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UNIVERSITY OF CAPE TOWN

DEPARTMENT OF COMMERCE

RONDEBOSCH, CAPE TOWN, SOUTH AFRICA

Investigating the relationship between the Price-Earnings ratio and future stock returns in the South African market

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Abstract:

This paper replicates the statistical study conducted by Vivek Bhargava and D. K. Malhotra to determine whether P/E ratios drive future share earnings or drive future share prices on various international markets. Statistical analysis is conducted on indices on the South African market, in order to determine if P/E ratios drive subsequent closing prices or closing prices adjusted for total return. The study is extended by constructing two trading models, to practically test the possible benefits of using the P/E ratio value as a predicting and trading measure in the South African market.

Although Johansen cointegration tests reveal that co-integration relationships exist between the P/E ratio and subsequent closing prices and adjusted closing prices for total return, the VAR and VECM models used to estimate these relations do not yield significant results. Granger causality tests show very weak causal relation between the P/E ratio values and future closing prices and closing prices adjusted for total return.

Declaration

1. I know that plagiarism is wrong. Plagiarism is to use another's work and pretend that it is one's own.
2. This paper entitled: Investigating the relationship between the price earnings ratio and future stock returns in the SA market. is my own work.
3. I have used the following convention for citation and referencing: Do Price-Earnings Ratios Drive Stock Values? ....(FILL IN THE STYLE OR JOURNAL). Each significant contribution to, and quotation in, this paper from the work(s) of other people has been attributed, and has been cited and referenced.
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1 Introduction

In this paper the relationship between the historical price-earnings ratio and future stock returns is investigated on the JSE. The aim is to establish whether the P/E ratio is a viable factor in predicting future stock movements (returns), and as it is one of the most widely used financial ratios for company analysis, the study could be important in explaining how useful the P/E ratio is as a valuation measure.

The first part of this paper aims to replicate a study done by Bhargava and Malhotra, titled "Do Price-Earnings Ratios Drive Stock Values?" [11]. Their study aimed to determine whether a high price-earnings ratio indicates high or low future earnings growth and a high price-earnings ratio indicates higher or lower future stock prices. Their paper investigates the relation between the beginning-of-the-month P/E ratio and end-of-the-month closing price index values, and the beginning-of-the-month P/E ratio and end-of-the-month earnings yield values, over a time period of 20 years.

The statistical study was conducted on four different indexes, namely the Standard & Poor's 500 (S&P 500), the Morgan Stanley Composite Index (MSCI) world index, the MSCI Europe Index, and the Europe, African, and Far East (SAFE) index. The goal of the study was to determine whether P/E ratios drive future earnings or drive future prices.

They found that P/E ratios may not have as much of an impact on prices as they initially expected and as widely believed, and have no impact whatsoever on subsequent yields.

As the primary aim of this paper is to analyze the relationship between P/E ratio values and stock price returns, the relationship between the price-earnings ratio and earnings yield will not be investigated, as it seems unclear how an investor would act on this information. However the relationship between P/E ratios and closing prices adjusted for total returns (i.e. dividend payout etc), which incorporates the return that an investor will realize in reality, will be analyzed. It is of fundamental importance and significant results will add much value.

The statistical study and process of Bhargava and Malhotra is replicated on the JSE, focusing on the ALSI and TOP40 indexes as well as the Shareholder weighted counterparts, the SWIX ALSI and SWIX TOP40. The indexes chosen represent the South African market, and future contracts on the TOP40 and SWIX TOP40 are liquidly traded. A study on the indexes will be consistent with the replicated study and is more attractive than single share studies as the indexes will represent an average of the market, hence much noise is eliminated by the diversification effect, improving the clarity of the results. The diversification effect is caused by the formation of portfolios of companies, which results in the risk of the portfolio being less than the individual companies. Risk is broken up into market and unique risk. A diverse portfolio as an index will result in the majority of individual risk being diversified away and the portfolio consisting of only the market risk.

The second part of this paper consists of testing for the relationship between the price-earnings ratio and stock price returns in a more direct manner, by constructing a trading model using daily P/E ratio and price data. The investigation will aim to analyze the returns an investor would have made by trading on a mean-reverting strategy between the price-earnings ratio and adjusted closing price data over the exact same data sets used in the statistical study. The trading model is constructed in a similar way to a pairs trading strategy, using the beginning-of-the-day P/E ratio value and the end-of-the-day closing price adjusted for total return value as trading pairs. The motivation for an empirical trading model being:

- The initial statistical tests conducted may not have been powerful enough.
- The use of daily data in the trading model may increase the power of the test by increasing the number of data points.
- The assumptions of the statistical tests employed were possibly not the true underlying processes for the time series data (i.e. not normally distributed, stochastic etc.).
- A trading strategy executing trading signals using a simple mean-reversion strategy will further test the statistical and financial significance of the claimed presence of mean-reversion on the JSE 1124
- Significant relationships may exist between the P/E ratios and subsequent stock returns for shorter periods of time, but may not be significant over the entire period analyzed (in the statistical analysis), and hence a trading model may be able to pick up on these relationships.

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- The trading model will represent a simple possible method of achieving superior risk adjusted returns.

1.1 Objectives of the report

- Conduct a statistical analysis on the relationship between beginning of the month P/E ratio values against i.) the end-of-the-month closing price and II.) the total return adjusted closing price data on for the ALSI, TOP40, SWIX ALSI and SWIX TOP40 indexes.
- Discuss the findings of the statistical analysis and compare to the results of Bhargava and Malhotra 111).
- Construct a mean-reverting P/E ratio trading strategy model.
- Test the same data periods used in the statistical analysis using the trading model.
- Discuss the results and findings of the trading model.
- Conclude on the significance of the relationship between P/E ratios and subsequent prices and returns.
- Recommend further work on the topic.

2 Literature Review

2.1 Financial Ratio analysis and factor models

Some investors rely on public information to select which securities to purchase, whereas others use sophisticated models that they believe will provide them with an investment advantage in the competitive securities market. Using these models, the investors continuously evaluate the investment positions they have entered, and while some investors become rich using these strategies, many more will suffer extreme lasses. Approximately two-thirds of active investors under perform the index funds every year [ii.

The majority of the investors' portfolios will perform more poorly as a whole than a market basket and hence from this low success rate in financial markets it is clear that it is very difficult to find a robust model for making good financial predictions. The concept of the efficient market hypothesis renders these models invalid, and many analysts believe that the market is an efficient mechanism, and there are no superior returns to be made as all the security information will already be reflected in the in the price of the security [1].

There are few comparative tools for use in the financial analysis field, however the accounting field have provided financial ratios that are valuable in determining a company's relative performance and have also been valuable in predicting future performance of financial firms.

Much research has been conducted in the field of financial ratios' ability to forecast stock returns. James 0. Horrigan (1965) proved through an empirical study that financial ratios and their underlying factors play a significant role in the market over a longer term, i.e. 5 years or more. John H. Cochrane did a study involving ratios in 1997 and showed that dividend ratios are able to predict long-run dividend growth and stock returns. Jonathon Lewellan conducted a study in 2004, where he concluded that financial ratios are still a valid tool for predicting stock prices in a more recent environment. DI

2.2 The P/E Ratio

2.2.1 The concept of the P/E ratio

The price earnings ratio represents a market consensus of the value of the earnings of a company, an industry or the market, and an alternative term is the earnings multiple. The P/E ratio inverted is known as the earnings yield, a frequently quoted financial ratio.

The P/E ratio is calculated by dividing the current share price Po, by the reported attributable earnings over the prior 12 month period, *E0,* or the forecast earnings for the following 12 month period, E_h, The former is the historical or reported P/E ratio, and the latter is the prospective or forward PE ratio [2].

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$$PE_{Historical} = \frac{P_0}{E_0}$$

$$PE_{Prospective} = \frac{P_0}{E_1}$$

The P/E ratio reported by the JSE is the historical P/E ratio where the share price, Pp, is the current closing price of the share, and the value used for the earnings, Eo, is the earnings per share for past 12 months (updated on a rolling 6-month basis). The P/E ratios for the indexes are calculated by dividing the sum of the market capitalization's of the constituents by the sum of the earnings reported by the constituents [2].

2.2.2 P/E ratio studies

The unadjusted P/E ratio has been widely studied and it has been found that it is useful in forecasting stock returns. An example is a study done by Basu, where P/E values are used as an investment strategy guide and it is shown how portfolios of low price-earning shares had higher returns than that of high-price earnings shares over the period studied. [3, 7, ?I.

Trevino and Robertson [20021 studied the relationship between the current P/E ratios and the subsequent stock returns, and concluded that the current P/E ratios have no correlation with the subsequent short-term returns (i.e. three years). It was found that investing in stock of higher P/E ratios lead to lower returns over five year periods or more BE.

Campbell and Shiller [6, 111 report that future dividends may be forecast by using the moving average of earnings and that the P/E ratios are powerful predictors of the long-term stock returns. In a mean-reversion study later conducted on historical data, it was determined that higher P/E ratios are followed by lower growth, and it was predicted that stock prices having very high P/E ratios will drop significantly in the future. Campbell and Shiller conclude that P/E ratios and dividend-price ratios are poor predictors of future dividend growth, future earnings growth or prices, but these ratios are however good predictors of future stock price changes [7, 8, 111.

Park [2002] advises that an investor should not be alarmed by a high P/E ratio by itself, and that the P/E ratio is explained fairly well by the future earnings and interest rates. Fisher and Statman [20021 investigated the relationship between P/E ratios and dividend yield and future returns, and concluded that P/E ratios and dividend yields are not good indicators of future stock prices, and are very poor for shorter period (less than 2 years), but P/E ratios and dividend yields provide much better forecasts when used to estimate the stock returns over longer period of time (10 years) [11].

A study on mean reversion of returns of shares on the JSE was conducted by Cubbin. The existence of mean reverting returns contradicts the market efficiency theory as it implies that future stock prices may be predicted from historical prices. The mean-reversion anomaly was observed on the SSE, where a portfolio of low P/E shares significantly outperforms the portfolio of high P/E shares [12]. A latter paper developed the economic validity of this conclusion by applying liquidity constraints to the portfolio formation, which slightly dampened the observed effects but still confirmed the significant presence of mean reversion on the JSE [13].

2.3 The paper by Bhargava and Malhotra

In the paper "Do Price-Earnings Ratios Drive Stock Values?", Bhargava and Malhotra [111 investigate the relationship between historical P/E ratios and subsequent price and historical P/E ratios and subsequent yield/earnings. They use monthly data for a period of 20 years on four international indexes, the Standard & Poor 500 (S&P 500), the Morgan Stanley Composite Index (MSCI) world index, the MSCI Europe Index, and the Europe, African, and Far East (SAFE) index, with the goal of determining whether P/E ratios drive future earnings or future prices. They first regress the beginning of the month P/E values against the end of the month period's prices and yields. The regression model is:

$$Yield/Price = \alpha + \beta\,(P/E) + \varepsilon$$

Where the Yield is the subsequent yield (end-of-the-month yield), Price is the subsequent price (end-of-the-month price), and P/E is the beginning-of-the-month P/E ratio and α and β are the regression coefficients.

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Their regression results showed a positive relationship between the closing price and P/E ratios and a negative relationship between P/E ratios and the yield, which indicate that subsequent prices increase and yields decrease as the P/E ratios increase. The regressions were then tested for autocorrelation and heteroscedasticity, and from the results, autocorrelation is present in all eight. of their regressions, and heteroscedasticity present in all regressions except when yield is regressed against the P/E ratio for the S&P 500.

Tests for stationarity were conducted on all three series (P/E ratio, price and yield) for all four the indexes, using the Phillips and Perron (P&P) test for four lags (test for unit root). The test was done for three different state assumptions, intercept, intercept with trend and no intercept and trend, and the results could not reject the presence of unit roots and hence the series were considered non-stationary [111.

Stationarity arising from linear combination of variables, i.e. cointegration, was tested for using the Johansen cointegration test. The test results showed two cointegrating relationships between the P/E ratio and closing price for the S&P 500 and one cointegrating equation between the P/E ratio and closing price for the EAFE index, and all the other series did not show evidence of cointegration

Vector error correction models (VECM) are used for the two series where cointegration is found present and vector autoregression models (VAR) for the other six cases where no evidence of cointegration was found. These models are used to explore the relation between the variables and Granger causality is used to test whether relation is causal and are discussed in the next section.

The results from the P/E ratio and subsequent price relation show that prices rise in response to the P/E ratio but not as much as was suggested originally by the regression analysis and that only one of the four lags is positive and significant for all four indexes. Results from the P/E ratio and subsequent yield shows that there is no significant relation.

