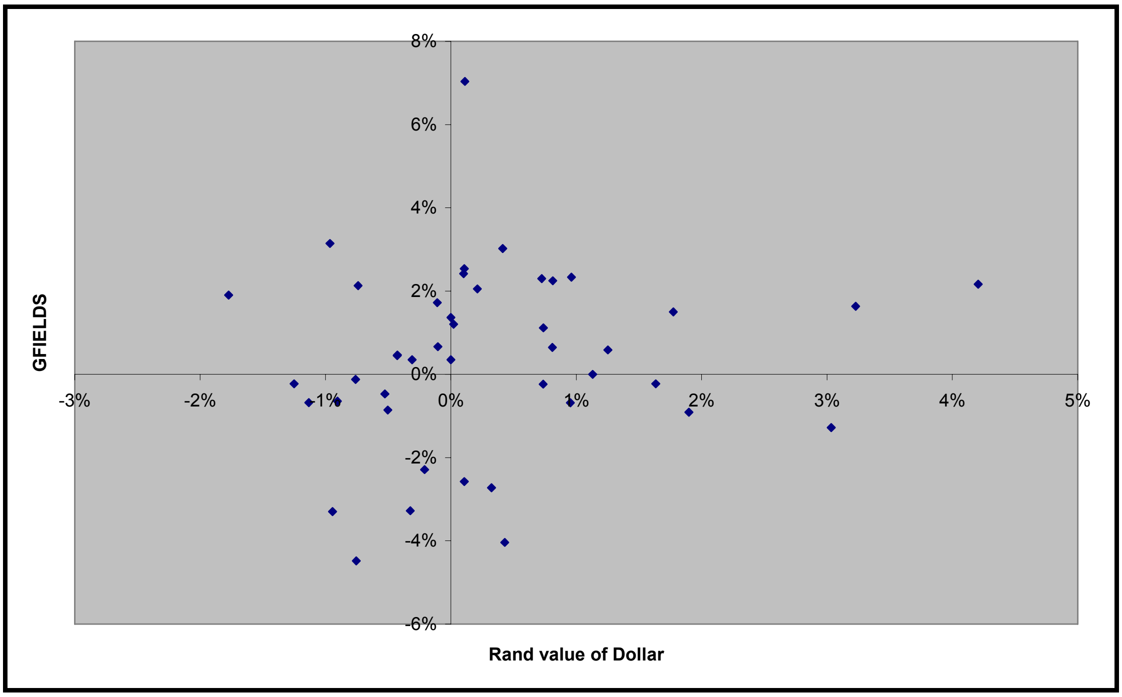


Table 15 – Correlation Coefficient of Goldfields and Rand/Dollar Exchange Rate over Period of Rand's Crash

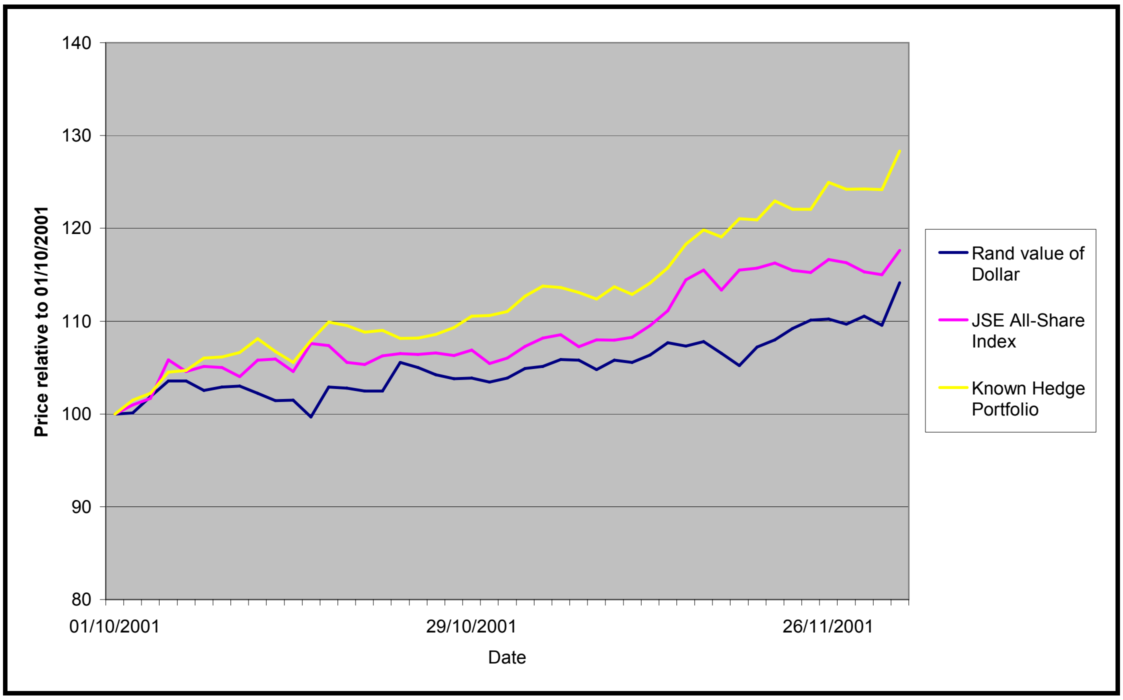
Statistic	Value
X	Rand value of Dollar daily percentage change
Y	Goldfields daily percentage change
Correl(X,Y)	**0.132**

Analysis of the cross-correlation results for the weekly data presented in **Table 14** once again does not identify any clear patterns, and a number of significant negative correlation coefficients are again present. In the case of Goldfields and Harmony, there are significant negative coefficients at lag 0, indicating that these shares have a negative relationship with the rand value of the dollar during the same week as movements of the exchange rate. These shares would be expected to weaken and strengthen in tandem with the rand. However, as shown in **Figure 23**, Harmony and Goldfields are two of the best-performing hedge stocks during the period of the rand's crash. As discussed above, it appears that long-term hedging ability is not necessarily prevented by short term negative relationships with the rand value of the dollar.

6.5.2 *Graphical Evaluation of Known Hedge Portfolio*

The performance of the individual shares in the known hedge portfolio is shown in **Figure 23** of Appendix B. Most of the shares closely match or outperform the rand value of the dollar, except Naspers which loses 25.8% value over the period under investigation. **Figure 18** shows a comparison of the performances of the portfolio of known hedge stocks, the rand value of the dollar, and the ALSI.

Figure 18 – Performance of Known Hedge Portfolio against Rand/Dollar Exchange Rate and ALSI during Period of Rand's Crash



The known hedge portfolio consistently outperforms both the ALSI and the rand value of the dollar throughout the evaluation period. At the end of the period the known hedge portfolio had grown by 28.3%, considerably more than the 17.6% growth of the ALSI and even more so than the 14.2% growth of the exchange rate over the same period. The statistical significance of these observations is evaluated in the following sections.

6.5.3 *Statistical Evaluation of Known Hedge Portfolio*

The portfolio of known hedge stocks was subjected to the same battery of statistical tests that was performed on the potential hedge portfolios, namely: Confidence

Interval Analysis, the Sign Test, and the Wilcoxon Signed-rank Test. The results of these tests are discussed in the following sections.

Confidence Interval Analysis

The results of Confidence Interval Analysis are presented in **Table 16**. The standard deviation of the percentage change during the period of the rand's crash is relatively large, as was the case for the potential hedge portfolios. As a result, the 95 percent confidence interval is wide and clearly includes the percentage increase of the ALSI. As a result, no significant difference in performance between the known hedge portfolio and the ALSI can be claimed by this metric.

Table 16 – Confidence Interval Analysis for Known Rand Hedge Portfolio

Statistic	Value
Mean % change	28.3%
Standard Deviation % change	13.7%
Portfolio size (n)	7
2-sided t-statistic (n-1, α = 0.05)	2.36
Lower Confidence Interval	-4.1%
Upper Confidence Interval	60.7%
% Change of ALSI	17.6%

Sign Test

The performance of the known rand hedge portfolio was tested with the same hypothesis test used for the potential hedge portfolios, as described in Section 6.2.2:

> ***H₀***: The performance of the selected hedging portfolio is not different from that of the ALSI during a period of depreciation of the rand.
>
> ***H_A***: The performance of the selected hedging portfolio is better than that of the ALSI during a period of depreciation of the rand.

The hypothesis test is expressed statistically as follows:

$\boldsymbol{H_0}$: $median(X_i) = 0$

$\boldsymbol{H_A}$: $median(X_i) > 0$

The formulation of X_i is presented in Section 5.3.2. Details of the calculations for the daily and weekly hedge portfolios are presented in **Table 24** of Appendix A. The theoretical background of the Sign Test is presented in Section 4.4

The results of the Sign Test analysis are presented in **Table 17**. For the purposes of evaluating the null hypothesis, a one-sided critical value from the normal distribution with a significance level of α = 5% was used.

Table 17 - Sign Test Results for Known Hedge Portfolio

Statistic	Value
m (number of values > 0)	6
n	8
Critical value (α=0.05)	1.645
Critical value (α=0.1)	1.282
Z	1.507
Decision (10%)	**Reject H_0 at α=0.1 level**

In this case, the calculated Z-value of 1.507 lies below the critical value of 1.645 at the α=5% level, but above the critical value of 1.282 at the α=10% level. Thus the null hypothesis can not be rejected at the 5% level, but can be rejected at the 10% level. As a result, it can be concluded that the performance of the known hedge portfolio was better than that of the ALSI during the rand's crash at a significance level of 10%.

Wilcoxon Signed-Rank Test

The results of the application of the Wilcoxon Signed-rank Test are presented in **Table 18**.

Table 18 - Wilcoxon Signed-Rank Test Results for Known Hedge Portfolio

Alternative Hypothesis	P-value	Decision
Median>0	0.076	**Reject H_0 at α=0.1 level**

The p-value of 0.076 is greater than 0.05 but less than 0.1, indicating that the null hypothesis can not be rejected at the 5% level, but can be rejected at the 10% level. Thus the Wilcoxon Signed-rank Test confirms the result of the Sign Test. These results indicate that the known hedge portfolio significantly outperformed the ALSI during the period of the rand's crash.