They conclude that in response to an increase in the P/E ratio, subsequent prices will increase and subsequent yields will decrease. With the adjustments for autocorrelation, heteroscedasticity, unit roots and non-stationarity, the P/E ratios may not have as a significant impact as they initially expected on subsequent prices and may have no impact on subsequent yields at all [11].

2.4 Statistical Analysis

2.4.1 VAR - Vector Autoregression

The vector autoregressive (VAR) model is commonly used to forecast systems of interrelated (but not cointegrated) time series and to analyze the dynamic impact of random disturbances on the a system of variables. The VAR model avoids the need for structural modeling as every variable is endogenous in the system as a function of the lagged values of all the variables in the system. The word "vector" refers to a vector of two or more variables being included in the system model and the word "autoregressive" refers to the appearance of the lagged values of the dependent variable on right-hand-side of the equation [17].

Suppose we have in time series yit, i = 1, ... in, and t 1, ...T (the common length of the time series), then the VAR model is defined as (in matrix form) [161:

$$y_t = \mu + \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + \epsilon_t$$

where

$$y_t = (y_{1t}, y_{2t}, \ldots, y_{mt})$$

which may be further simplified by using the matrix of the lag operator

$$\phi(L) = I - \phi_1 L - ... - \phi_p L^p$$

Hence we are left with

$$\phi(L) y_t = \epsilon_t$$

The basic assumption of the above model is that the residual vector follows a multivariate white noise process

$$E(t) = 0$$

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$$E(\epsilon_t \epsilon_s') = \begin{cases} \Sigma_\epsilon & t = s \\ 0 & t \neq s \end{cases}$$

2.4.2 Cointegration and VECM

The econometricians Engle and Granger studied multivariate series to determine statistically if there is a causal relationship between the variables represented by a time series and found that even though two time series may themselves be non-stationary, in some circumstances a specific linear combination of the two exists which is stationary 114]. Typically economic theory will propose forces which will tend to keep such series together, examples include short and long term interest rates, household income and expenditures.

If xi is a vector of economic variables, then they may be in equilibrium when there exists a specific linear constraint:

$$\alpha' x_t = 0$$

However in the majority of time periods, It will not be in equilibrium and the univariate quantity zt = *ø'xt* is referred to as the equilibrium vector ɱ.

Engle and Granger showed that a class of models, namely error-correcting will allow long-run components of variables to obey equilibrium constraints while the short-run components will have a flexible dynamic specification. The required condition for this class of model to be valid is that co-integration needs to he present.

Commonly economic series must be differenced before the assumptions of stationarity can be presumed to hold, and hence a series x_t with no deterministic component which has a stationary, invertible, ARMA1 representation alter differencing *d* times, is defined to be integrated of order d and is denoted by x_i —1(d)191.

The components of a vector *xt* are said to be co-integrated of order *d, b* which is denoted as x_t***CI(d, b),*** if i.) all components of *xt* are *1(d),* ii.) a vector a(= 0) exists that z_t = *ø'xt* *1(d -* > 0. This vector a is known as the co-integrating vector [9].

In simpler terms, if y_t and x_t are two nonstationary time series, and if for a certain value 7, the series *yt - γxt* is stationary, then these two series are said to be co-integrated. Then let ex $_t$, and e_s, be the white noise processes that corresponds to the time series *xt, yt* respectively. The error correction representation is then [14]:

$$y_t \quad y_{t-1} = \alpha_y (y_{t-1} - \gamma x_{t-1}) + \varepsilon_{y_t}$$

$$x_t - x_{t-1} = \alpha_x (y_{t-1} - \gamma x_{t-1}) + \varepsilon_{x_t}$$

2.4.3 Johansen cointegration test

The methodology starts with a vector autorregressive (VAR) process of order p [18]

$$y_t = \mu + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t$$

where y_t is an $n \times 1$ vector of variables integrated of order one, i.e. *I(1)* and ε_t is an $n \times 1$ vector of innovations. The VAR model may be re-written as

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t$$

where

$$\Pi = \sum_{i-1}^{p} A_i - I$$

and

[1]ARMA: Autoregressive moving average

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$$\Gamma_i = -\sum_{j=i+i}^{p} A_j$$

If the coefficient matrix II has a reduced rank of r G n, then n x r matrices a and $_3$ will exist each with rank r such that U = øB' and Btyt is stationary. Here r is the number of cointegrating relationships, and the elements of a are known as the adjustment parameters in the VECM model and each column of 0 is a cointegrating vector. For a given r, the maximum likelihood estimator of a defines the combination of that will yield the r largest canonical correlations of Ay_e with

tests for the significance of the canonical relationships, i.e. the trace test and the max eigenvalue test [18]. The max eigenvalue test will be employed in this paper and is detailed below [18].

$$J_{max} = -T \ln\left(1 - \hat{\lambda}_{r+1}\right)$$

T is the sample size and as is the i-th largest canonical correlation. It tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r + 1 cointegrating vectors. More information on the Johansen methodology for cointegration may be found in [10, 18].

2.4.4 Tests for unit root/stationarity

In the following, y(t), e(t), Ly(t) = y(t -1), are the time series of observed data, the model residuals, and the lag operator respectively.

In our analysis we use the following Matlab functions.

Augmented Dickey-FuHer unit root tests (Matlab test)

dfARTEST (no intercept with no trend) This function performs an augmented Dickey-Fuller univariate unit root test under the assumption that the true underlying process is a zero drift unit root process. Under the null hypothesis the true underlying process is a zero drift ARIMA(P,1,0) model

$$y(t) = y(t-1) + B1 \times (1-L) \times y(t-2) + ... + BP \times (1-L)y(t-P) + e(t)$$

equivalent to an integrated AR(P + 1) model, and as alternative, the estimated OLS regression model is

$$y(t) = A \times y(t-1) + B1 \times (1-L)y(t-1) + B2 \times (1-L) \times y(t-2) + ... + BP \times (1-L)y(t-P) + e(t)$$

for some AR(1) coefficient A < 1 [15].

dfARDTEST (intercept with no trend) This function performs an augmented Dickey-Fuller univariate unit root test under the assumption that the true underlying process is a zero drift unit root process. Under the null hypothesis the true underlying process is a zero drift ARIMA(P,1,0) model

$$y(t) = y(t-1) + B1 \times (1-L)y(t-1) + B2 \times (1-L) \times y(t-2) + ... + BP \times (1-L)y(t-P) + e(t)$$

equivalent to an integrated AR(P + 1) model, and as an alternative, the estimated OLS regression model is

$$y(t) = C + A \times y(t-1) + B1 \times (1-L)y(t-1) + B2 \times (1-L) \times y(t-2) + ... + BP \times (1-L)y(t-P) + e(t)$$

for some constant C and AR(1) coefficient A < 1 [15].

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dfTSTEST (intercept with trend) This function performs an augmented Dickey-Fuller univariate test under the assumption that the true underlying process is a unit root process with drift. Under the null hypothesis the true underlying process is an ARIMA(P,1,0) model with drift

$$y(t) = C + y(t-1) + B1 \times (1-L)y(t-1) + B2 \times (1-L) \times y(t-2) + \ldots + BP \times (1-L)y(t-P) + e(t)$$

equivalent to an integrated AR(P + 1) model, and as an alternative, the estimated OLS regression model is

$$y(t) = C + A \times y(t-1) + D \times t + B1 \times (1-L)y(t-1) + B2 \times (1-L) \times y(t-2) + \ldots + BP \times (1-L)y(t-P) + e(t)$$

for some constant C, AR(1) coefficient A < 1 and a trend stationary coefficient D [15].efficient A < 1, and trend stationary coefficient D.

Philips-Perron unit root tests (Matlab test)

ppARTEST (no intercept with no trend) This function performs a Phillips-Perron univariate unit root test under the assumption that the true underlying process is a zero drift unit root process. Under the null hypothesis the true underlying process is assumed to be

$$y(t) = y(t-1) + e(t)$$

and as an alternative the estimated OLS regression model is

$$y(t) = A \times y(t-1) + e(t)$$

for some AR(1) coefficient A < 1 [15].

ppARDTEST (intercept with no trend) This function performs a Phillips-Perron univariate unit root test under the assumption that the true underlying process is a zero drift unit root process. Under the null hypothesis the true underlying process is assumed to be

$$y(t) = y(t-1) + e(t)$$

and as an alternative the estimated OLS regression model is

$$y(t) = C + A \times y(t-1) + e(t)$$

for some constant C and AR(1) coefficient A < 1 [15].

ppTSTEST (intercept with trend) This function performs a Phillips-Perron univariate unit root test under the assumption that the true underlying process is a unit root process with drift. Under the null hypothesis the true underlying process is assumed to be

$$y(t) = C + y(t-1) + e(t)$$

for an arbitrary constant C and as an alternative, the estimated OLS regression model is

$$y(t) = C + A \times y(t-1) + B \times t + e(t)$$

for some constant C, AR(1) coefficient A < 1, and a trend stationary coefficient B [15].

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2.5 Pairs Trading Models

In section 5 we develop a trading model that is partly based on a model originally intended for pairs trading.

The general aim for investing in the market from a valuation perspective is to buy undervalued shares and sell overvalued shares. It is only possible to determine whether a security is undervalued or overvalued if the "true" unobservable value of the security is known. It is very hard to determine this value, and pairs trading aims to resolve this problem by employing the relative pricing concept, i.e. that if two securities have similar characteristics, then the prices of the securities must be approximately the same. If the prices of the two securities differ it is possible that one of the securities is overpriced and the other is under priced, or the mispricing is a combination of both i141.

Hence pairs trading involves shorting (or selling) the higher-priced security and going long (or buying) the lower-priced security with the expectation that the mispricing will be corrected in the future. The degree of mispricing is captured by the notion of spread and the greater the spread, the greater the mispricing and therefore the larger the profit potential. The key to succeed in pairs trading lies in the identification of suitable security pairs. The methodology behind selecting pair securities are based on analyzing historical price movements. One strategy for designing a pairs trading model might consist of three steps, namely identification of stock pairs, cointegration testing and trading rule formulation [14].

Therefore statistically pairs trading is a relative value arbitrage on two securities and is based on the theory that there exists a long-run equilibrium between the pair of stock prices. Deviation from the long-run equilibrium is compensated for in the subsequent movements of the time series, and hence pairs trading involves trading on the oscillations about this equilibrium value. A distance measure is defined in [14], and is based on an APT model with fundamental risk factors. The candidates for pairs trading are constructed by selecting potentially cointegrated stock pairs and then choosing pairs with distance values within a certain threshold. It is possible to trade pairs of stocks even though they deviate from the ideal conditions of cointegration, and the test for tradability is a two-step process consisting of evaluating the linear relationship and measuring the degree of mean reversion of the residual [141.

The linear relationship may be estimated by ordinary least squares regression, and the spread series will be calculated by applying the linear relationship. The degree of mean-reversion can be determined by conducting statistical analysis (e.g Dickey-Fuller test for unit roots on the residuals of the least-squares regression).

In trading the spread between the pairs, it is recommendable to trade at a level that will result in the maximum profits being realized. Large threshold levels will result in infrequent trading for large profits, whereas small threshold value trades will trade frequently for small profits. An optimal value for this threshold level is between the two extreme levels [14].

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3 Data Description

The data required for the study consisted of the daily closing price values, corresponding closing P/E ratio values and the closing price values adjusted for total return (i.e. Dividend payout etc.) for the Indexes. Lastly the 3-month JIBAR rate was required as a proxy for the return/cost of investing/borrowing cash, which would be used in the trading model section. Two sets of historical data was obtained from I-Net Bridge. The first set was the daily data from 1999/11/30 to 2009/12/15 for the ALSI and TOP40 indexes and the second set was the daily data from 2003/05/30 to 2009/12/15 for the ALSI, TOP40, SWIX ALSI and SWIX TOP40. The reason for the for the two sets of data, was that the Shareholder weighted indexes, i.e. the SWIX counterparts did not exist until 2002 and the price-earnings ratio data was only available on I-Net from 2003. As South Africa is an emerging market with ever changing and developing economic climate, a ten year period (i.e. from 1999) was deemed to be a sufficiently long-term period for the study to be conducted on, and the shorter six year period from 2003 will represent the more recent financial data.

The earnings yield value was derived from the P/E ratio values as it is the reciprocal. The monthly data was retrieved from the daily data for the statistical analysis procedure, for the replication of the work done by Bhargava eta' ill]. The daily data was used for the Trading strategy model, to incorporate greater power into testing compared to that of the statistical analysis and to simulate realistic daily trading conditions.