7 Interpretation of Results

The results obtained from the application of the research method are interpreted below. In all cases, references to the exchange rate refer to the rand value of the dollar.

It should be noted that in all cases where significant results were found, these results were observed at the 10% significance level (as opposed to the more noteworthy 5% level), indicating only weak evidence of true relationships between the variables.

7.1 Interpretation of Analyses of Potential Hedge Portfolios

Analysis of the potential hedge portfolios found evidence of significant hedging performance in the daily hedge portfolio, but not in the weekly potential hedge portfolio.

Visual analysis of the performance of the daily hedge portfolio plotted against the rand value of the dollar, indicating that the portfolio had significantly outperformed the ALSI during the period of the rand’s crash, was confirmed by statistical analysis. The Sign Test found that at a significance level of 10% the daily hedge portfolio outperformed the ALSI. (It should, however, be mentioned that the Wilcoxon Signed-Rank test did not find a significant difference in performance between the daily hedge portfolio and the ALSI).

Analysis of performance of the daily hedge portfolio immediately after sudden short-term devaluations of the rand showed some graphical evidence of rand-hedge behaviour, although this was not always the case.

In contrast with the findings for the daily hedge portfolio, statistical analyses found that the weekly hedge portfolio failed to perform significantly better than the ALSI. In addition, graphical analyses indicated that the weekly hedge portfolio underperformed both the daily hedge portfolio and the ALSI during long- and short-term periods of depreciation of the rand.

These results indicate that the existence of historical short-term (i.e. daily) positive relationships between share price and exchange rate time series is a predictor for long term hedging performance. Conversely, the existence of longer term (i.e. weekly) positive relationships with the rand does not result in hedging behaviour in either the short or the long term.

7.2 Interpretation of Analyses of Potential Anti-hedge Portfolios

Analysis of the potential anti-hedge portfolios found significant anti-hedging behaviour in the weekly anti-hedge portfolio, but not in the daily anti-hedge portfolio.

Graphical analysis of the potential anti-hedge portfolios in both cases suggested potentially significant underperformance against the ALSI during the period of the rand's crash. Statistical testing identified significant underperformance against the ALSI (at the 10% level) in the weekly anti-hedge portfolio, but detected no significant difference in performance of the daily anti-hedge portfolio against that of the ALSI. This lack of anti-hedging behaviour in the daily anti-hedge portfolio was confirmed by the confidence interval analysis which found that the daily anti-hedge portfolio was considerably more variable than the weekly anti-hedge portfolio over the period of the rand's crash.

These results indicate that that weekly negative relationships with the exchange rate act as predictors of anti-hedging behaviour, whereas the existence of shorter term (i.e. daily) negative relationships with the exchange rate provide no significant prediction of anti-hedging behaviour.

7.3 Interpretation of Analyses of Known Hedge Stocks

Analysis of the performance of the known hedge stocks found significant hedging performance over the period of the rand's crash, and provided further insight into the conditions under which shares may behave as hedges.

The performance of the known hedge stocks confirmed the market sentiment of their hedging ability, significantly outperforming the ALSI over the period of the rand's crash in both graphical and statistical analyses at the 10% significance level.

In order to further understand the conditions under which shares may behave as hedges, additional analysis of the performance of individual known hedge stocks was carried out, and it was found that short-term positive relationships with the exchange rate are not a necessary condition for long-term hedging performance.

Analysis of the share price performance of Goldfields, an acknowledged rand hedge stock, over the period of the rand's crash in late 2001 indicated that long-term hedging ability is not necessarily prevented by short term negative (i.e. anti-hedging) relationships with the exchange rate. Application of the research method on the time series of this share resulted in only negative significant cross-correlations with the exchange rate, suggesting that the share should perform in an anti-hedging fashion. This anti-hedging behaviour was indeed found in graphical analysis of short-term movements of the share price during the period of the rand's crash. However, over the entire period of the rand's crash the Goldfields share price behaved in a clear hedging fashion, outperforming most other shares on the JSE. In this example the share's long-term trend 'overwhelmed' its short-term anti-hedging behaviour.

These results indicate that short-term positive relationships with the exchange rate can predict hedging behaviour, but that hedging behaviour may exist even in the presence of short-term negative relationships with the exchange rate.

8 Conclusions and Suggestions for Further Research

8.1 Conclusions

The objective of this research was to investigate whether removing the long-term trends in share price and exchange rate data could lead to the reliable identification of rand hedge stocks on the JSE. The underlying hypothesis was that by removing long-term trends in share-price time-series, the occurrence of spurious correlations between share price and exchange rate movements could be eliminated, thus facilitating the identification of shares possessing fundamental inverse relationships with short-term movements in the rand exchange rate.

To test this hypothesis, portfolios of shares exhibiting short-term positive and negative relationships with the exchange rate after the removal of long-term trends in their time series were identified, and the performance of these potential hedging portfolios were evaluated over a period of devaluation of the rand. In addition, a basket of generally accepted rand hedge shares was analysed by application of the research methodology in order to investigate the underlying reasons for the hedging ability of these shares.

Analysis of the potential hedge portfolios confirmed, under certain conditions, the efficacy of the research methodology. Shares displaying short-tem positive (hedging) relationships with the exchange rate were found to behave as hedges over a long-term devaluation of the rand, while shares with longer term negative (anti-hedging) relationships with the exchange rate behaved as anti-hedges.

Application of the research methodology to a basket of acknowledged rand hedge shares confirmed their ability to act as hedges using both graphical and statistical analyses. In addition, analysis of the characteristics of a selection of these shares revealed that hedging behaviour may exist even in the presence of short-term negative relationships with the exchange rate.

These results indicate that the methodology proposed in this research is effective in identifying the subset of hedge stocks which have underlying short-term positive (hedging) relationships with the exchange rate. However, there exist hedge stocks which do not exhibit this short-term positive relationship, and these will not be identified by the methodology.

A summary of the methodology developed in this research is presented below.

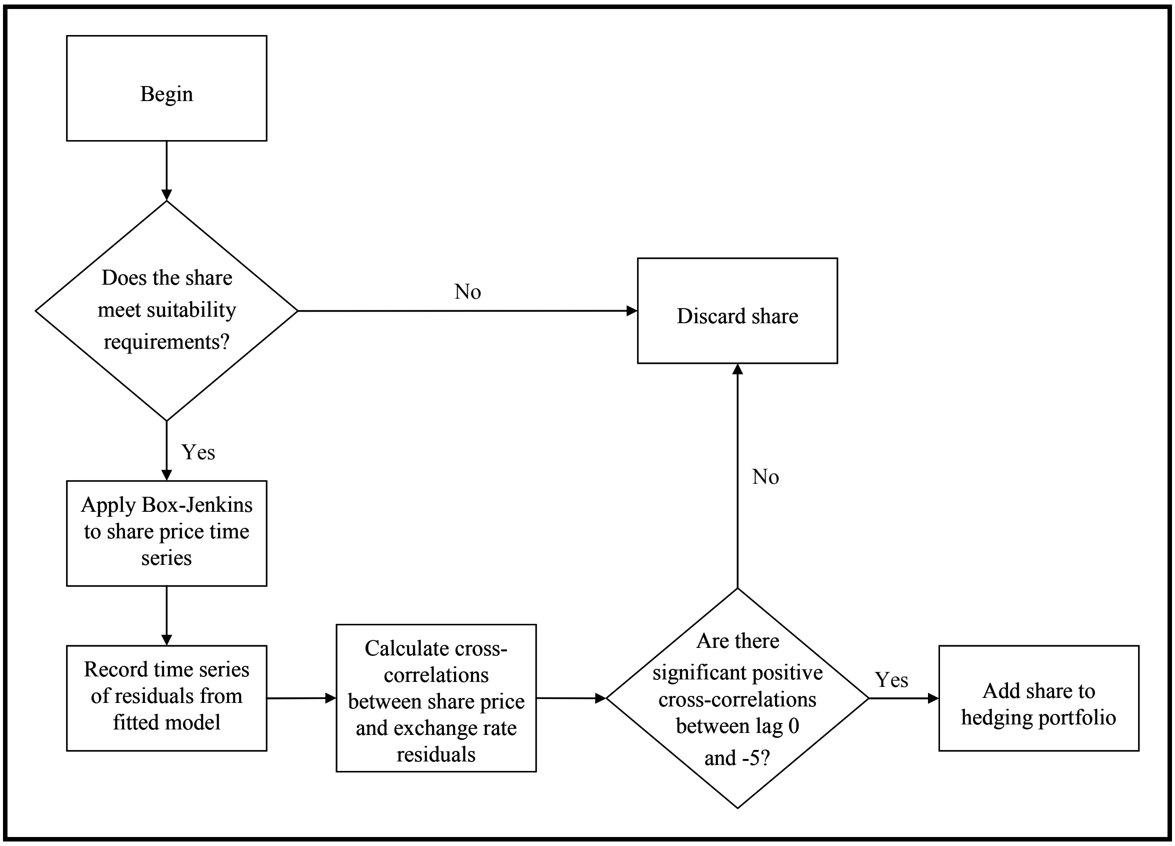
8.1.1 Summary of Research Methodology

The research methodology used to identify a portfolio of hedge stocks which have short-term positive relationships with the exchange rate is summarised as follows:

1. Obtain daily closing price time series for the rand/dollar exchange rate (rand value of the dollar) and shares listed on the JSE spanning the desired identification period.
2. Discard unsuitable shares (illiquid shares, shares with discontinuities in share price, and delisted shares).
3. Apply the Box-Jenkins methodology to the exchange rate and each of the share price time series, recording the residuals from the resulting fitted ARIMA models (refer to Appendix A for details on the application of the Box-Jenkins methodology).
4. Perform cross-correlation analysis between the ARIMA residuals of the exchange rate and the ARIMA residuals of each of the shares.
5. Select all shares displaying significant positive cross-correlation coefficients at zero or negative lags up to lag -5 (i.e. corresponding to share price movements at periods following movements in the exchange rate). These shares comprise the rand hedging portfolio.

The process of applying the research methodology to a single share listed on the JSE is illustrated by means of a flow diagram in **Figure 19**.

Figure 19 – Flow Diagram of Research Methodology Applied to a Single Share Listed on the JSE



A detailed description of the research methodology is presented in section 5.3.1.

8.2 Suggestions for Further Research

Future research should focus on three areas: firstly on investigating the underlying reasons for the relationships with the exchange rate observed in the hedging and anti-hedging portfolios, secondly on classifying the short-term relationships between share prices and various commodity values by using the research methodology to remove long-term trends in the time series, and thirdly on exploring the reasons for the patterns of cross-correlations identified during the research.

Suggested sub-problems and propositions for these areas of future research are presented in the following sections.

8.2.1 Investigation of the Reasons for Relationships between Shares and the Exchange Rate

The first sub-problem would be to determine the underlying reasons for the positive relationships with the exchange rate observed in the daily hedging portfolio. This sub-problem could be formulated as the following proposition:

> Shares displaying positive relationships with the exchange rate are characterised by significant foreign assets and/or earnings.

The second sub-problem would be to determine the underlying reasons for the negative relationships with the exchange rate observed in the weekly anti-hedging portfolio. This sub-problem could be formulated as a research proposition as follows:

> Shares displaying negative relationships with the exchange rate are characterised by high levels of exchange rate exposure due to significant foreign costs and/or rand earnings.

8.2.2 Classification of Relationships between Shares and Commodities

The set of sub-problems for this future area of research would be to classify, by application of the research methodology, the nature of the relationships between shares on the JSE and different commodities, including

- the Euro
- the gold price

- the oil price

These sub-problems could be formulated as a general proposition as follows:

> A share with significant dependence on a commodity will demonstrate significant short-term relationships between its share price and the value of the commodity.

8.2.3 Investigation of Patterns of Cross-Correlations

The sub-problems within this area of future research would be to investigate the reasons behind the patterns of cross-correlations observed during the application of the research methodology as described below:

1. Investigating the reasons for the rand-leading behaviour observed in certain shares, as discussed in Section 5.3.1.
2. Exploring the reasons behind the groupings of significant positive and negative cross-correlations at specific lags observed in during the research, and relating these groupings to the hedging performance of the corresponding shares (taking into account the possibility that these groupings of observations may themselves be due to type I errors). The investigation should cover:
    a. the grouping of significant positive correlations at lag -2 observed in the analysis of daily data shown in **Figure 7** of Section 6.1;
    b. the grouping of significant positive correlations at lag -3 observed in the analysis of weekly data shown in **Figure 8** of Section 6.1;
    c. the grouping of significant negative correlations at lag -4 observed in the analysis of weekly data shown in **Figure 13** of Section 6.4.1.
3. Investigating the reasons for some shares exhibiting large positive as well as negative cross-correlations at different daily lags, (as shown in **Figure 6** of Section 5.3.1 for Anglogold) and exploring the influence of these combinations on the shares' short- and long-term hedging performance, considering the possibility that the opposing cross-correlations may negate each others' influence when observing the shares' performance over longer periods.

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Appendix A – The Box-Jenkins Methodology

Autoregressive / Integrated / Moving Average (ARIMA) models were initially popularised by Box & Jenkins (1970), who comprehensively described the theory and methodology of the models, and whose names are now used synonymously with the models.

Chatfield (1989) describes the formulation of an ARIMA process by investigating each of its components. The salient points of Chatfield's formulation are presented below.

Define $\{Z_t\}$ as a purely random process with mean zero and variance σ^2_Z. Then time series $\{X_t\}$ is a moving average process of order q (abbreviated as MA(q)) if:

$$X_t = \beta_0 Z_t + \beta_1 Z_{t-1} + ... + \beta_q Z_{t-q}$$

where $\{\beta_i\}$ are constants. Similarly, time series $\{X_t\}$ is autoregressive process of order p (abbreviated as AR(p)) if:

$$X_t = \alpha_1 X_{t-1} + ... + \alpha_p X_{t-p} + Z_t$$

Similarities with the multiple regression formula are evident in the equation above, but in this case X_t is regressed on earlier values of X_t; hence the 'auto' prefix of the classification. Combining the two expressions above, a mixed autoregressive moving-average process or order (p,q) (abbreviated as ARMA(p,q)) can be denoted as:

$$X_t = \alpha_1 X_{t-1} + ... + \alpha_p X_{t-p} + Z_t + \beta_1 Z_{t-1} + ... + \beta_q Z_{t-q}$$

In order to account for non-stationarity in the mean of the time series, differencing is performed by replacing X_t with $\nabla^d X_t$ in the equation above. This model is called 'integrated' since in order to provide a model for the non-stationary data, the stationary model must be summed or 'integrated'. By defining the backward shift operator B such that:

$$BW_t = W_{t-1}$$

The series $\{W_t\}$ can be defined as:

$$W_t = \nabla^d X_t = (1-B)^d X_t$$

Thus the general ARIMA(p,q,d) process can be written as:

$$W_t = \alpha_1 W_{t-1} + \ldots + \alpha_p W_{t-p} + Z_t + \ldots + \beta_q Z_{t-q} \qquad [16]$$

[16] may be written in the form:

$$\Phi(B)W_t = \Theta(B)Z_t \qquad [17]$$

where $\Phi(B)$ and $\Theta(B)$ are polynomials of order p, q respectively, such that

$$\Phi(B) = 1-\alpha_1 B - \ldots - \alpha_p B^p$$

and

$$\Theta(B) = 1-\beta_1 B - \ldots -\beta_q B^q$$

Makridakis, Wheelwright & Hyndman (1998) provide a good explanation of the application of the Box-Jenkins methodology, describing three different phases in its use, namely: (1) *identification*, (2) *estimation*, and (3) *diagnostic checking*. During the initial identification phase of the process, the variance is stabilised, non-stationary patterns (trends) in the data are eliminated, and a tentative choice is made of the appropriate ARIMA model. In the second stage, the parameters of the model are estimated and iteratively refined, before the identification stage is revisited to select the best of the remaining models. Next, the model is checked for adequacy by searching for patterns in the residuals when fitting the model to the existing data. Once these stages are completed, the model can be used for forecasting. The three phases of application of the Box-Jenkins methodology are described below in more detail.

Identification

ARIMA models are defined by three parameters (p, d, q), where p denotes the autoregressive order, d denotes the degree of differencing, and q denotes the moving average order. The identification stage of the Box-Jenkins methodology involves determining a first estimate of values for p, d, and q.

Determining the degree of differencing

The degree of differencing required in order to make the data stationary can be determined by inspection of the time plot of the data. If the data appear stationary, then no differencing is required and a provisional value of $d = 0$ is used. However, for data with apparent non-stationarity, successive differencing of the series is performed until the time plot appears stationary. Diggle (1990) indicates that $d = 1$ or 2 usually suffices in practice. However, in time plots for which the existence of stationarity is unclear, the correlogram of the data can be computed. A correlogram which fails to decay to zero is an indication of non-stationarity. Refer to Section 4.1.2 for a detailed description of the correlogram of a time series.

Determining the Autoregressive Order

A variant of the correlogram, the *partial correlogram*, is used to determine the autoregressive order of the ARIMA model. The partial correlogram is constructed by successively fitting autoregressive processes of order 1, 2, … and at each stage defining the partial autocorrelation coefficient, a_k, to be the estimate of the final autoregressive coefficient: thus a_k is the estimate of α_k in an $AR(k)$ process. If the underlying process is $AR(p)$, then $\alpha_k = 0$ for all $k > p$, and the partial correlogram should show a cut-off after lag p (Diggle, 1990). Thus the autoregressive order parameter p can be identified by visual inspection of the partial correlogram; p can be estimated as the number of lags before a sharp cut-off in the partial correlogram.

Determining the Moving Average Order

The value of the moving average order parameter, q, is determined in a similar way to that for determining the autoregressive order parameter as described above; however, q is determined by searching for a cut-off on the correlogram instead of on the partial correlogram. An $MA(q)$ process can be thus identified through visual inspection by identifying that all r_k for k greater than some integer q are approximately zero on the correlogram (Diggle, 1990).

Parsimony

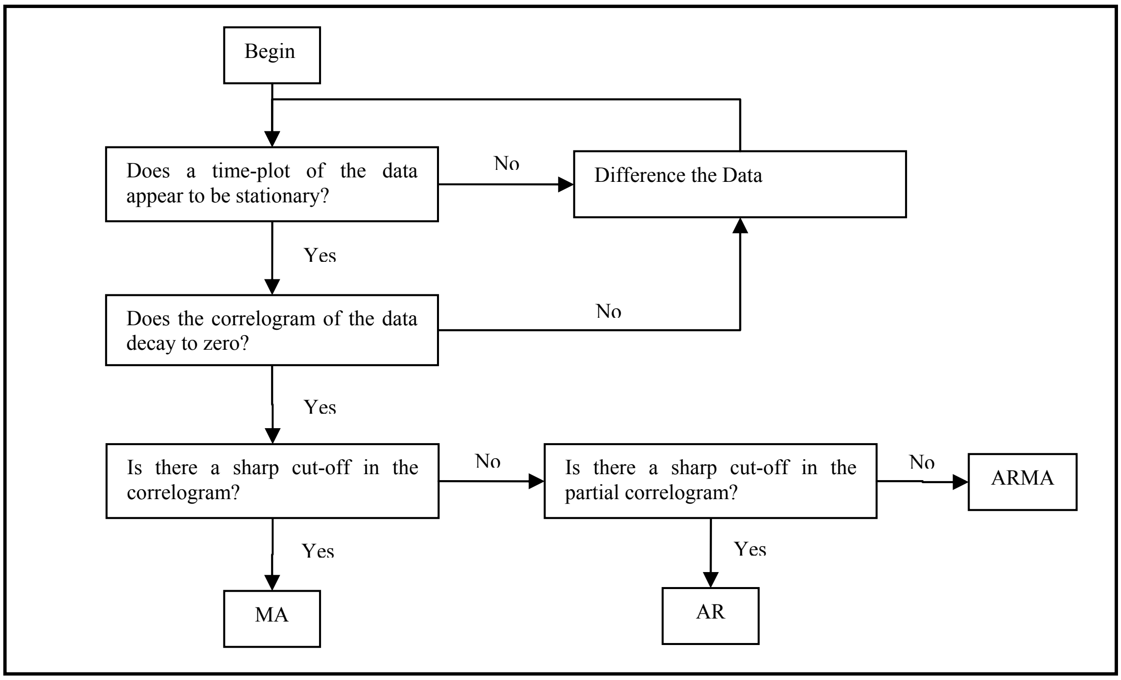
Model identification is a subjective process, and parsimony should be the guiding principle. Diggle (1990) states that if in doubt, one should opt for fewer rather than more parameters in the identified model. The third, diagnostic checking, stage of the

ARIMA process (described below) serves to assess whether additional parameters are needed to give an adequate fit.