Figures 1-3 below present the data graphically.

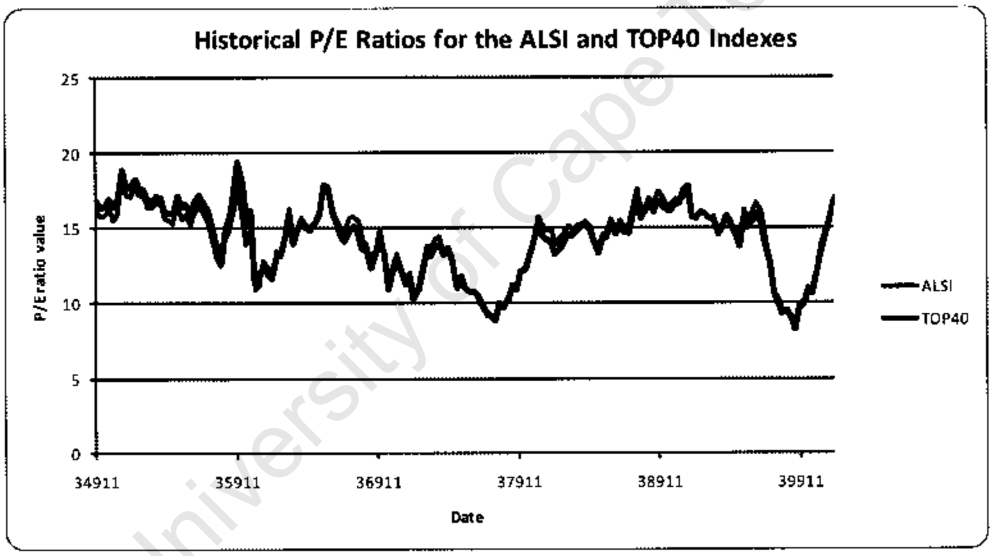

Figure 1: Historical P/E ratios for the ALSI and TOP40 indexes.

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The ALSI and TOP40 closing price series for the last ten years is illustrated below, the series adjusted for dividend payouts, the total return adjusted closing prices follow the same trend.

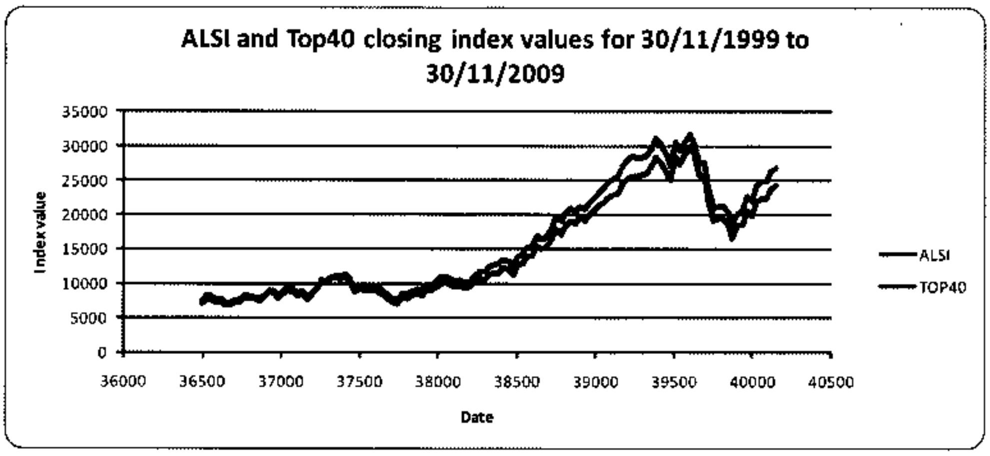

Figure 2: The ALSI and TOP40 closing index values for 30/11/1999 to 30/11/2009

The P/E ratio values for the second analysis period, i.e. the last six years are detailed below for the four indexes investigated.

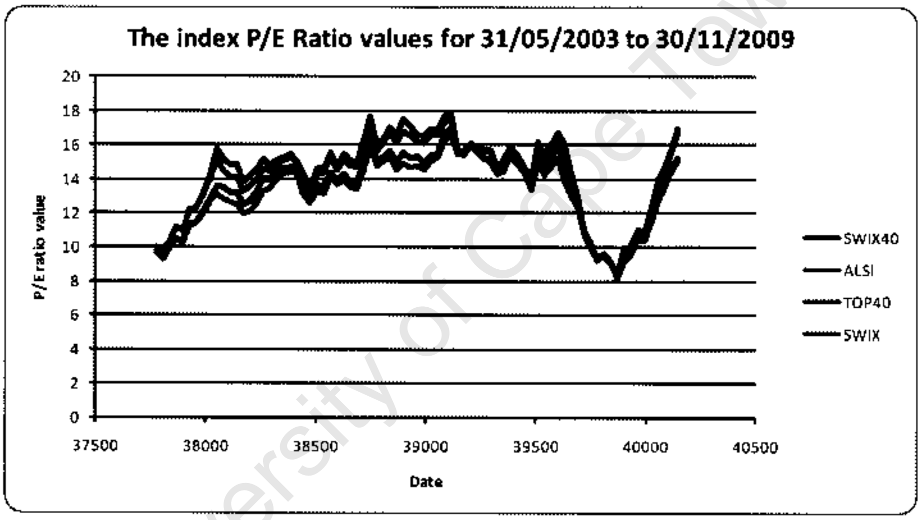

Figure 3: The index P/E ratio values for 31/05/2003 to 30/11/2009

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4 Statistical Analysis

4.1 Methodology

The methodology detailed below is repeated for the two time data sets mentioned previously, and hence effectively six data groups will be analyzed, namely the ALSI and TOP40 indexes for the ten year period and the ALSI, TOP40, SWIX ALSI (SWIX) and SWIX TOP40 (SWIX40) for the six year period.

The first step is to evaluate the relationship between the P/E ratio values and i.) closing prices, yields or iii.) adjusted closing prices. To do this an ordinary least squares (linear OLS) regression is performed. The end-of-the-month i.) closing prices and ii.) adjusted closing prices are regressed against the beginning-of-the-month P/E ratio values. Note that the beginning-of-the-month values are the values at the end of the previous month. The results of the regression model are then interpreted, followed by testing the regressions for autocorrelation and heteroscedasticity using the Durbin-Watson statistic and White test 1j.

If autocorrelation is present in the regressions, tests for stationarity should be conducted on the time series data. Three different types of augmented Dickey-Fuller tests are used to test for unit roots in all the time series data (i.e. P)E ratio data, closing price data etc.) up to four lags. The three different types of tests being a.) no intercept with no trend, b.) intercept with no trend and c.) intercept with trend.

Assuming the presence of a unit root in the series (i.e. series is non-stationary) the difference of the series is calculated and tested for unit root. The differenced series should be stationary and hence of integrating order *1(1).* If all the series are *1(1),* co-integrating relations may exist between them, where linear combinations of the non-stationary time series can be stationary. Augmented Dickey-Fuller tests as detailed earlier and corresponding Phillips-Perron tests on the residuals of the performed regressions are conducted as tests for cointegration on the performed OLS regressions.

A more general cointegration test is performed by using the Johansen's cointegration test for series of *1(1),* which will enable testing for more than one cointegration vector and will check stationarity due to linear combination of variables [11j.

As suggested by Engle and Granger, if a system of variables is cointegrated, the economic forces will interact to bind these variables together in a long-term equilibrium relation and hence these cointegrated variables may be represented by a vector error correction model (VECM). Where no cointegration is found, unrestricted vector autoregression is used to represent the relationship between the variables. From the VECM and VAR models, the significance of the coefficients may be evaluated and hence it may be determined to what extent P/E values affect subsequent closing prices and and closing prices adjusted for total return. The Granger causality test is then employed to determine whether the Pit ratio values "Granger-causes" the closing prices and closing prices adjusted for total return to change [11].

The results are compared to that obtained in the international markets by Bhargava and Malhotra and discussed further.

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4.2 Results

Note the results for the period 1 data are presented first, followed by the results for the period 2 data, throughout the section:

Period 1: 1999/11/30 to 2009/11/30

Period 2: 2003/05/31 to 2009/11/30

Also the significance is tested at the 5% level (i.e. P-val of 0.05)

4.2.1 OLS Regressions

The regression results from i) the end-of-the-month closing price values and ii.) the end-of-the-month closing price values adjusted for total return regressed on the beginning-of-the-month P/E ratio values, for the corresponding two data periods are detailed below.

$$Price = \alpha + \beta \times P/E + \varepsilon$$

$$AdjustedPrice = \alpha + \beta \times P/E + \varepsilon$$

α is the intercept coefficient value, β is the P/E ratio coefficient value; and the corresponding t-statistic and P-value are detailed for the α and β coefficients. The R^2 value for the OLS regression model is also included. The intercept coefficient, α is not significant in any of the cases and is not discussed. The results correspond to that of the Bhargava study.

Period 1 The OLS regression results for period 1 are detailed and discussed below.

Table 1: Subsequent closing price regressed on P/E ratio

	Intercept coefficient			*P/E ratio coefficient*			*Model fit*
Index	α	t-stat	P-value	β	t-stat	P-value	R^2
ALSI	-724.322	-0.180	0.857	1234.702	4.240	4.47E-05	0.132
TOP 40	805.064	0.226	0.821	1003.709	3.973	1.23E-04	0.118

The regression results indicate that the P/E ratio (independent variable) coefficient is highly significant for all the ALSI and TOP40 regression models for both the Periods. There is a positive relation between the closing price and the P/E ratios, indicating that subsequent prices rise as P/E ratios increase. The P/E ratio coefficient is less significant for the regression model where the adjusted closing price is the dependent variable, as well as the R^2 value of the model being slightly less. The R^2 value is very low for the both the models, indicating that the P/E ratio explains very little of the subsequent price and adjusted price movements.

Table 2: Subsequent adjusted closing price regressed on P/E ratio

	Intercept coefficient			*P/E ratio coefficient*			*Model fit*
Index	α	t-stat	P-value	β	t-stat	P-value	R^2
ALSI	-97.797	-0.209	0.835	126.627	3.722	3.04E-04	0.105
TOP 40	63.325	0.151	0.880	103.789	3.492	6.75E-04	0.094

Period 2 The OLS regression results for period 2 are detailed and discussed below.

Table 3: Subsequent closing price regressed on P/E ratio

	Intercept coefficient			*P/E ratio coefficient*			*Model fit*
Index	α	t-stat	P-value	β	t-stat	P-value	R^2
ALSI	5332.230	1.111	0.270	1040.541	3.082	2.87E-03	0.111
SWIX ALSI	-106.546	-0.110	0.913	322.2268	4.428	3.14E-05	0.205
TOP 40	5564.494	1.284	0.203	878.4265	2.939	4.35E-03	0.102
SWIX TOP40	-47.757	-0.053	0.958	288.105	4.375	3.82E-05	0.201

The regressions are robust and the P/E ratio coefficients significant in all cases for the subsequent closing price and subsequent adjusted closing price regressed on the P/E ratio for period 2. There is, as expected, a positive relation between P/E ratio and price, P/E ratio and adjusted price. The R^2 values for the SWIX ALSI and SWIX TOP40 indexes are greater (by a factor of two) than the ALSI and TOP40 indexes. The SWIX index's price movements seem to be better explained by the P/E ratios, although the R^2 values are still very poor.

Table 4: Subsequent adjusted closing price regressed on P/E ratio

	Intercept coefficient			*P/E ratio coefficient*			*Model fit*
Index	α	t-stat	P-value	β	t-stat	P-value	R^2
ALSI	717.279	1.293	0.200	96.932	2.483	1.52E-02	0.075
SWIX ALSI	201.983	0.154	0.878	358.607	3.649	4.80E-04	0.149
TOP 40	719.731	1.433	0.156	83.067	2.398	1.89E-02	0.070
SWIX TOP40	192.841	0.161	0.872	322.087	3.681	4.33E-04	0.151

4.2.2 Autocorrelation and Heteroscedasticity Tests

The OLS regression results need to be checked for the presence of Autocorrelation and Heteroscedasticity, and the Durbin-Watson (DW) and White tests are used to do the corresponding

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tests. The results of the tests are presented below for Periods 1 and 2. The 'DW' column is the Durbin-Watson statistic value, the 'P-value' column the corresponding the P-Value for the Durbin-Watson statistic and the 'White p-val' column is the P-value for the White tests.