Summary of identification process

The model identification process is summarised in **Figure 20** below.

Figure 20 - Flowchart of identification process



Source: Diggle (1990)

Estimation

Once stationarity in the mean of the process has been achieved through differencing, and the general class of ARIMA model has been postulated, the parameters of the model are estimated using the method of maximum likelihood. Diggle (1990:173-176) describes the derivation of the method of maximum likelihood estimation in some detail. For the purposes of this study it is sufficient to state that maximum likelihood estimation is practically equivalent to the more intuitive least-squares estimation method, but is more efficient in cases where the two algorithms differ significantly from each other.

Fortunately, most statistical software packages include an implementation of the somewhat complex maximum likelihood algorithm. Diggle (1990) concludes that maximum likelihood estimation provides a unified approach to parameter estimation for ARIMA-processes, thus explaining its wide application.

Diagnostic Checking

The third step in the Box-Jenkins methodology is to assess the adequacy of the fitted model using various diagnostic checks. Diggle (1990) states that in the usual approach a sequence of residuals (which should correspond to the underlying white noise sequence) is extracted from the fitted model and the statistical properties of the residuals are tested for consistency with white noise.

Box & Jenkins (1970) recommend that this analysis of residuals be combined with a procedure they termed 'trial overfitting'. In this procedure, the postulated ARIMA model is compared with alternate ARIMA models which include an additional autoregressive (*p)* or moving average (*q*) parameter, to determine whether an improved fit is obtained.

Hintz (2001) proposes a number of standard techniques for testing the fit of the ARIMA model based on analysis of the autocorrelations of the residuals calculated at various lags. The first, and the key diagnostic of the adequacy of the model, entails visually analysing the plot of the autocorrelations. The observation of large autocorrelations or a pattern of autocorrelations in the residuals indicates a sub-optimal model. The second technique is based on the fact that a white noise sequence will contain no significant autocorrelations at any of the lags. Thus the existence of significant autocorrelations indicates that the model should be changed. The third technique uses the Portmanteau test, which evaluates the significance of the autocorrelations up to a certain lag to determine whether there is any pattern remaining in the residuals.

Diggle (1990) suggests a further, infrequently used, approach which entails comparing the fitted ARIMA spectrum to a non-parametric spectral estimate. Details of this approach fall outside the scope of this study.

Appendix B – Tables

Table 19 – ARIMA Models for Daily Exchange Rate and Share Price Data for Period 1 September 2000 to 31 August 2001

Company	ARIMA model	Company	ARIMA model	Company	ARIMA model
ABI	(1,1,0)	GLENMIB	(1,1,0)	PRISM	(1,1,0)
ABIL	(1,1,0)	GLOTEC	(2,1,0)	RAINBOW	(1,1,0)
ABSA	(1,1,0)	GOLDREEF	(1,1,0)	REBSERV	(2,1,0)
ADCORP	(2,1,0)	GRAYPROP	(1,1,0)	REDEFINE	(1,1,0)
ADVTECH	(2,1,0)	GRINTEK	(1,1,0)	REUNERT	(1,1,0)
AECI	(1,1,0)	HARMONY	(1,1,0)	RICHEMONT	(1,1,0)
AFLIFE	(1,1,0)	HCI	(1,1,0)	SAAMBOU	(1,1,0)
AFROX	(1,1,0)	ILLOVO	(1,1,0)	SAB	(1,0,0)
ANGLO	(1,1,0)	IMPERIAL	(1,1,0)	SAGEGRP	(1,1,0)
ANGLOGOLD	(2,1,0)	IMPLATS	(1,1,0)	SANLAM	(2,1,0)
ANGLOPLAT	(2,1,0)	ISPATISC	(1,1,0)	SANTAM	(1,1,0)
ARI	(1,1,0)	JASCO	(1,1,0)	SAPPI	(1,1,0)
ASPEN	(1,1,0)	JOHNNIC	(1,1,0)	SASFIN	(1,1,0)
AVENG	(1,0,0)	LIBERTY	(1,1,0)	SASOL	(1,1,0)
A-V-I	(1,1,0)	LIB-HOLD	(1,1,0)	SPESCON	(1,1,0)
BARPLAT	(1,1,0)	LIBINT	(1,1,0)	STANBANK	(2,1,0)
BHPBILL	(1,1,0)	M&R	(1,1,0)	STEINHOFF	(2,1,0)
CADIZ	(1,1,0)	MARTPROP	(1,1,0)	SUPRGRP	(1,1,0)
CAPTALL	(1,1,0)	MEDCLIN	(1,1,0)	TIGBRANDS	(1,1,0)
CONTROL	(1,1,0)	MUSTEK	(1,1,0)	TIWHEEL	(1,1,0)
CORPCAP	(1,1,0)	MVELA_RES	(1,1,0)	TOURVEST	(1,1,0)
DATATEC	(1,1,0)	NAMPAK	(1,1,0)	TRANSHEX	(1,1,0)
DIDATA	(1,1,0)	NASPERS	(1,1,0)	UCS	(1,1,0)
DISCOVERY	(1,1,0)	NEDCOR	(1,1,0)	UNISERV	(1,1,0)
EDCON	(1,1,0)	NETCARE	(1,1,0)	VENFIN	(1,1,0)
ELLERINE	(1,1,0)	NORTHAM	(1,1,0)	WOOLIES	(2,1,0)
FOSCHINI	(1,1,0)	OLDMUTUAL	(1,1,0)	WOOLTRU	(1,1,0)
FRONTRNGE	(2,1,0)	PERGRIN	(2,1,0)		
GFIELDS	(1,1,0)	PIKWIK	(1,1,0)	RAND/DOLLAR	(1,1,0)

Table 20 - ARIMA Models for Weekly Exchange Rate and Share Price Data for Period 1 September 2000 to 31 August 2001

Company	ARIMA model	Company	ARIMA model	Company	ARIMA model
ABI	(1,0,0)	ERM	(1,0,0)	PERGRIN	(1,1,0)
ABIL	(1,1,0)	FIRSTRAND	(1,0,0)	PICKNPAY	(1,1,0)
ABSA	(1,0,0)	GENCOR	(1,1,0)	PIKWIK	(1,1,0)
ADVTECH	(1,1,0)	GFIELDS	(1,0,0)	PSG	(1,1,0)
AECI	(1,1,0)	GLENMIB	(1,0,0)	RA HOLD	(1,1,0)
AFLIFE	(2,1,0)	GRAYPROP	(2,1,0)	RAINBOW	(1,1,0)
ALEXFBS	(1,1,0)	GRINTEK	(1,1,0)	REUNERT	(1,1,0)
ALTECH	(2,1,0)	HARMONY	(1,1,0)	RICHMONT	(1,1,0)
ANGLO	(1,1,0)	HCI	(1,1,0)	SAAMBOU	(0,1,0)
ANGLOGOLD	(1,1,0)	HIVELD	(2,1,0)	SACHROME	(1,1,0)
ANGLOPLAT	(1,1,0)	ILLOVO	(2,1,0)	SAGEGRP	(1,1,0)

ARGENT	(1,1,0)	**IMPERIAL**	(1,1,0)	**SANLAM**	(1,1,0)
ASPEN	(1,1,0)	**IMPLATS**	(1,1,0)	**SANTAM**	(1,1,0)
AVENG	(1,0,0)	**INVLTD**	(1,1,0)	**SAPPI**	(2,1,0)
BARPLAT	(1,1,0)	**ISPATISC**	(1,1,0)	**SASFIN**	(1,1,0)
BASREAD	(2,1,0)	**JASCO**	(1,1,0)	**SASOL**	(1,1,0)
BELL	(1,1,0)	**JCI**	(1,1,0)	**SHOPRIT**	(0,1,0)
BHPBILL	(1,1,0)	**JOHNNIC**	(1,1,0)	**SPESCOM**	(1,0,0)
BIDVEST	(1,1,0)	**LIBERTY**	(1,1,0)	**STANBANK**	(1,0,0)
BJM	(2,1,0)	**LIB-HOLD**	(1,1,0)	**STEINHOFF**	(1,1,0)
BTG	(1,1,0)	**LIBINT**	(2,1,0)	**SUNINT**	(1,1,0)
CADIZ	(1,1,0)	**M-&-F**	(1,0,0)	**SUPRGRP**	(1,1,0)
CAPTALL	(2,1,0)	**MARTPROP**	(1,1,0)	**TIWHEEL**	(1,1,0)
CONNECT	(1,1,0)	**METOREX**	(1,1,0)	**TONGAAT**	(1,0,0)
CORPCAP	(1,1,0)	**MR PRICE**	(1,1,0)	**TOURVEST**	(1,0,0)
DATATEC	(1,1,0)	**MTN GROUP**	(1,1,0)	**TRUWTHS**	(1,1,0)
DAWN	(1,1,0)	**MUSTEK**	(2,1,0)	**UCS**	(1,1,0)
DBN-DEEP	(1,1,0)	**MVELA RES**	(1,0,0)	**UNISERV**	(1,1,0)
DELTA	(1,1,0)	**NAMPAK**	(1,1,0)	**VENFIN**	(1,1,0)
DIDATA	(1,1,0)	**NASPERS**	(1,1,0)	**WBHO**	(1,1,0)
DIGICOR	(1,1,0)	**NEDCOR**	(1,1,0)	**WES AREAS**	(1,1,0)
DISCOVERY	(1,1,0)	**NETCARE**	(1,1,0)	**WOOLIES**	(1,1,0)
DISTELL	(1,1,0)	**NORTHAM**	(1,1,0)	**WOOLTRU**	(1,1,0)
EDCON	(1,1,0)	**OLD_MUTUAL**	(1,1,0)		
ELLERINE	(1,1,0)	**PALAMIN**	(1,1,0)	**RAND/DOLLAR**	(1,1,0)

Table 21 – Cross-Correlations of Daily Share Price and Rand/Dollar Exchange Rate Residuals

Lag	-5	-4	-3	-2	-1	0
ABI	-0.047704	0.023327	-0.080631	0.051232	-0.009816	0.045140
ABIL	0.030997	-0.057690	-0.065150	0.053598	-0.067329	0.011919
ABSA	-0.062715	-0.082157	0.075658	**0.187322**	***-0.136500***	-0.036958
ADCORP	-0.044387	-0.024346	-0.018064	-0.110261	0.003976	***-0.129716***
ADVTECH	-0.097930	0.059963	-0.058461	-0.011137	-0.015733	0.076280
AECI	-0.013690	0.061121	-0.051153	0.001868	-0.008856	-0.044382
AFLIFE	-0.020499	0.088162	-0.008317	-0.028586	0.011830	-0.041917
AFROX	-0.075590	0.011880	0.019848	0.083582	-0.056016	-0.041269
ANGGOLD	-0.102991	0.008244	-0.097707	**0.137772**	0.009689	0.019621
ANGLO	0.115770	-0.035952	0.047030	-0.032477	0.003622	-0.121724
ANGLOPLAT	-0.105501	0.066132	-0.012099	0.021205	-0.065600	-0.036939
ARI	**0.172746**	-0.001601	0.019060	0.003935	0.029763	-0.047164
ASPEN	0.028577	0.055333	0.073357	-0.013701	-0.019076	-0.003330
AVENG	-0.042542	-0.014844	-0.096270	-0.047878	-0.010321	0.039325
A-V-I	-0.058758	-0.033367	0.002639	0.067801	0.069730	0.049675
BARPLAT	-0.003943	0.013969	-0.090638	-0.072231	0.012114	-0.078932
BHPBILL	-0.045269	-0.021964	-0.048768	-0.055222	0.011565	-0.038071
CADIZ	-0.062784	0.120114	0.075798	**0.157028**	-0.106588	0.001603
CAPTALL	0.041782	0.045504	-0.010880	-0.024629	***-0.193285***	0.083271
CORPCAP	-0.100205	-0.024235	0.122410	0.058187	-0.069411	***-0.142396***
DATATEC	-0.050039	-0.035034	0.004060	0.113755	-0.059086	-0.026932
DIDATA	-0.012248	-0.004411	-0.013473	**0.142264**	-0.020024	0.022772
DISCOVERY	-0.106253	-0.000408	0.043255	0.065658	0.055704	-0.035532
EDCON	-0.081085	0.014664	0.081890	0.023827	-0.077554	-0.075698
ELLERINE	-0.000452	-0.017430	0.060539	-0.053674	0.051483	***-0.127292***

FOSCHINI	-0.058984	0.034497	0.060089	0.043047	-0.025750	-0.019650
FRONTRNGE	-0.121676	-0.056696	***-0.160784***	0.010754	0.073415	-0.075196
GFIELDS	-0.024279	0.081229	-0.026003	0.086654	-0.005814	0.006268
GLENMIB	0.009072	-0.005982	-0.078489	0.039703	0.054778	0.037189
GLOTEC	0.026316	0.044058	0.051716	-0.052893	0.027066	0.073294
GOLDREEF	0.032412	-0.002062	0.108384	-0.061325	-0.087591	0.003953
GRAYPROP	-0.037276	-0.082239	-0.073909	-0.015447	-0.036245	0.060494
GRINTEC	0.012124	-0.051886	-0.087820	-0.051203	0.082545	0.103326
HARMONY	-0.043157	0.051137	-0.001650	**0.149422**	-0.008312	-0.041608
HCI	-0.041192	0.019569	-0.006634	0.011586	0.004556	-0.070893
ILLOVO	-0.020843	-0.086618	-0.015827	0.037686	-0.040302	0.031196
IMPERIAL	-0.038327	-0.012306	0.065194	0.058751	-0.029417	-0.103408
IMPLATS	-0.032739	-0.007656	0.066091	-0.038379	-0.094781	0.050921
ISPATISC	-0.005120	-0.061294	0.047810	-0.087909	-0.009950	-0.049590
JASCO	0.012387	0.009460	-0.050259	0.026202	-0.017508	-0.028332
JCI	0.012387	0.009460	-0.050259	0.026202	-0.017508	-0.028332
JOHNNIC	0.009181	-0.076243	0.033990	0.079083	0.004568	-0.027916
LIBERTY	0.103333	-0.005573	0.061811	-0.094057	0.005624	0.010409
LIB-HOLD	0.080276	0.012815	0.075460	-0.069827	0.023881	-0.030849
LIBINT	0.025801	0.022603	-0.059876	0.047448	-0.091213	0.024752
M&R-HOLD	0.063850	-0.041612	-0.027102	-0.022358	-0.003972	0.042172
MARTPROP	0.042777	***-0.130323***	0.053515	-0.067862	0.056681	-0.030127
MEDCLIN	0.050649	0.018452	-0.021510	0.034948	-0.078508	0.026462
MERCANTIL	-0.067070	-0.044114	-0.036494	-0.097497	0.095267	***-0.209194***
MMG	0.095878	0.041149	0.000642	-0.036925	-0.043057	0.009035
MOBILE	-0.006398	-0.050625	0.006438	-0.017315	0.089832	-0.025519
MR_PRICE	-0.025760	-0.065020	-0.031023	0.033554	0.123565	-0.104443
MUSTEK	0.029473	**0.153759**	0.035661	0.083483	-0.016701	-0.036799
MVELA_RES	0.008703	0.021267	0.080622	-0.009319	0.046157	0.023906
NAMPAK	0.040220	-0.057600	-0.064317	0.057729	0.006062	0.040079
NASPERS	-0.018707	-0.056861	-0.039975	0.106575	-0.073891	-0.001060
NEDCOR	0.058435	0.030163	-0.036378	0.056001	-0.082936	0.080215
NETCARE	-0.056924	0.069962	0.072850	-0.093418	0.056313	-0.043882
NORTHAM	0.031864	-0.035668	-0.053744	0.016187	-0.017418	0.074533
OLD_MUTUAL	0.084852	-0.066187	-0.038636	0.051962	-0.106644	-0.073060
PERGRIN	-0.052726	0.044844	0.034969	**0.159197**	-0.057655	0.038193
PIKWIK	0.022323	-0.000024	-0.003546	0.016092	-0.092138	***-0.135095***
PRISM	0.017003	0.001597	0.019815	-0.058448	0.026243	***-0.144466***
RAINBOW	0.027477	0.032400	0.054223	0.009086	-0.026593	-0.021046
REBSERV	0.032302	-0.124878	-0.023523	0.045639	-0.010538	-0.046033
REDEFINE	0.032712	-0.005037	0.059915	-0.037333	-0.044048	-0.088027
REUNERT	0.063233	0.080560	-0.037704	-0.075227	-0.078468	-0.046994
RICHEMONT	0.038920	-0.016434	0.010129	0.099948	0.080954	**0.142564**
SAAMBOU	0.032964	-0.065456	0.083078	-0.040333	0.069056	0.099149
SAB	0.089245	0.055830	-0.039018	-0.085025	***-0.143941***	-0.096771
SAGEGRP	0.049113	-0.049884	-0.002144	-0.033540	-0.001723	-0.028626
SANLAM	0.049929	-0.088742	-0.022372	0.004020	-0.045818	-0.066952
SANTAM	-0.004761	0.057253	-0.081564	-0.050816	0.016175	-0.088717
SAPPI	-0.081539	-0.009456	0.050084	**0.131359**	***-0.146506***	-0.072105
SASFIN	-0.112738	-0.014652	-0.003658	0.028859	0.061640	-0.059952
SASOL	-0.077159	0.117672	-0.050113	0.019714	0.047504	0.035937
SPESCOM	-0.039109	-0.092273	0.075361	-0.023249	0.048371	-0.058587
STANBANK	-0.016907	-0.032257	-0.063781	-0.009330	***-0.129165***	-0.033698
STEINHOFF	-0.084817	-0.051938	-0.004080	0.014339	-0.003325	0.112817
SUPRGRP	-0.064812	-0.031992	0.029923	0.118589	0.044576	-0.048849
TIGBRANDS	-0.025527	-0.044940	-0.097859	0.025003	-0.053555	-0.001181
TIWHEEL	-0.006190	-0.025271	-0.093773	0.027908	-0.024799	-0.022497

TOURVEST	0.100088	0.076121	-0.061615	-0.051626	0.000021	0.010767
TRANSHEX	0.023652	0.041089	0.035809	-0.004071	-0.036643	-0.023626
UCS	-0.098517	-0.104618	-0.091093	0.039461	-0.005961	0.009723
UNISERV	-0.007955	0.066100	-0.100589	0.019793	-0.003724	0.010635
VENFIN	-0.000889	***-0.165815***	0.050500	-0.080445	0.036308	0.092080
WOOLIES	-0.042873	-0.060699	0.005208	0.048117	0.038628	-0.064217
WOOLTRU	-0.078219	-0.004100	0.022765	-0.028489	0.034929	-0.100622

Table 22 – Cross-Correlations of Weekly Share Price and Rand/Dollar Exchange Rate Residuals