Period 1 The results for regression on period 1 are detailed below. It is clear from the two tables below that autocorrelation is present in all the regressions performed, but we cannot reject Homoscedasticity (the White test null hypothesis is that Homoscedasticity exists), hence we only accept that autocorrelation is present (AC).

Table 5: Price Regressed on P/E Ratio: DW and White Tests

Index	DW	P-Value	White p-val	ACC & HET
ALSI	0.037	5.21E-93	0.135	**AC acccept*
TOP 40	0.039	7.36E-92	0.087	**AC acccept*

Table 6: Adjusted Price Regressed on P/E Ratio: DW and White Tests

Index	DW	P-Value	White p-val	ACC & HET
ALSI	0.029	3.37E-100	0.345	**AC acccept*
TOP 40	0.031	7.43E-99	0.258	**AC acccept*

Period 2 The results for the shorter period shows that the autocorrelation and heteroscedasticity is present in all the regressions performed. The 'Accept' in the ACC & HET columns illustrate this.

Table 7: Price Regressed on P/E Ratio: DW and White Tests

Index	DW	P-Value	White p-val	ACC & HET
ALSI	0.043	2.04E-59	1.52E-05	*Accept*
SWIX ALSI	0.056	3.35E-54	2.86E-05	*Accept*
TOP 40	0.046	4.32E-58	1.55E-04	*Accept*
SWIX TOP40	0.063	2.99E-52	5.57E-04	*Accept*

Table 8: Adjusted Price Regressed on P/E Ratio: DW and White Tests

Index	DW	P-Value	White p-val	ACC & HET
ALSI	0.033	3.10E-64	2.24E-06	*Accept*
SWIX ALSI	0.042	1.49E-59	1.84E-06	*Accept*
TOP 40	0.037	2.06E-62	4.85E-05	*Accept*
SWIX TOP40	0.048	5.67E-57	5.74E-05	*Accept*

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4.2.3 Tests for Unit Root and Stationarity

The presence of autocorrelation in all the regression performed, suggests that tests for stationarity should he conducted **III]**. All the time series data are tested for a unit root using the Dickey-Fuller test (up to 4 lags) and some of the results are presented below.

The time series data, i.e. the P/E ratio, closing price, and adjusted closing price data for all the indexes in both the periods was found to he non-stationary (i.e. unit root was not rejected by the Dickey-Fuller test).

An example for each of the periods are illustrated below, and the complete results may be found in Appendix A.

Period 1 From the Dickey-Fuller test results for the P/E ratio in period 1 it is clear that in none of the cases (for any of the underlying assumptions), may the presence of the unit root be rejected at the 5% significance level.

Table 9: Dickey-Fuller Test: P/E Ratio

		P/E ratio					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.510	-0.381	0.267	-2.068	0.526	-2.130
	1	0.416	-0.639	0.105	-2.557	0.266	-2.665
	2	0.439	-0.576	0.124	-2.476	0.294	-2.607
	3	0.517	-0.363	0.119	-2.498	0.288	-2.620
	4	0.551	-0.268	0.117	-2.507	0.279	-2.638
TOP40	*0*	0.507	-0.389	0.250	-2.106	0.520	-2.143
	1	0.414	-0.645	0.106	-2.555	0.285	-2.626
	2	0.436	-0.585	0.125	-2.473	0.316	-2.562
	3	0.503	-0.402	0.103	-2.568	0.271	-2.654
	4	0.535	-0.313	0.095	-2.602	0.251	-2.697
Test-Stat Critical Value		-1.944 (0.05 P-val)		-2.887 (0.05 P-val)		-3.450 (0.05 P-val)	

Period 2 From the Dickey-Fuller test results for the Price data in period 2 it is also evident that in none of the cases (for any of the underlying assumptions), may the presence of the unit root be rejected at the 5% significance level.

Table 10: Dickey-Fuller Test: Price

		Closing Price					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.948	1.285	0.602	-1.300	0.920	-1.112
	1	0.927	1.091	0.612	-1.277	0.903	-1.200
	2	0.892	0.853	0.614	-1.273	0.846	-1.423
	3	0.860	0.679	0.550	-1.419	0.735	-1.692
	4	0.815	0.475	0.554	-1.410	0.573	-2.030
TOP40	*0*	0.936	1.169	0.604	-1.296	0.913	-1.150
	1	0.914	0.996	0.611	-1.280	0.894	-1.243
	2	0.877	0.766	0.607	-1.288	0.823	-1.494
	3	0.844	0.602	0.539	-1.444	0.691	-1.785
	4	0.803	0.427	0.543	-1.435	0.543	-2.092
SWIX ALSI	*0*	0.956	1.368	0.568	-1.379	0.928	-1.063
	1	0.934	1.146	0.577	-1.358	0.912	-1.157
	2	0.912	0.980	0.577	-1.357	0.889	-1.263
	3	0.876	0.763	0.523	-1.482	0.813	-1.520
	4	0.822	0.504	0.527	-1.471	0.632	-1.906
SWIX TOP40	*0*	0.944	1.236	0.568	-1.378	0.924	-1.087
	1	0.921	1.046	0.573	-1.366	0.907	-1.182
	2	0.899	0.893	0.571	-1.371	0.880	-1.298
	3	0.854	0.650	0.507	-1.518	0.763	-1.635
	4	0.803	0.428	0.508	-1.517	0.583	-2.009
Test-Stat Critical Value		-1.945 (0.05 P-val)		-2.900 (0.05 P-val)		-3.470 (0.05 P-val)	

4.2.4 Cointegration Testing - Stationarity of Regression Residuals

The unit root presence in the time series data suggests testing for the possibility that cointegrating relationships may exist between the series, i.e. that linear combinations of non-stationary time series may be stationary [11]. Dickey-Fuller and Phillips-Perron tests are performed on the residuals of the OLS regressions performed earlier. However none of the tests conducted could reject the presence of the unit root and hence the residuals of all the regressions performed are non-stationary as well. The result does not reject the presence of cointegrating relationships between the time series, but merely rejects the hypothesis that the specific linear combination of the series from the OLS regressions is a cointegrating relationship.

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An example of the tests are presented for each of the periods, and the complete results may be found in Appendix A.

Period 1 The Dickey-Fuller test on the residuals (up to 4th lag) of the PIE ratio regressed on the closing price for period 1 on the ALSI and TOP40 indexes cannot reject the presence of the unit root. and hence the residuals are non-stationary. Therefore the PfE ratio and subsequent price linear OLS regression relationship is not a cointegrating relation.

Table 11: Dickey-Fuller Test: Residuals - Price Regressed on P/E ratio

		Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.195	-1.245	0.632	-1.236	0.328	-2.538
	1	0.192	-1.254	0.623	-1.254	0.742	-1.687
	2	0.170	-1.326	0.577	-1.360	0.866	-1.364
	3	0.228	-1.152	0.643	-1.209	0.883	-1.295
	4	0.228	-1.152	0.647	-1.201	0.837	-1.459
TOP40	*0*	0.212	-1.197	0.653	-1.187	0.354	-2.484
	1	0.224	-1.164	0.665	-1.160	0.766	-1.637
	2	0.202	-1.224	0.626	-1.248	0.880	-1.308
	3	0.251	-1.090	0.676	-1.134	0.886	-1.282
	4	0.237	-1.127	0.662	-1.166	0.825	-1.496
Test-Stat Critical Value		-1.944 (0.05 P-val)		-2.887 (0.05 P-val)		-3.450 (0.05 P-val)	

Period 2 The Phillips-Perron test on the residuals of the P/E ratio regressed on the adjusted closing price for the indexes in Period 2 also shows that the presence of the unit root cannot be rejected and hence the residuals are non-stationary. This linear regression relationship is hence not a cointegrating relation.

Table 12: Phillips-Perron Test: Residuals - Adjusted Price regressed on P/E ratio

		Adjusted Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.318	-0.904	0.780	-0.891	0.576	-2.025
	1	0.359	-0.792	0.822	-0.767	0.726	-1.712
	2	0.367	-0.771	0.831	-0.735	0.746	-1.671
	3	0.366	-0.774	0.833	-0.728	0.732	-1.701
	4	0.355	-0.801	0.828	-0.746	0.685	-1.797
TOP40	*0*	0.307	-0.934	0.767	-0.921	0.590	-1.996
	1	0.349	-0.819	0.814	-0.795	0.730	-1.704
	2	0.358	-0.795	0.824	-0.761	0.749	-1.665
	3	0.356	-0.799	0.825	-0.756	0.732	-1.700
	4	0.345	-0.829	0.819	-0.777	0.686	-1.796
SWIX ALSI	*0*	0.307	-0.933	0.767	-0.920	0.143	-2.986
	1	0.366	-0.772	0.828	-0.746	0.275	-2.650
	2	0.390	-0.706	0.848	-0.667	0.316	-2.565
	3	0.395	-0.694	0.854	-0.641	0.300	-2.598
	4	0.386	-0.718	0.851	-0.654	0.253	-2.695
SWIX TOP40	*0*	0.285	-0.994	0.741	-0.982	0.183	-2.855
	1	0.349	-0.819	0.814	-0.796	0.339	-2.516
	2	0.378	-0.739	0.839	-0.704	0.389	-2.413
	3	0.383	-0.727	0.844	-0.682	0.371	-2.451
	4	0.372	-0.757	0.839	-0.703	0.318	-2.560
Test-Stat Critical Value		-1.945 (0.05 P-val)		-2.899 (0.05 P-val)		-3.469 (0.05 P-val)	

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9.2.5 Cointegration Testing - Johansen's Cointegration Test

A more general cointegration test, the Johansen Test is conducted for the different relations with the model assumption of a constant and a time trend. A requirement for the Johansen Cointegration test is that series analyzed for cointegrating relation must be of the same integrating order. Therefore all the time series data for period 1 and 2 were investigated, and all are of order 1, i.e. 1(1). This means that the non-stationary series data, when differenced once, becomes stationary.

Hence the Johansen Cointegration test was performed for lag 1 (i.e. integrating order 1) for all the P/E ratio and closing price and P/E ratio and adjusted price data The test determines whether no cointegrating relations may be rejected (i.e. reject 'None') and secondly to test whether there are more than one cointegrating relationships present (i.e. reject 'At most 1'). Since all the tests involve two time series, the most cointegrating relationships that may exist is two. The shaded cells indicate significance at the 570 critical level.

Period 1 The Johansen Cointegration tests for period **1** are detailed in the table below. It shows that there exists two cointegrating relationships between the **P/E** value and price and P/E value and adjusted price.

Table 13: Johansen Cointegration Tests (Period 1)

Johansen cointegration test, constant with time trend, 1 Lag						
INDEX	**Price regressed on P/E**		**Adj price regressed on P/E**		**Critical Values**	
ALSI	*Eigenvalue*	*Max-Eigen Stat*	*Eigenvalue*	*Max-Eigen Stat*	*5%*	*1%*
None	0.152	**19.494**	0.142	**18.127**	17.148	21.747
At most 1	0.041	**4.949**	0.041	**4.945**	3.842	6.635
TOP40						
None	0.147	**18.786**	0.138	**17.502**	17.148	21.747
At most 1	0.040	**4.814**	0.040	**4.838**	3.842	6.635

Period 2 The Johansen Cointegrating test results below indicate that only one cointegrating equation exists between **P/E** ratio and price for the SWIX TOP40 data and two cointegrating relations between P/E ratio and adjusted price data for the SWIX TOP40 data. All other series do not show evidence of cointegration in period 2.

Table 14: Johansen Cointegration Tests (Period 2)

Johansen cointegration test, constant with time trend, 1 Lag						
INDEX	**Price regressed on P/E**		**Adj price regressed on P/E**		**Critical Values**	
ALSI	*Eigenvalue*	*Max-Eigen Stat*	*Eigenvalue*	*Max-Eigen Stat*	*5%*	*1%*
None	0.189	15.891	0.185	15.538	17.148	21.747
At most 1	0.044	3.403	0.048	3.742	3.842	6.635
TOP40						
None	0.196	16.595	0.193	16.264	17.148	21.747
At most 1	0.042	3.258	0.046	3.597	3.842	6.635
SWIX ALSI						
None	0.199	16.859	0.194	16.355	17.148	21.747
At most 1	0.047	3.643	0.052	4.035	3.842	6.635
SWIX TOP40						
None	0.214	**18.316**	0.208	**17.761**	17.148	21.747
At most 1	0.046	3.589	0.051	**3.999**	3.842	6.635

9.2.6 VAR and VECM relation outputs

According to Engle and Granger 19], if a system of variables is cointegrated, a long-term equilibrium relation may exist, and the cointegrated variables may be represented by a vector error correction model (VECM). Hence for the data where cointegrating relationships were present according to the Johansen tests, VECM will be used to estimate the relation between the variables. The other variables that did not show cointegrating relationships, the relation between the variables will be estimated using the VAR model.