Lag	**-5**	**-4**	**-3**	**-2**	**-1**	**0**
ABI	-0.075707	**0.275420**	-0.156437	-0.032897	-0.169849	0.048269
ABIL	***-0.291972***	-0.192520	0.054275	-0.083424	0.019734	-0.175496
AECI	-0.070989	0.121327	-0.145293	0.069995	-0.161637	0.119994
ALEXFBS	-0.148147	**0.308884**	0.027112	-0.129685	-0.185742	-0.091976
ANGGOLD	-0.118733	0.116980	-0.111177	-0.018277	-0.219130	-0.153424
ANGLO	0.050343	0.056949	**0.285072**	-0.137805	0.032676	-0.202385
ANGLOPLAT	-0.087069	-0.005824	0.236942	0.232710	-0.139200	-0.126517
ARGENT	-0.121546	-0.009333	0.029973	0.001637	-0.092864	0.135433
ASPEN	-0.251718	-0.044977	-0.012908	0.082548	-0.078775	0.178543
AVENG	-0.079595	-0.049632	0.253989	-0.073225	-0.066852	-0.092282
BARPLAT	0.003426	0.179479	**0.274940**	0.091482	-0.125152	-0.116618
BASREAD	-0.154970	-0.123790	-0.012524	-0.023196	0.027598	-0.204856
BELL	0.001469	-0.010193	-0.190546	-0.061510	0.019586	0.201681
BHPBILL	-0.070250	-0.099981	0.262210	-0.101005	-0.061398	-0.115370
BIDVEST	-0.210482	***-0.302677***	0.046234	0.136701	-0.088112	***-0.335940***
BJM	-0.193504	-0.197116	0.037791	-0.020954	-0.054120	-0.067426
BTG	0.194886	-0.102794	0.049407	0.032759	0.033797	**0.279643**
CADIZ	-0.095425	-0.210513	0.003236	-0.078269	0.140418	0.160749
CAPTALL	0.038373	0.011316	-0.171342	-0.074536	0.081979	-0.104864
CONNECT	***-0.428502***	0.016285	0.005548	0.193309	***-0.418763***	0.177552
CORPCAP	-0.007988	-0.172186	0.140906	-0.225443	-0.018545	0.007058
DATATEC	-0.047195	***-0.294040***	-0.094347	0.075266	0.034312	-0.030553
DAWN	0.090315	-0.224208	-0.025081	0.075185	0.236207	***-0.309764***
DBN-DEEP	-0.195541	0.134295	-0.214777	0.007134	-0.151169	-0.139725
DELTA	**0.344289**	-0.070796	-0.082477	0.066864	**0.430556**	-0.093756
DIDATA	-0.242465	-0.025920	0.028472	0.095399	0.106211	0.071956
DIGICOR	0.117763	-0.005107	0.185662	-0.182668	0.057295	0.065377
DISCOVERY	-0.016460	0.177356	-0.039203	-0.098147	-0.024625	0.114123
DISTELL	-0.191288	0.100134	-0.032375	0.015896	0.038971	0.035643
EDCON	0.129604	-0.122727	-0.165768	0.024532	-0.154168	-0.258679
ELLERINE	-0.008016	-0.237573	-0.081724	-0.192447	-0.014828	-0.154565
ERM	-0.256674	***-0.299902***	-0.003731	-0.007117	0.004424	-0.099062
FIRSTRAND	-0.105904	0.012686	**0.301217**	0.019650	-0.188140	***-0.354075***
GENCOR	0.077255	0.018895	0.268270	0.129607	-0.130646	-0.111378
GFIELDS	-0.222489	0.024506	0.003911	0.053283	0.133482	***-0.304798***
GLENMIB	-0.185055	0.051513	-0.062840	0.170156	0.063103	-0.087263
GRAYPROP	***-0.298463***	0.041587	**0.355676**	0.238554	-0.170040	-0.196601
GRINTEK	0.125182	-0.072046	-0.007637	0.118552	-0.021205	-0.082032
HARMONY	-0.171359	-0.061497	***-0.273410***	0.027633	-0.032185	***-0.377413***
HCI	-0.032410	-0.168584	-0.223087	0.090134	0.137921	-0.239626
IMPERIAL	-0.104446	0.075440	0.119912	-0.036762	-0.019933	-0.186696
IMPLATS	0.069081	0.079999	0.233305	0.099813	-0.122393	-0.065301

INVLTD	0.010708	-0.068540	0.179839	0.111969	-0.033079	-0.198664
ISPATISC	***-0.318934***	***-0.355250***	**0.388276**	-0.019418	-0.178498	-0.179945
JASCO	-0.189398	-0.107122	0.109208	-0.063561	-0.022002	-0.112667
JCI	0.086332	0.031420	-0.072614	0.033721	0.234564	-0.039003
JOHNNIC	-0.096686	-0.118041	-0.031694	0.091077	0.055737	-0.036340
LIBERTY	0.018703	0.072329	-0.049486	-0.250519	0.014514	-0.139733
LIB-HOLD	0.016622	0.051034	-0.051028	***-0.284733***	0.028254	-0.107028
LIBINT	0.201866	-0.031899	-0.195030	-0.118034	0.096649	0.082306
M&F	-0.002718	0.183606	0.124471	-0.153214	-0.053036	0.169512
MARTPROP	-0.122472	0.065109	-0.075244	0.157986	-0.243095	-0.065977
METOREX	0.069415	**0.274119**	-0.009020	0.121613	0.131785	0.029139
MR_PRICE	-0.179316	-0.102380	***-0.399852***	0.181782	-0.020994	0.072457
MTN-GROUP	-0.098939	-0.107432	-0.091972	0.022255	0.207215	0.023215
MVELA_RES	-0.052556	**0.335089**	-0.006244	-0.176139	0.027342	0.206670
NAMPAK	-0.111920	0.031896	-0.029943	-0.257036	-0.152866	-0.097404
NASPERS	-0.169226	***-0.299300***	0.124548	0.135886	0.017341	-0.180876
NEDCOR	-0.182639	-0.034999	0.168622	0.147518	-0.140876	-0.012183
NETCARE	0.199632	***-0.371630***	-0.170812	-0.082719	0.171021	-0.080871
NORTHAM	-0.112639	0.232558	**0.376877**	-0.083022	-0.124199	0.026163
OLD_MUTUAL	***-0.337794***	0.021870	**0.399856**	0.047008	-0.111784	***-0.274759***
PALAMIN	-0.052545	0.162504	0.265202	-0.168340	-0.226035	0.054422
PERGRIN	-0.253403	0.017821	-0.029728	-0.265082	-0.024594	0.181812
PICKNPAY	-0.066698	-0.132344	0.194598	0.004065	0.003151	***-0.354844***
PIKWIK	-0.131185	-0.126747	0.174506	0.012025	0.046776	***-0.418074***
PSG	-0.047983	0.042837	***-0.282249***	0.160316	0.086411	-0.028813
RA-HOLD	-0.193293	0.186634	-0.016654	0.142249	0.159423	0.048354
RAINBOW	***-0.284462***	-0.091688	-0.054497	0.044700	0.154106	-0.138650
REBSERV	-0.028015	-0.242490	0.076923	0.112300	0.015061	-0.054313
REUNERT	-0.134863	0.075823	0.091514	0.026015	-0.096382	***-0.274682***
RICHEMONT	-0.248151	0.248775	-0.057102	0.136538	0.178653	0.185526
SAAMBOU	0.162416	-0.053254	-0.048496	-0.027744	-0.041607	-0.009412
SACHROME	0.012408	0.094475	-0.129016	-0.043750	0.125570	0.165994
SAGEGRP	-0.233087	0.035333	0.233584	0.062123	-0.024440	-0.203020
SANLAM	-0.257925	0.049500	0.139355	0.070875	-0.140260	***-0.314384***
SANTAM	-0.035582	-0.204798	-0.036599	0.050046	0.048663	-0.267161
SAPPI	-0.000431	-0.132920	0.158501	-0.004043	0.005703	-0.228844
SASFIN	-0.114792	0.121953	0.010370	-0.016624	-0.039848	-0.009395
SASOL	0.140245	-0.143805	-0.164230	-0.082533	0.046248	-0.013315
SHOPRIT	***-0.275396***	-0.034114	-0.014347	0.087294	-0.144087	-0.052651
SPESCOM	-0.088513	-0.080344	0.026733	0.123420	-0.122013	-0.217472
STANBANK	-0.203118	-0.042374	**0.306219**	-0.000169	***-0.284251***	-0.234511
STEINHOFF	-0.248761	-0.016523	0.105773	-0.110701	-0.070241	-0.071185
SUNINT	0.173516	0.077672	0.066872	-0.040319	0.033879	-0.171500
SUPRGRP	***-0.405780***	-0.093981	0.008077	-0.047320	-0.237621	0.036260
TIWHEEL	0.037722	0.020980	0.240317	0.004930	-0.015939	-0.005088
TONGAAT	-0.222109	0.197303	-0.231776	-0.172661	-0.194840	0.118317
TOURVEST	0.081592	-0.045941	0.040211	-0.054517	-0.047267	-0.154754
TRUWRTHS	-0.117282	***-0.392481***	-0.001887	-0.113971	-0.018504	-0.006594
UCS	0.092031	-0.153806	-0.112719	-0.177387	-0.176148	-0.094589
UNISERV	-0.251514	-0.099046	-0.248274	0.078229	-0.015590	-0.055170
VENFIN	-0.078850	0.094500	-0.000754	-0.138663	-0.098356	-0.002362
WBHO	***-0.373481***	0.097625	-0.050742	-0.081354	-0.101789	-0.140770

Table 23 –Difference in Proportional Daily Increases of ALSI and Potential Hedge Portfolios