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Further the Granger-Causality test results is attached to the tables, which tests whether the P/E ratio cause the closing price or adjusted closing price to change according to the Granger methodology. The test statistic for the Granger test is a chi-squared statistic and is displayed, accompanied by the corresponding p-value.

Coefficients that are significant in the VAR and VECM result tables following are in bold and accompanied by a '*'.

In this study we are interested in i.) the closing price as the dependent variable (D(CLOSING)) and ii.) the adjusted closing price as the dependent variable (D(ADJ_CLOSING)) and their columns are clearly shaded in the model outputs.

Period 1 The relation between the price and P/E ratio is detailed below by VECM. For the subsequent price as the dependent variable it is evident that none of the coefficients for either the lagged prices or P/E ratio values are significant.

Table 15: VECM Results with Price and P/E Ratios (Period 1)

	VECM results of Closing price and P/E Ratio			
	DEPENDENT			
	ALSI		TOP40	
INDEPENDENT	D(CLOSING)	D(PE)	D(CLOSING)	D(PE)
D(CLOSING(-1))	0.03449	**0.00063**	0.03369	**0.00069**
	[0.358]	**[12.436]***	[0.348]	**[12.226]***
D(CLOSING(-2))	0.09525	-0.00002	0.09865	-0.00003
	[0.630]	[-0.230]	[0.656]	[-0.307]
D(CLOSING(-3))	0.13623	0.00017	0.12707	0.00017
	[0.895]	[2.094]	[0.840]	[1.943]
D(CLOSING(-4))	0.23265	-0.00003	0.18138	-0.00003
	[1.495]	[-0.320]	[1.179]	[-0.308]
D(PE(-1))	45.83763	0.12899	49.32602	0.13730
	[0.267]	[1.434]	[0.320]	[1.522]
D(PE(-2))	7.60198	-0.18709	27.89781	-0.18390
	[0.044]	[-2.060]	[0.179]	[-2.020]
D(PE(-3))	-128.66180	0.09956	-82.36824	0.10417
	[-0.726]	[1.073]	[-0.521]	[1.126]
D(PE(-4))	-87.67945	0.01390	-104.66630	0.02482
	[-0.748]	[0.226]	[-0.986]	[0.400]
C	89.33453	-0.11636	89.54164	-0.11136
	[0.853]	[-2.123]	[0.902]	[-1.919]
	D(CLOSING)		*D(CLOSING)*	
Granger	Chi-sq	Prob.	Chi-sq	Prob.
Causality test	1.345	0.854	1.633	0.803

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The Granger Causality test shows that the PEE ratio does not cause the closing price to change for the ALSI or TOP40 data over period 1.

The relation between adjusted price and PEE ratios yield similar results for the adjusted closing price being the dependent variable in the model. None of the coefficients are significant.

Table 16: VECM Results with Adjusted Price and P/E Ratios

	VECM results of Adjusted Closing price and P/E Ratio			
	DEPENDENT			
	ALSI		*TOP40*	
INDEPENDENT	D(ADJ_CLOSING)	D(PE)	D(ADJ_CLOSING)	D(PE)
D(ADJ_CLOSING(-1))	0.03688 [0.382]	0.00581 [11.428]*	0.03577 [0.370]	0.00634 [11.253]*
D(ADJ_CLOSING(-2))	0.09774 [0.676]	-0.00003 [-0.042]	0.10180 [0.707]	-0.00010 [-0.116]
D(ADJ_CLOSING(-3))	0.11696 [0.806]	0.00164 [2.146]	0.10897 [0.753]	0.00168 [1.995]
D(ADJ_CLOSING(-4))	0.22447 [1.517]	-0.00007 [-0.088]	0.17352 [1.181]	-0.00012 [-0.134]
D(PE(-1))	5.38297 [0.314]	0.11512 [1.274]	5.80131 [0.373]	0.12399 [1.369]
D(PE(-2))	3.71145 [0.215]	-0.18484 [-2.034]	5.43298 [0.347]	-0.18262 [-2.004]
D(PE(-3))	-11.12416 [-0.633]	0.08044 [0.870]	-6.96067 [-0.439]	0.08994 [0.973]
D(PE(-4))	-7.48302 [-0.612]	0.00846 [0.131]	-9.52449 [-0.853]	0.01977 [0.304]
C	11.65396 [1.040]	-0.14307 [-2.424]	11.58954 [1.086]	-0.13587 [-2.186]
	D(ADJ_CLOSING)		*D(ADJ_CLOSING)*	
Granger Causality test	Chi-sq	Prob.	Chi-sq	Prob.
	1.112	0.892	1.454	0.835

The Granger Causality test shows that the P/E ratio does not cause the adjusted closing prices to change for the ALSI or TOP40 indexes for the data in period I.

Period 2 As Cointegrating relations were only present in the SWIX TOP40 data, VECM is only used for estimating relations between the variables in the SWIX T0P40 data sets. Neither the VECM nor VAR models indicate significant coefficients for the closing price and P/E ratio relationship (where the closing price is the dependent variable).

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Table 17: VECM and VAR Results with Price and P/E Ratios

	VAR/VECM Results of Closing price and P/E Ratio							
	VAR						VECM	
	ALSI		TOP40		SWIX ALSI		SWIX TOP40	
INDEPENDENT	D(CLOSING)	D(PE)	D(CLOSING)	D(PE)	D(CLOSING)	D(PE)	D(CLOSING)	D(PE)
D(CLOSING(-1))	1.01953	0.00053	1.01728	0.00058	1.02382	0.00254	0.02589	0.00276
	[8.278]*	[10.036]*	[8.217]*	[9.687]*	[8.281]	[12.751]*	[0.210]	[12.210]*
D(CLOSING(-2))	0.01561	-0.00051	0.03007	-0.00055	-0.01563	-0.00258	0.15295	-0.00009
	[0.066]	[-5.086]*	[0.126]	[-4.763]*	[-0.059]	[-6.017]*	[0.672]	[-0.208]
D(CLOSING(-3))	0.09839	0.00014	0.07694	0.00013	0.05347	0.00087	0.05680	0.00088
	[0.350]	[1.194]	[0.276]	[0.978]	[0.161]	[1.631]	[0.251]	[2.109]
D(CLOSING(-4))	-0.15699	-0.00016	-0.14899	-0.00016	-0.08353	-0.00081	0.43101	0.00005
	[-0.79388]	[-1.850]	[-0.762]	[-1.728]	[-0.361]	[-2.161]	[1.824]	[0.109]
D(PE(-1))	125.27840	0.97521	107.02160	0.96157	11.64286	1.00136	-3.52570	0.12670
	[0.444]	[8.121]*	[0.425]	[7.929]*	[0.157]	[8.403]*	[-0.056]	[1.097]
D(PE(-2))	-171.02350	-0.22422	-127.14100	-0.21173	9.23588	-0.26913	54.41930	-0.15134
	[-0.428]	[-1.317]	[-0.359]	[-1.241]	[0.087]	[-1.570]	[0.853]	[-1.293]
D(PE(-3))	106.48350	0.22102	58.21807	0.20707	0.49806	0.23723	-72.79516	0.03857
	[0.314]	[1.534]	[0.192]	[1.415]	[0.006]	[1.733]	[-1.119]	[0.323]
D(PE(-4))	-80.28518	-0.09919	-59.66545	-0.08891	-25.69099	-0.08281	-29.75756	0.00115
	[-0.440]	[-1.277]	[-0.366]	[-1.134]	[-0.622]	[-1.244]	[-0.798]	[0.017]
C	928.80440	1.70996	925.01870	1.85886	189.66660	1.30622	17.03662	-0.10153
	[0.892]	[3.859]*	[0.928]	[3.872]*	[0.906]	[3.875]*	[0.578]	[-1.875]
	D(CLOSING)		D(CLOSING)		D(CLOSING)		D(CLOSING)	
Granger	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.
Causality test	1.180	0.882	1.220	0.875	2.252	0.689	2.562	0.634

The Granger-Causality results show that P/E ratio values do not cause closing prices to change for any of the Indexes in period 2.

The VECM and VAR models also do not result in any of the coefficients for the Adjusted price and P/E ratio relations being significant (the adjusted closing price being the dependent variable).

Table 18: VECM and VAR Results with Adjusted Price and P/E Ratios

	VAR/VECM results of Adjusted Closing price and P/E Ratio							
	VAR						VECM	
	ALSI		TOP40		SWIX ALSI		SWIX TOP40	
INDEPENDENT	D(ADJ_CLOSING)	D(PE)	D(ADJ_CLOSING)	D(PE)	D(ADJ_CLOSING)	D(PE)	D(ADJ_CLOSING)	D(PE)
D(ADJ_CLOSING(-1))	1.02304	0.00488	1.01994	0.00530	1.02539	0.00206	0.02752	0.00227
	[8.292]*	[9.719]*	[8.223]*	[9.393]*	[8.284]*	[12.253]*	[0.224]	[11.882]*
D(ADJ_CLOSING(-2))	0.01353	-0.00471	0.03027	-0.00499	-0.02094	-0.00208	0.14506	-0.00002
	[0.057]	[-4.917]*	[0.128]	[-4.617]*	[-0.080]	[-5.829]*	[0.651]	[-0.065]
D(ADJ_CLOSING(-3))	0.07629	0.00128	0.05276	0.00117	0.02681	0.00069	0.01020	0.00072
	[0.276]	[1.138]	[0.192]	[0.936]	[0.083]	[1.562]	[0.046]	[2.089]
D(ADJ_CLOSING(-4))	-0.13109	-0.00148	-0.12279	-0.00154	-0.04696	-0.00066	0.42096	0.00012
	[-0.672]	[-1.864]	[-0.636]	[-1.747]	[-0.208]	[-2.167]	[1.833]	[0.349]
D(PE(-1))	13.34767	0.96807	11.51385	0.95544	15.00507	0.99596	-3.72073	0.11420
	[0.452]	[8.055]*	[0.432]	[7.874]*	[0.171]	[8.348]*	[-0.050]	[0.988]
D(PE(-2))	-14.59506	-0.21319	-10.27292	-0.20279	22.51315	-0.25591	79.54276	-0.14414
	[-0.349]	[-1.254]	[-0.274]	[-1.190]	[0.179]	[-1.494]	[1.058]	[-1.233]
D(PE(-3))	7.91820	0.21509	2.89766	0.20144	-10.13217	0.23198	-83.92081	0.01124
	[0.222]	[1.483]	[0.090]	[1.369]	[-0.010]	[1.678]	[-1.095]	[0.094]
D(PE(-4))	-9.45261	-0.09411	-6.95690	-0.08411	-34.68931	-0.07924	-33.46850	-0.00270
	[-0.486]	[-1.190]	[-0.398]	[-1.056]	[-0.690]	[-1.160]	[-0.744]	[-0.0386]
C	99.99041	1.69627	98.94457	1.85444	235.15790	1.27304	26.77597	-0.12939
	[0.904]	[3.768]*	[0.924]	[3.804]*	[0.932]	[3.713]*	[0.723]	[-2.249]
	D(ADJ_CLOSING)		D(ADJ_CLOSING)		D(ADJ_CLOSING)		D(ADJ_CLOSING)	
Granger	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.
Causality test	1.069	0.899	1.144	0.887	2.290	0.683	2.748	0.601

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Lastly as illustrated in the previous table, according to the Granger test for causality, P/E ratio does not cause the adjusted closing price to change for any of the indexes for the period 2 monthly data.

4.3 Additional comments on the Bhargava and Malhotra paper

Firstly before discussing the results from our statistical study and comparing these to that of the replicated paper, we provide some additional comments on the Bhargava and Malhotra results, detailed in their Methodology and Discussion sections.

They state that according to the price-earnings ratio data plot for the S&P 500, MSCI World, MSCI Europe and EAGE indexes, mean reversion behaviour is evident. It is not entirely obvious from the graphs that this is the case, and no additional justification is provided. In addition they claim that their preliminary OLS regressions reaffirm mean reversion theory, but this is not clear and is not discussed further. The R [1] values for the regressions performed are not discussed, but are surprisingly high.

They argue that the presence of a unit root in the time series suggests that 'a cointegrating relation may exist'. The Phillips-Perron test conducted for the presence of unit root does not suggest that such a relation may exist, only that a test for such a relation may be conducted (assuming series are of similar integrating order, i.e. 1(1)).

Their model assumptions for the Johansen Cointegration test are not stated and hence the test methodology is vague.

Inspection of the results published on the "VECM and VAR Results with Price and P/E Ratios" (Exhibit 6) and the "VAR. Results with Yield and P/E Ratios" (Exhibit 7) reveals that the world index VAR data for the earnings yield and the price series are exactly the same, which is highly unlikely and probably a typographical error. The authors input the incorrect data into one of the tables. From this error they follow to discuss the incorrect VAR results for the World index series for both the price and earnings yield as dependent variable discussions respectively, with the two results being identical and clearly discussed, it is surprising that they did not realize this error.

However the statistical analysis process followed appears sound, as well as their conclusions and interpretation of results not mentioned above.

Lastly the investigation to determine whether P/E ratios drive future earnings [2] seems to have little practical use. The earnings yield is merely a reciprocal of the P/E ratio and hence it D a form of autocorrelation that is being investigated. The prediction of the future stock price is the key to successful and viable trading strategies, and although the price may be extracted from the earnings yield, in the cases where the historical earnings yield is not known (before public results released) this only adds uncertainty to the power of the prediction model.

[2] 1t is not exactly clear if it is the earnings yield itself or the change in earnings yield

4.4 Discussion

The objective of the first part of the report was to determine whether the P/E ratio impacts subsequent stock prices or stock prices adjusted for total return for the ALSI, SWIX ALSI, TOP40 and SWIX TOP40 indexes. Two time periods were used, but the SWIX index counterparts were only included in the shorter time periods as they were not in existence prior. The relationships were estimated using VAR and VECM models and Granger causality was employed to test whether the relations are causal.

Ordinary least squares regression was run with the price or adjusted price as the dependent variable and P/E ratio as the independent variable. The regression results were significant and an increase in P/E ratios corresponds to an increase in the subsequent closing price and subsequent adjusted closing price, as expected. The simple regressions were tested for heteroscedasticity and autocorrelation, and autocorrelation was found to be present in an regressions but heteroscedasticity could only be accepted in the regressions performed in the shorter time period 2.

The time series were tested for unit root, and as the presence of the unit roots could not be rejected all the series were non-stationary, and were determined to be of integrating order 1(1). The OLS regression residuals were then tested for unit roots which is a preliminary method to test for cointegration, and it was found that the residuals were non-stationary and hence the linear OLS regression relationships between the variables are not cointegrating relations.

The more general Johansen's test was then employed to test for cointegration. The results showed that cointegration relationships existed in a number of cases. Up to this point the results corresponded closely to that of the Bhargava and Malhotra study.

However both the VAR and VECM models yielded no significant results in modelling the closing price and adjusted closing price variables as the dependent variables for all the data sets, and neither did Granger causality tests show that P/E ratios caused the closing and adjusted closing prices to change. The Bhargava and Malhotra paper found isolated significant coefficients in both the VAR and VECM models. Also the Granger causality showed a strong causal relation between the P/E ratio values and the closing prices for the VECM models on the S&P 500 and EAFE data. The rest of the data showed very weak causal relation according to the Granger tests however.

They stated that according to their study, subsequent prices rise in response to P/E ratio but not as much as would be suggested by the regression analysis conducted and that only one of the four lags of the P/E ratio coefficients is positive and significant for all four the indexes 111j. In contrast our results show no significant relation between P/E ratios and subsequent closing prices or adjusted closing prices for the indexes and periods studied, and that causal relation is very weak.

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5 Trading Strategy

5.1 Methodology

The trading strategy is investigated as the initial statistical tests may not have been powerful enough and the assumptions of the statistical tests for the underlying processes may not have been the true underlying processes for the time series. Further significant relationships may exist between the P/E ratios and the subsequent stock returns for shorter periods of time and hence the trading model may pick up on these relations.

The daily data for the two data periods are used in the trading strategy investigation. The data used is the 3-month JIBAR rate, the P/E ratio values and the closing prices adjusted for total return. The trading model will use the beginning-of-the-day P/E ratio values and end-of-the-day adjusted closing prices in the trading model and run on one index at a time.

The model must be simple and parameters plausible to avoid the possibility of data mining, where good results are merely due to optimizing the parameters to the data set. The model will start with a portfolio of funds invested in cash, earning the 3 month JIBAR rate. Trading signals will be generated during the course of the strategy and will either be to go long, short, unwind the trading position or exit the trading position due to stop-loss. The portfolio will be invested in cash when trades are not active, and when long/short signals are generated, 100% of the portfolio will be used to invest in these positions. Trading costs will be incorporated to add realism.

The model will commence on the first day of the data set, and after a rolling learning period of a set number of days have passed, the model will regress the beginning-of-the-day P/E ratio values against the end-of-the-day closing prices adjusted for total return, using linear OLS regression over this rolling learning period. Therefore the time period that the actual model runs over is the total period less the rolling learning period length. The residual data from the OLS regression will be analyzed to determine the occurrence of trading signals.

The standard deviation of the residuals, $\sigma_{residuals}$, is calculated and will be used to calculate the threshold or trading signal levels. The mean of the residuals will be zero by construction, hut they are included below for clarity.

$$Long_{threshold} = mean_{residuals} - short_{factor} \times \sigma_{residuals}$$

$$Short_{threshold} = mean_{residuals} + long_{factor} \times \sigma_{residuals}$$

As the model runs through the data period, at each day long and short signal levels are calculated and if the most recent residual exceeds one of the signal levels a trade will be executed immediately. It is assumed that trades will occur at the end of each trading day period, as the closing price value becomes available. Once a trade is active, the portfolio is invested 100% into that position and the trade must first be exited before another trade may be entered. Trade positions will be unwound when the residuals change sign, i.e. it is deemed that the price has been restored to the equilibrium level, or when the stop-loss level for a trade is reached. A trade profit position variable is set to zero once a trade is entered and the profit/loss on that trade will be monitored as the equity price shifts. The variable will be a rolling value, and will be set to zero as soon as trade portfolio value decreases (conditional on the profit variable being positive however).

Due to the outputs of the "normal trading model" where the inputs are the original time series values i.e. the adjusted stock price data and P/E ratio values, it was decided to construct a second, "difference trading moiler where the inputs are the 1st differences of the time series values. The motivation will be detailed further in the report. For this second model the unwind signal generated by residuals changing signs will be removed, where the reasons will be explained later.

The returns and risk-adjusted returns for the models are analyzed for the various indexes over the two periods. The risk-return space for the difference model is also investigated.

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5.2 Construction of Model

The trading model based on pairs trading theory was constructed in Matlab. The basic structure overview of the trading model is detailed below. Note that the main trading loop will either be the i.) normal trading model or ii.) difference trading model. The difference trading model uses the same inputs, but during the initializing of vectors and variables stage, the differenced vectors are constructed automatically and used in the main trading loop.

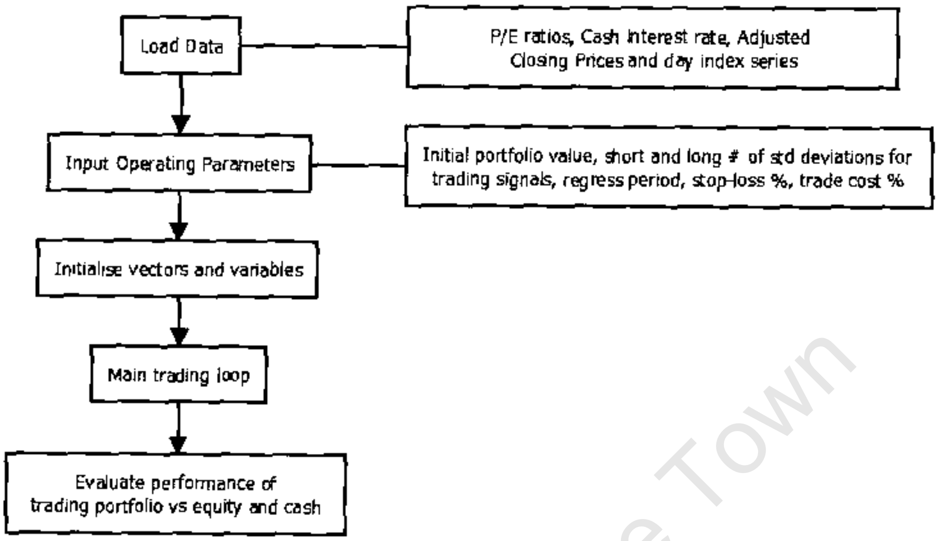

Figure 4: Trading model structure

The main trading loop decision process is illustrated in the following figure.

Note that '4' indicates that the decision parameters differ for the "Normal trading model" and the "Difference trading model", the '44' indicates that the decision and action is only applicable to the "Normal trading model".

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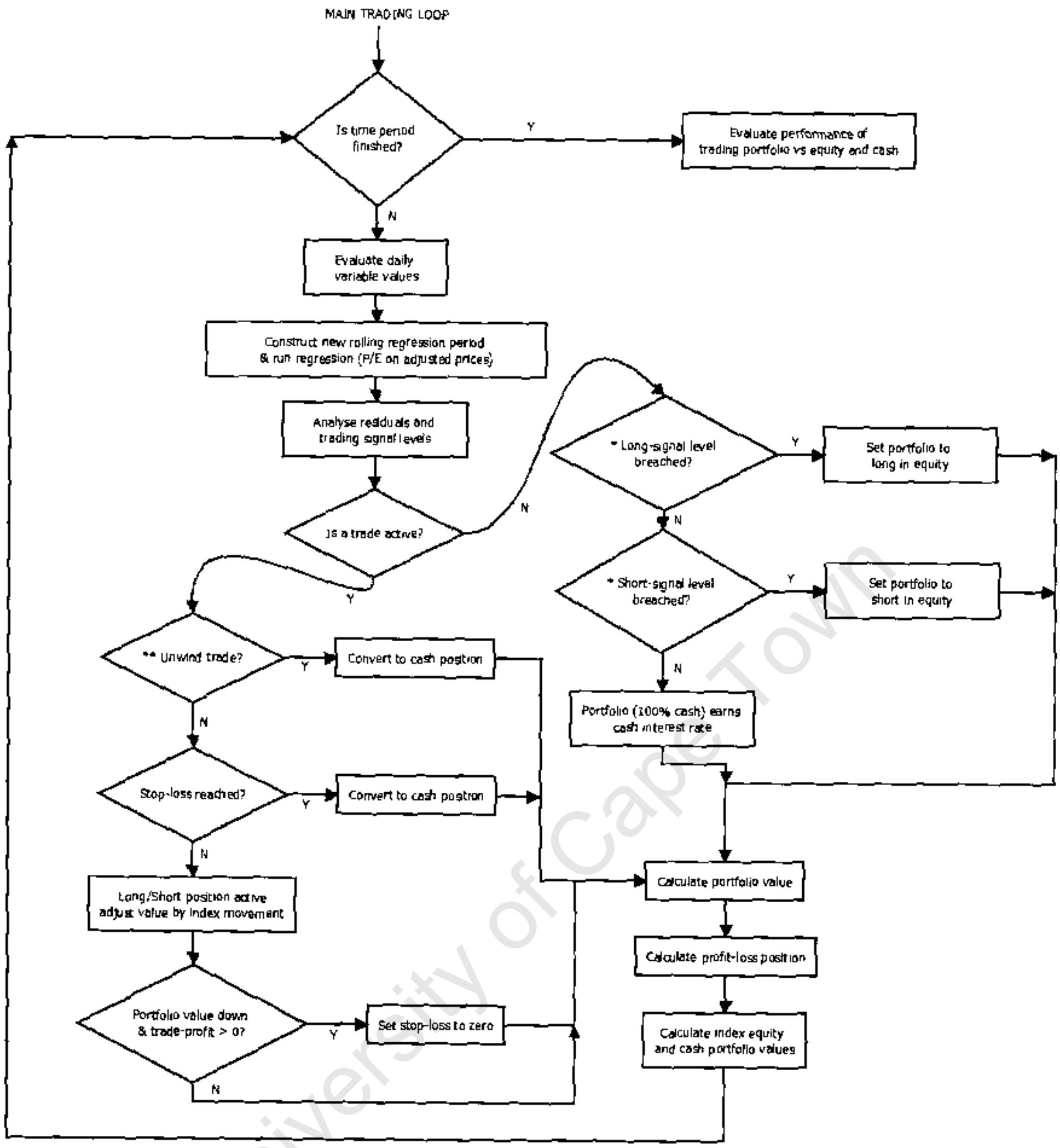

Figure 5: Main Trading loop process

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5.2.1 General parameters

The following parameters were used in both the models:
- Regression or learning period length: 150 days
- Rolling stop-loss level: 5%
- Trading cost: 0.1% of trade value (i.e. of portfolio)

5.2.2 Trading signals

The long and short factors used to generate the daily long or short trading signals required some testing and evaluation. Various ranges of values were run in order to determine feasible values which result in attractive returns in comparison to the cash and equity returns.