ALSI		Daily hedge portfolio			Weekly hedge portfolio		
Values	% increase	Values	% increase	Difference	Values	% increase	Difference
100.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00
100.98	0.98	102.30	2.30	1.32	98.88	-1.12	-2.10
101.69	0.70	100.98	-1.29	-1.99	99.09	0.22	-0.49
105.83	4.07	102.69	1.69	-2.38	102.27	3.20	-0.87
104.55	-1.21	102.17	-0.51	0.70	102.16	-0.10	1.10
105.10	0.53	102.42	0.24	-0.28	101.86	-0.30	-0.82
104.99	-0.10	102.87	0.44	0.54	102.13	0.26	0.37
104.03	-0.91	102.02	-0.83	0.09	100.58	-1.51	-0.60
105.78	1.68	103.98	1.92	0.24	102.96	2.36	0.68
105.89	0.10	103.38	-0.58	-0.68	103.04	0.08	-0.02
104.58	-1.24	102.76	-0.60	0.64	103.17	0.12	1.36
107.59	2.88	104.36	1.56	-1.32	104.98	1.76	-1.12
107.37	-0.20	106.33	1.89	2.09	105.47	0.47	0.68
105.57	-1.68	105.88	-0.42	1.25	103.75	-1.64	0.04
105.32	-0.24	105.76	-0.11	0.12	102.74	-0.97	-0.73
106.25	0.88	105.84	0.08	-0.81	103.24	0.49	-0.39
106.50	0.24	106.42	0.55	0.31	103.25	0.01	-0.23
106.42	-0.08	106.73	0.29	0.37	103.21	-0.04	0.04
106.57	0.14	107.54	0.76	0.62	103.01	-0.19	-0.34
106.30	-0.25	107.78	0.22	0.48	103.46	0.43	0.69
106.89	0.56	107.47	-0.29	-0.84	104.69	1.19	0.63
105.43	-1.37	106.87	-0.56	0.81	103.52	-1.12	0.25
106.00	0.54	107.07	0.19	-0.35	103.63	0.11	-0.43
107.29	1.22	106.28	-0.74	-1.95	104.22	0.57	-0.65
108.19	0.84	106.81	0.50	-0.34	103.86	-0.35	-1.19
108.52	0.31	107.71	0.84	0.54	104.41	0.53	0.22
107.26	-1.16	108.16	0.42	1.58	103.02	-1.32	-0.16
107.97	0.66	108.29	0.12	-0.54	103.60	0.56	-0.10
107.96	-0.01	110.20	1.76	1.77	103.38	-0.22	-0.21
108.27	0.29	109.19	-0.92	-1.20	102.79	-0.57	-0.86
109.52	1.15	110.73	1.41	0.26	103.63	0.82	-0.33
111.12	1.46	112.61	1.70	0.24	104.54	0.88	-0.59
114.44	2.99	115.18	2.28	-0.71	107.73	3.05	0.07
115.51	0.93	117.30	1.84	0.91	108.58	0.79	-0.15
113.35	-1.87	118.81	1.29	3.16	109.34	0.70	2.57
115.51	1.91	120.93	1.78	-0.12	110.44	1.01	-0.90
115.70	0.16	119.00	-1.60	-1.76	111.20	0.69	0.52
116.25	0.48	120.14	0.96	0.48	111.17	-0.02	-0.50
115.45	-0.69	120.03	-0.09	0.60	110.37	-0.72	-0.03
115.25	-0.17	120.89	0.72	0.89	110.91	0.48	0.65
116.62	1.19	122.95	1.70	0.52	111.59	0.61	-0.58
116.29	-0.28	122.64	-0.25	0.03	111.01	-0.51	-0.23
115.31	-0.84	121.82	-0.67	0.17	110.01	-0.91	-0.06
115.00	-0.27	120.83	-0.81	-0.54	110.13	0.11	0.38
117.64	2.30	123.15	1.92	-0.38	112.78	2.41	0.11

Table 24 –Difference in Proportional Daily Increases of ALSI and Potential Anti-Hedge Portfolios

ALSI		Daily anti-hedge portfolio			Weekly anti-hedge portfolio		
Values	% increase	Values	% increase	Difference	Values	% increase	Difference
100.00	0.00	100.00	0.00	0.00	100.00	0.00	0.00
100.98	0.98	99.68	-0.32	-1.30	100.56	0.56	-0.42
101.69	0.70	98.76	-0.92	-1.62	100.57	0.01	-0.69
105.83	4.07	101.23	2.50	-1.58	102.89	2.31	-1.76
104.55	-1.21	101.29	0.07	1.28	101.39	-1.46	-0.25
105.10	0.53	99.40	-1.87	-2.40	100.62	-0.76	-1.29
104.99	-0.10	99.10	-0.29	-0.19	100.93	0.32	0.42
104.03	-0.91	99.33	0.22	1.14	100.89	-0.05	0.87
105.78	1.68	99.31	-0.02	-1.70	101.92	1.02	-0.66
105.89	0.10	99.64	0.34	0.23	100.97	-0.93	-1.04
104.58	-1.24	99.29	-0.36	0.88	100.95	-0.02	1.21
107.59	2.88	100.16	0.88	-2.00	101.62	0.67	-2.21
107.37	-0.20	99.85	-0.32	-0.11	102.53	0.89	1.09
105.57	-1.68	97.82	-2.03	-0.35	101.75	-0.76	0.92
105.32	-0.24	98.09	0.28	0.51	101.30	-0.44	-0.20
106.25	0.88	98.99	0.92	0.04	100.83	-0.46	-1.34
106.50	0.24	100.50	1.52	1.28	100.26	-0.57	-0.81
106.42	-0.08	101.03	0.53	0.61	100.62	0.36	0.43
106.57	0.14	102.86	1.81	1.67	101.13	0.51	0.37
106.30	-0.25	102.37	-0.48	-0.23	100.02	-1.10	-0.85
106.89	0.56	100.46	-1.87	-2.42	100.84	0.82	0.27
105.43	-1.37	98.52	-1.93	-0.56	100.48	-0.36	1.01
106.00	0.54	99.02	0.50	-0.04	100.36	-0.13	-0.67
107.29	1.22	99.81	0.80	-0.42	101.24	0.88	-0.33
108.19	0.84	100.24	0.43	-0.41	101.97	0.72	-0.12
108.52	0.31	98.45	-1.78	-2.09	102.69	0.71	0.40
107.26	-1.16	97.68	-0.79	0.38	101.92	-0.75	0.42
107.97	0.66	98.41	0.75	0.09	102.48	0.55	-0.11
107.96	-0.01	99.11	0.71	0.72	103.89	1.37	1.38
108.27	0.29	99.27	0.16	-0.13	104.17	0.27	-0.02
109.52	1.15	99.65	0.38	-0.77	104.88	0.68	-0.48
111.12	1.46	99.57	-0.08	-1.54	105.08	0.20	-1.26
114.44	2.99	103.16	3.61	0.62	106.30	1.16	-1.83
115.51	0.93	103.33	0.17	-0.76	106.86	0.53	-0.41
113.35	-1.87	103.48	0.14	2.01	109.15	2.15	4.02
115.51	1.91	107.05	3.45	1.54	110.28	1.03	-0.87
115.70	0.16	107.17	0.11	-0.06	110.57	0.26	0.09
116.25	0.48	108.47	1.22	0.74	111.00	0.39	-0.08
115.45	-0.69	108.79	0.29	0.98	109.87	-1.02	-0.33
115.25	-0.17	109.84	0.97	1.14	110.51	0.58	0.76
116.62	1.19	111.80	1.78	0.59	111.28	0.70	-0.49
116.29	-0.28	118.88	6.33	6.62	110.64	-0.58	-0.30
115.31	-0.84	114.34	-3.82	-2.97	111.00	0.33	1.17
115.00	-0.27	113.91	-0.38	-0.11	110.78	-0.20	0.07
117.64	2.30	113.72	-0.17	-2.46	111.31	0.48	-1.81

Table 25 –Difference in Proportional Daily Increases of ALSI and Known Hedge Portfolios

ALSI		Known hedge portfolio		
Values	% increase	Values	% increase	Difference
100.00	0.00	100.00	0.00	0.00
100.98	0.98	101.49	1.49	0.51
101.69	0.70	102.22	0.72	0.02
105.83	4.07	104.51	2.24	-1.83
104.55	-1.21	104.68	0.16	1.37
105.10	0.53	106.00	1.26	0.74
104.99	-0.10	106.15	0.13	0.24
104.03	-0.91	106.59	0.42	1.34
105.78	1.68	108.09	1.40	-0.28
105.89	0.10	106.74	-1.25	-1.35
104.58	-1.24	105.54	-1.12	0.12
107.59	2.88	107.92	2.25	-0.63
107.37	-0.20	109.92	1.85	2.05
105.57	-1.68	109.50	-0.38	1.29
105.32	-0.24	108.82	-0.61	-0.38
106.25	0.88	109.01	0.17	-0.71
106.50	0.24	108.12	-0.81	-1.05
106.42	-0.08	108.18	0.05	0.13
106.57	0.14	108.59	0.38	0.24
106.30	-0.25	109.33	0.68	0.94
106.89	0.56	110.52	1.09	0.54
105.43	-1.37	110.62	0.09	1.46
106.00	0.54	111.03	0.36	-0.18
107.29	1.22	112.69	1.49	0.28
108.19	0.84	113.80	0.99	0.15
108.52	0.31	113.61	-0.16	-0.47
107.26	-1.16	113.09	-0.46	0.70
107.97	0.66	112.37	-0.64	-1.30
107.96	-0.01	113.69	1.17	1.18
108.27	0.29	112.88	-0.71	-1.00
109.52	1.15	114.09	1.07	-0.09
111.12	1.46	115.76	1.46	0.00
114.44	2.99	118.29	2.18	-0.80
115.51	0.93	119.80	1.28	0.35
113.35	-1.87	119.08	-0.61	1.26
115.51	1.91	121.04	1.65	-0.26
115.70	0.16	120.91	-0.10	-0.27
116.25	0.48	122.94	1.68	1.20
115.45	-0.69	122.04	-0.74	-0.05
115.25	-0.17	122.04	0.00	0.17
116.62	1.19	124.96	2.39	1.21
116.29	-0.28	124.22	-0.59	-0.31
115.31	-0.84	124.24	0.02	0.87
115.00	-0.27	124.15	-0.08	0.19
117.64	2.30	128.32	3.36	1.06

Appendix C – Figures

Figure 21 - Performance of Potential Daily Hedge Stocks and Rand/Dollar Exchange Rate