However as will be discussed in the results section, it was found that in order to generate good returns for the normal model, the parameters would need to be skewed significantly. The reason for this was the autocorrelation and non-stationarity present in the OLS regression residuals resulted in long trading signals not being generated for very long periods of time. The short and long factor values which generated good returns over the two periods and across the indexes were the following:

short-factor: 3 (standard deviations)
long-factor: 0.5 (standard deviations)

It is clear that these values are highly asymmetric and are unlikely to be used in reality to construct trading signals. They are merely provided to illustrate the values that were required to yield attractive returns and highlight the short-comings of the normal trading model.

A common technique for removing autocorrelation and generating a stationary time series, is taking first differences. This was applied to the trading model framework to create the difference model.

The short and long factors that generate good returns over the two periods and across the indexes are much more feasible:

short-factor: 2.5 (standard deviations)
long-factor: 1.75 (standard deviations)

The skew in the values are due to the SA market having more positive than negative returns historically.

5.2.3 Unwind signal excluded from Difference model

The unwind signal used in the normal trading model, i.e. when the residuals have changed sign and hence the trade is exited, is not used in the difference model. As the time series inputs have been

costs and exiting of good trade positions will compromise the trading model effectiveness.

5.3 Results

The results of the trading models are detailed for the two periods and the indexes. An example of the trading portfolio performance for an index for each period is illustrated (in a compound graph) and the rest of the results may be found in Appendix B. The blue line indicates the trading portfolio, the green line the equity, the red line the cash portfolio, and the short vertical lines at the bottom are trading signals where black is a long signal, red a short signal, magenta an unwind signal (only applicable to the normal model) and cyan is a stop-loss signal.

The returns and risk adjusted returns (Sharpe ratio) of the trading, cash and equity portfolios are also depicted.

5.3.1 Normal Model

Note that the normal model uses unfeasible parameters and the results are only provided as an illustration.

Period 1 The normal model in the ALSI index out-performs equity greatly as detailed below.

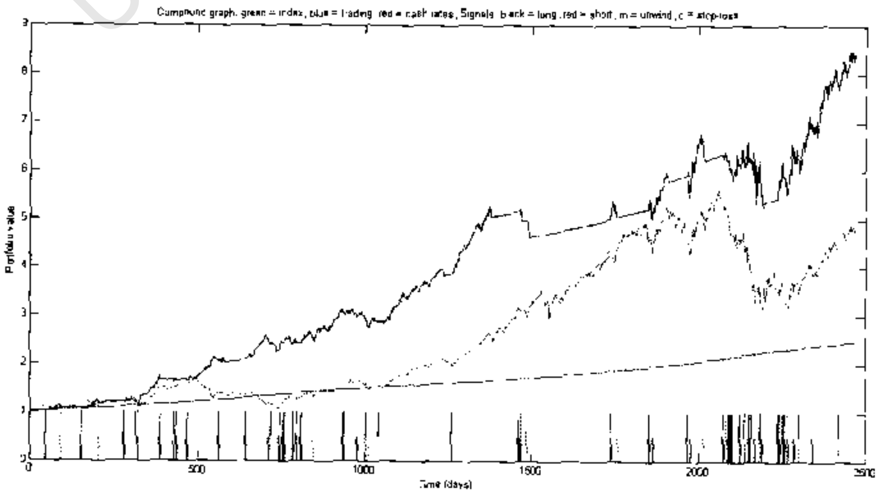

Figure 6: Normal Model performance for ALSI (period 1)

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The model shows superior returns relative to equity for the ALSI and TOP40 simulations during period 1. The risk-adjusted returns are also greater for the normal model.

Table 19: Returns and Sharpe ratios

	Returns	
	ALSI	TOP40
Cash	148.15%	
Equity	381.25%	357.63%
Normal model	**737.40%**	**648.47%**

	Sharpe ratio	
	ALSI	TOP40
Equity	3.418	3.431
Normal model	**4.268**	**4.011**
Improvement	0.850	0.580

Period 2 The performance of the normal model for the TOP40 index during period 2 is demonstrated.

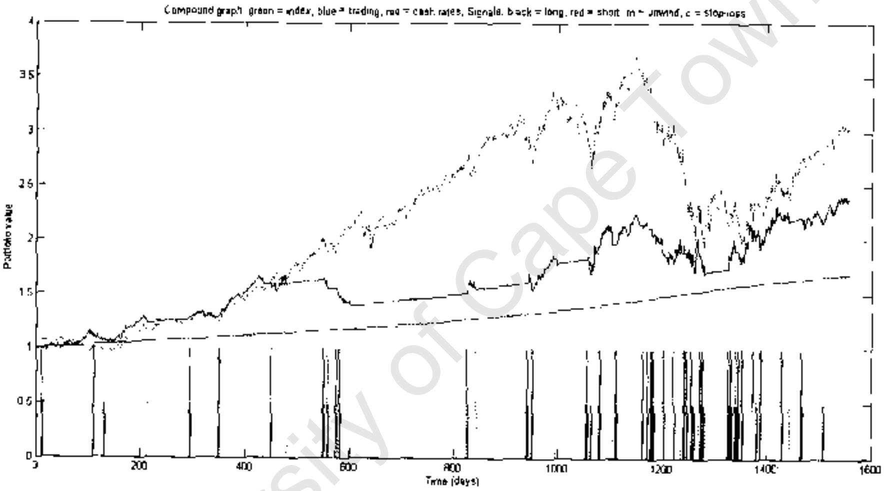

Figure 7: Normal Model Performance for TOP40 (period 2)

The normal model does not outperform any of the corresponding equity indexes during period 2 but yields great improvement in the risk-adjusted return values, which is evident in the following table.

Table 20: Returns and Sharpe Ratios

	Returns			
	ALSI	TOP40	SWIX	SWIX40
Cash	69.05%			
Equity	210.72%	204.66%	219.04%	209.09%
Normal model	**175.88%**	**138.68%**	**133.06%**	**182.87%**

	Sharpe ratio			
	ALSI	TOP40	SWIX	SWIX40
Equity	4.035	3.977	4.108	4.049
Normal model	**6.364**	**6.683**	**7.204**	**5.881**
Improvement	2.329	2.706	3.095	1.832

5.3.2 Difference Model

Period 1 The difference model yields superior return relative to equity for the TOP40 index during period 1 as illustrated by the figure below.

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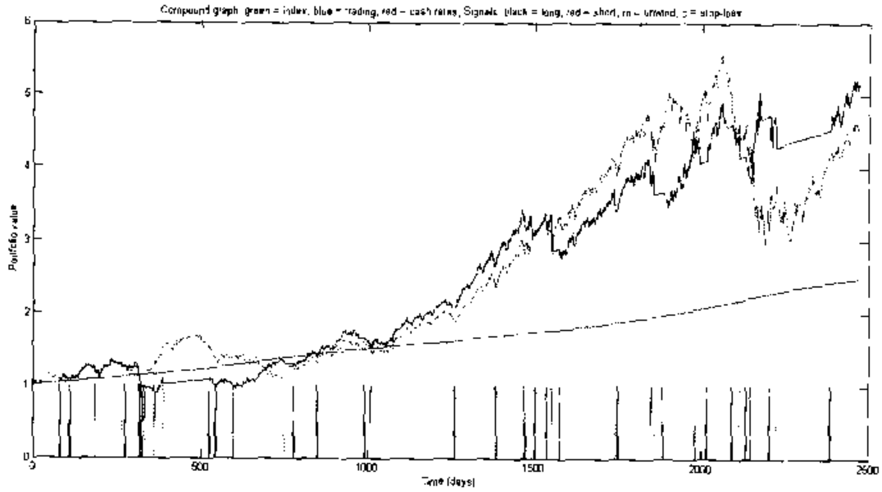

Figure 8: Difference Model Performance for TOP40 (period 1)

The difference model return is superior in the TOP40 case but inferior by some margin in the ALSI case. However the model has improved the risk-adjusted returns in both cases detailed in the following table.

Table 21: Returns and Sharpe ratio

	Returns	
	ALSI	TOP40
Cash	148.15%	
Equity	381.25%	357.63%
Difference model	**291.72%**	**413.65%**

	Sharpe ratio	
	ALSI	TOP40
Equity	3.418	3.4314
Difference model	**4.0733**	**3.8294**
Improvement	0.6553	0.398

Period 2 The difference model performance over period 2 for the SWIX ALSI index is detailed in the compound graph below, with a less volatile but similar return to equity.

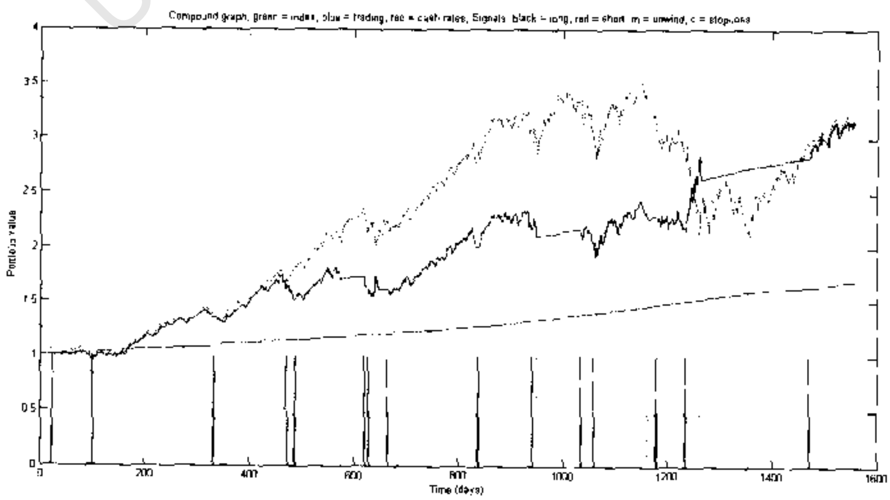

Figure 9: Difference Model Performance for SWIX ALSI (period 2)

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The returns and risk-adjusted returns (Sharpe ratio) for the difference model during period 2 is presented below. None of the model's returns were superior than equity, but in all cases the risk-adjusted returns were improved substantially.

Table 22: Returns and Sharpe Ratio

	Returns			
	ALSI	TOP40	SWIX	SWIX40
Cash	69.05%			
Equity	210.72%	204.66%	219.04%	209.09%
Difference model	177.49%	202.67%	214.25%	177.68%

	Sharpe ratio			
	ALSI	TOP40	SWIX	SWIX40
Equity	4.0348	3.977	4.1083	4.0493
Difference model	5.2018	4.9055	5.2731	5.5793
Improvement	1.167	0.9285	1.1648	1.53

5.3.3 Risk-Return analysis of Difference Model performance

As the parameters used in the normal model were not realistic or feasible it was decided only to conduct risk-return analysis for the difference model over the two periods and compare it to the alternative index equity or cash account investments for the time frame.

Table 23: Risk-Return analysis for Difference Model (period 1)

	Risk	Return
Cash	0.598%	9.995%
ALSI equity	19.598%	17.776%
*ALSI dif. model**	17.281%	15.348%
TOP40 equity	20.763%	17.142%
*TOP40 dif. model**	18.095%	18.690%

The risk-return plot for the difference trading model for period 1 is illustrated below (the 'differenced portfolio' is the trading simulation results and the 'equity' is the index results).

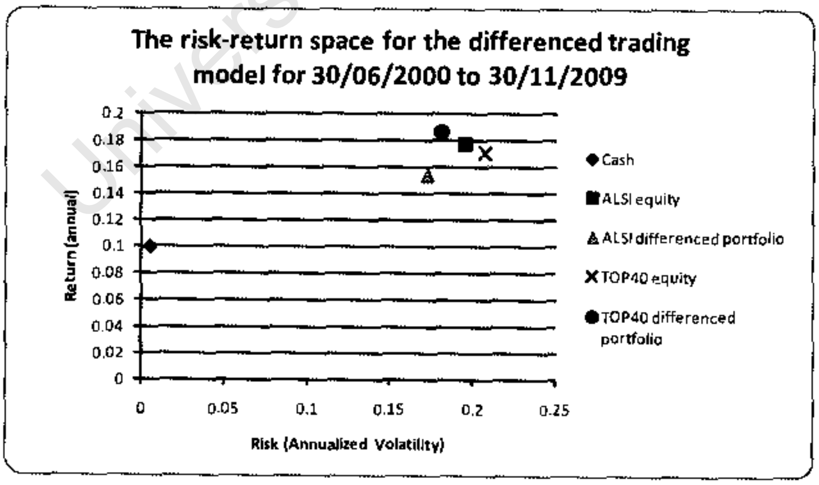

Figure 10: Risk-Return space for Difference Model (period 1)

The risk-return analysis for the difference model over the indexes are displayed in the following table for period 2.