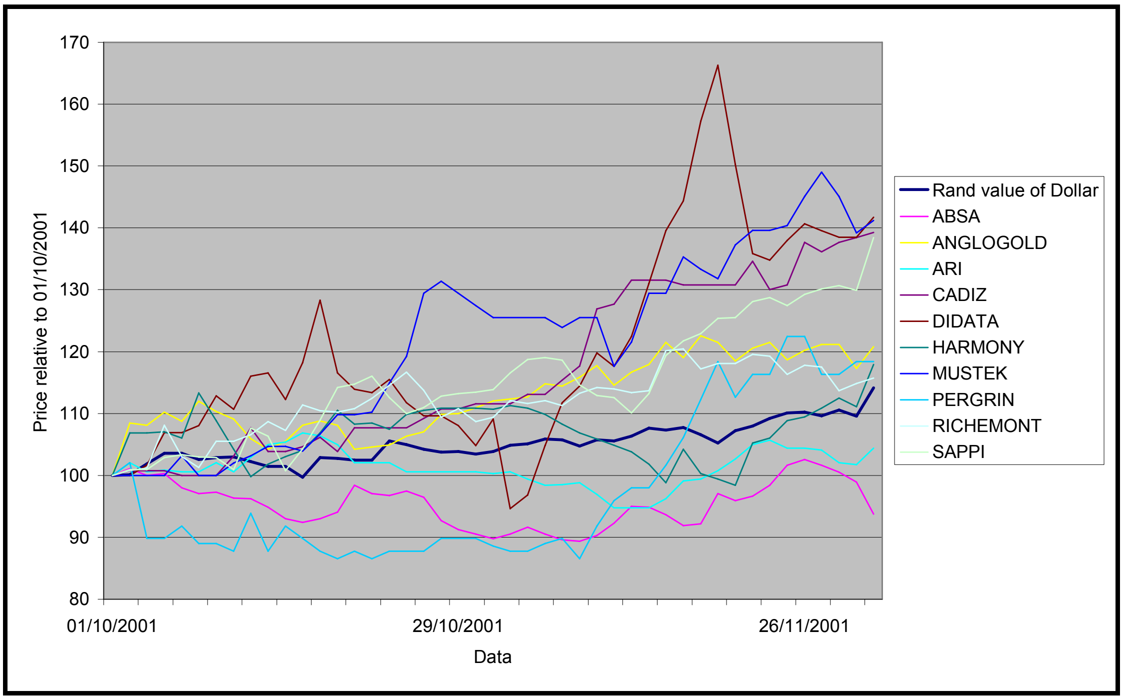


Figure 22 - Performance of Potential Weekly Hedge Stocks and Rand/Dollar Exchange Rate

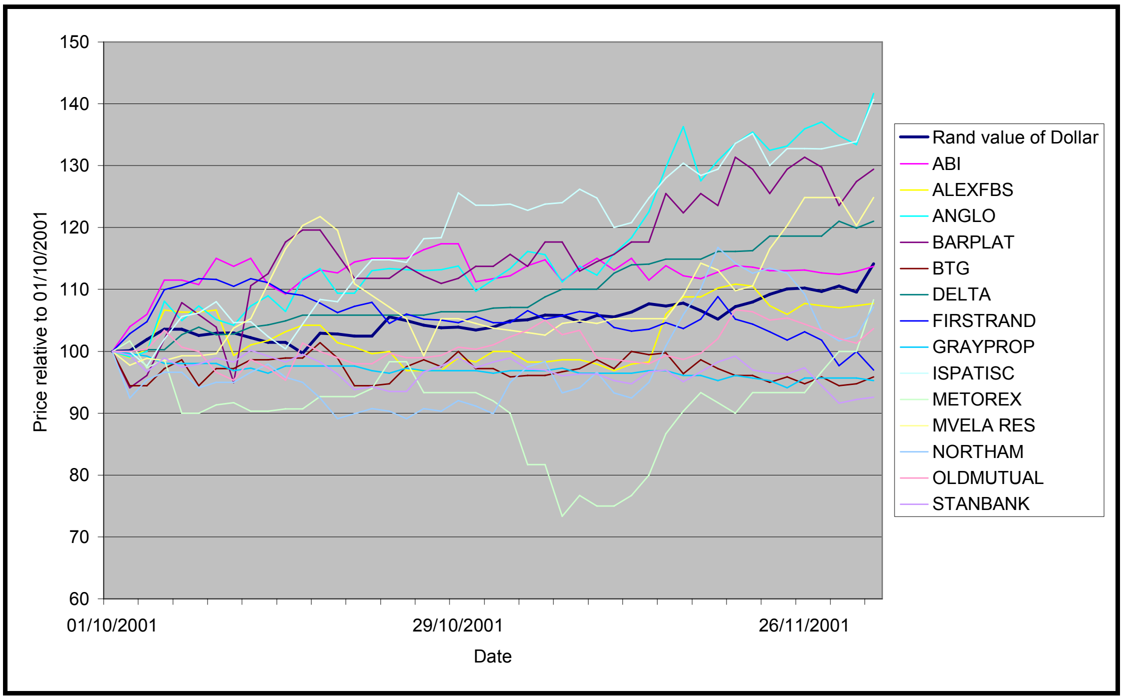


Figure 23 - Performance of Known Hedge Stocks and Rand/Dollar Exchange Rate

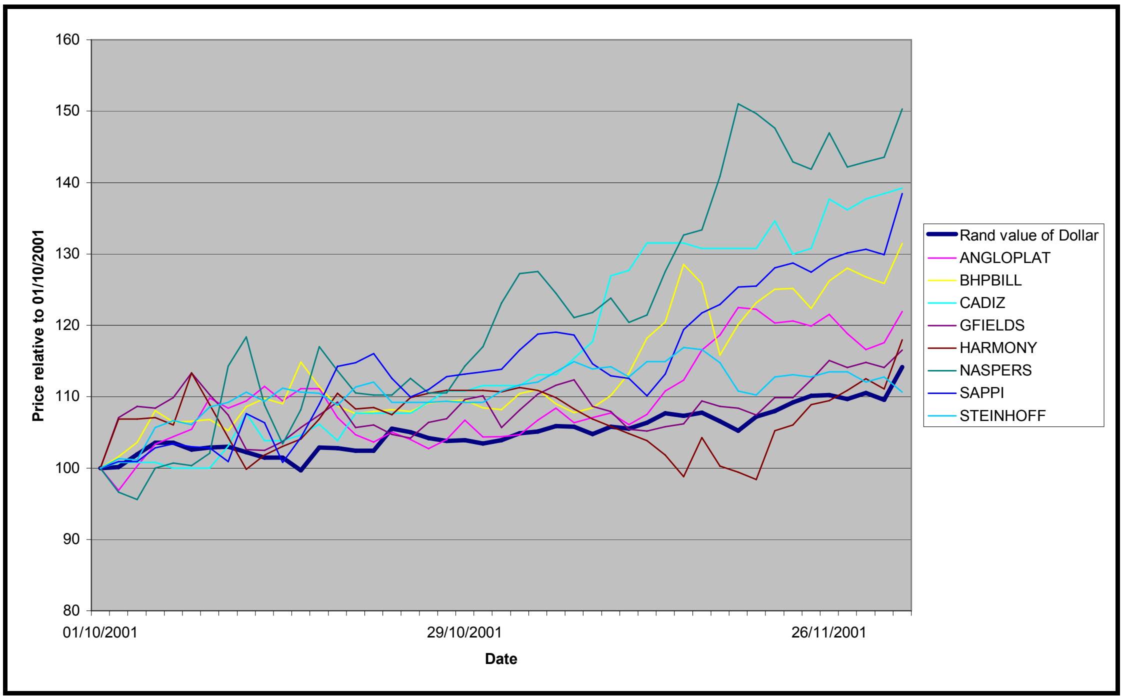


Figure 24 - Performance of Daily Anti-Hedging Shares and Rand/Dollar Exchange Rate

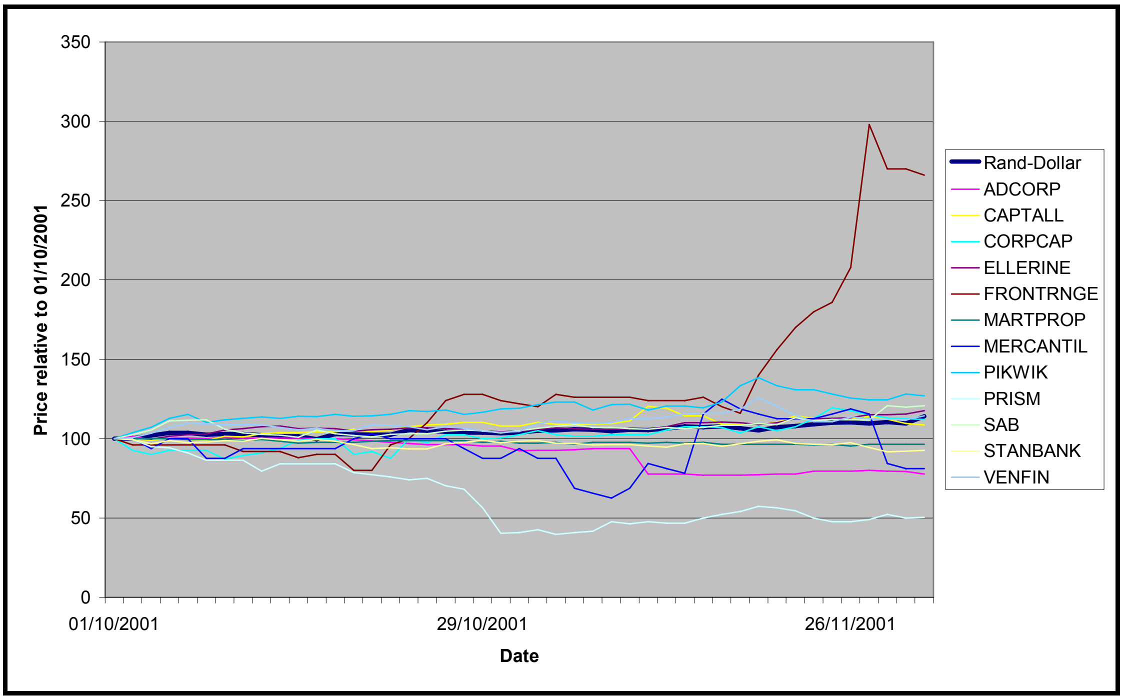


Figure 25 - Performance of Weekly Anti-Hedging Shares and Rand/Dollar Exchange Rate