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Table 24: Risk-Return Analysis for Difference Model (period 2)

	Risk	Return
Cash	0.534%	9.204%
ALSI equity	18.248%	20.836%
*ALSI dif. model**	**15.061%**	**18.644%**
TOP40 equity	19.278%	20.460%
*TOP40 dif. model**	**15.694%**	**20.405%**
SWIX ALSI equity	17.195%	21.223%
*SWIX ALSI dif. model**	**14.543%**	**21.100%**
SWIX TOP40 equity	18.147%	20.574%
*SWIX TOP40 dif. model**	**15.014%**	**18.592%**

The risk-return space for the difference trading model for period 2 is illustrated in the figure (the 'differenced portfolio' is the trading simulation results and the 'equity' is the index results).

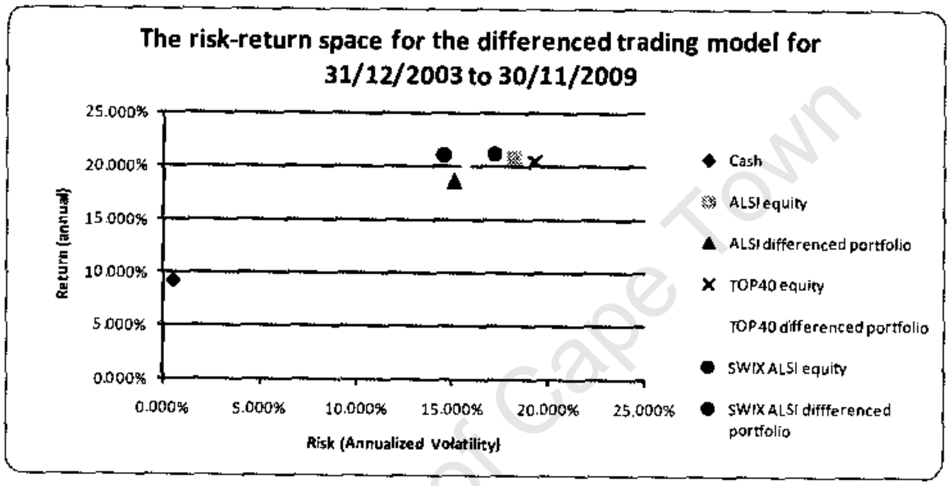

Figure 11: Risk-Return space for Difference Model (period 2)

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5.4 Discussion

The normal trading model yielded poor results before the parameters were adjusted to fit the data. The core reason for this poor performance is evident after analyzing the residuals from the regressions performed during the model's operation. The good performance by the normal model detailed in the results are therefore a function of the fitting of the parameters to the data and hence a form data mining". However the difference trading model does yield good returns and excellent risk adjusted returns for acceptable and realistic operation parameters. The trading model investigation using the price-earnings ratios and adjusted closing prices does therefore hold some promise.

The reason for the poor performance of the normal trading model is made evident by analysis of the residual vectors produced by the trading model during operation. The residual plot below was extracted at a point where the market had increased in value consistently and substantially, and then a sudden drop (or sets of drops) in price had been experienced. As the PEE value drop is not being analyzed it is hard to judge whether the residual positive end residual value is justified. However the residual vector is clearly not stationary and exhibits autocorrelation.

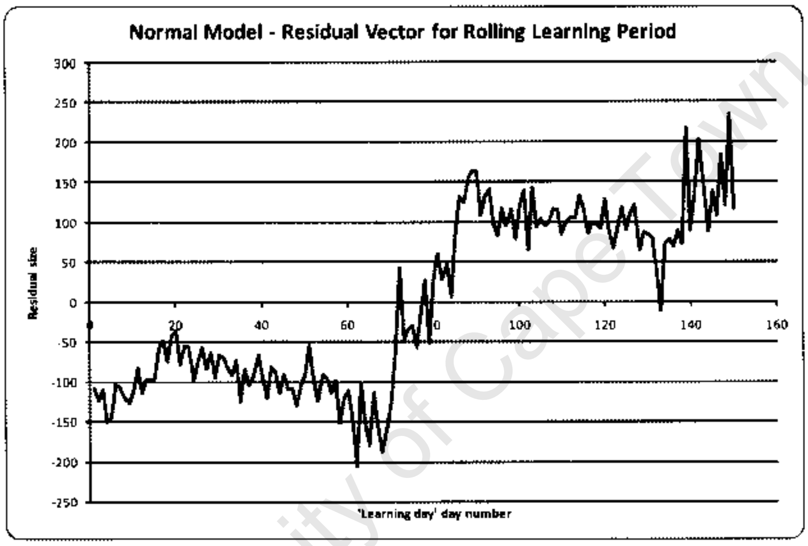

Figure 12: Normal Model - Residual Vector example 1

The non-stationary residual form is evident during extended periods of time in all the normal model simulations and compromises the trading model.

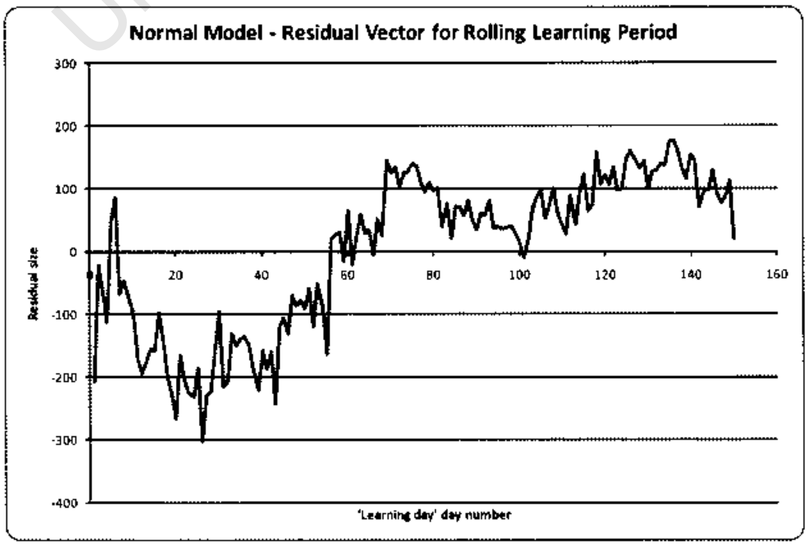

Figure 13: Normal Model - Residual Vector example 2

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Note however that this event is not constant and the residuals do exhibit stationarity and hence mean-reversion behaviour during various periods for the normal trading model. The normal model might be improved if trade signals are only implemented if the residuals over the regression period were stationary.

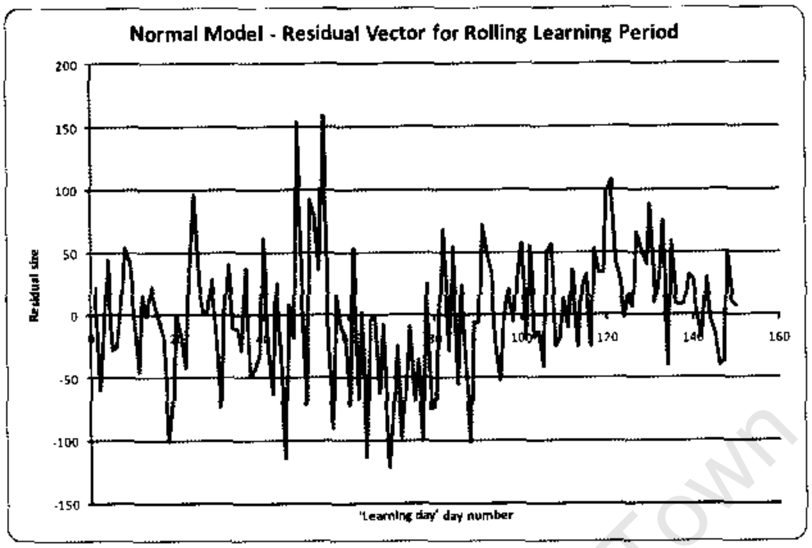

Figure 14: Normal Model - Residual Vector example 3

The effect of the non-stationarity of the residuals during large periods of the normal model simulation, especially during periods of sustained stock growth (bull markets), results in periods of up to 2 years passing without a single long signal being generated. In order to curb the affect of the model's bias for positive residuals and hence short signal generation, the short signal factor was made fairly large, and to ensure that long signals are generated more often, the long factor was made unfeasibly small.

The difference model results in consistent stationary residuals being produced as illustrated in the figure below, and hence yields a much more feasible trading model strategy.

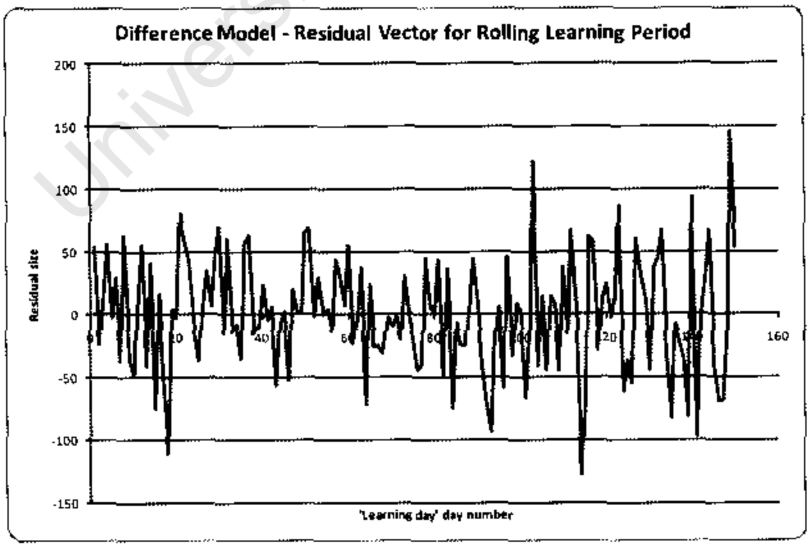

Figure 15: Difference Model - Residual Vector example

The risk-return space analysis for the difference model suggests that the trading model is capable of generating superior returns and may improve the investment space for asset managers.

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6 Conclusions

From the statistical analysis conducted there is very little evidence of a relationship between the beginning-of-the-month P/E ratios and end-of-the-month closing prices or closing prices adjusted for total return. Initially according to the OLS regressions the relationships were positive and significant, but after adjustments were made for autocorrelation, heteroscedasticity, unit roots, and non-stationarity, the P/E ratios did not have much of an impact on the subsequent prices or adjusted prices. Although the Johansen test indicated cointegration relations exist between the variables, the relationships were too weak to be picked up by VECM and VAR models. The Granger causality test concludes that P/E ratio values do not cause the adjusted prices to change. More powerful tests may yield significant results.

The statistical analysis conducted on the JSE therefore yielded weaker results than that of Bhargava and Malhotra. The data set used in this study was smaller than the one used in their investigation, and hence may have decreased the power of the tests.

However there are various factors that may have impacted the study significantly. For example the time periods selected may have some effects on the investigation and secondly as most companies on the JSE have their financial year ends at the end of February, their interim and final earnings would be released at the same time and result in significant shifts in the historical P/E values of the indexes at discrete intervals in time.

The normal trading model is not feasible as an investment strategy tool due to the non-stationary of the majority of residual vectors produced during simulation. However the difference trading model provides an attractive trading strategy and yielded attractive returns and excellent risk adjusted returns for realistic and practical operating parameters.

Further research into the field is motivated firstly by the significance of the Johansen cointegration tests and secondly by the promising difference trading model which uses P/E ratios and adjusted closing prices to determine a trading strategy. The incorporation of further factors into the study may yield more promising results as well as possible conducting the tests on different time data and indexes.

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Appendix A

Stationarity Testing, Dickey-Fuller Tests

The complete Dickey-Fuller tests for unit root are presented.

Table 25: Dickey-Fuller Test: P/E Ratio

		P/E ratio					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.510	-0.381	0.267	-2.068	0.526	-2.130
	1	0.416	-0.639	0.105	-2.557	0.266	-2.665
	2	0.439	-0.576	0.124	-2.476	0.294	-2.607
	3	0.517	-0.363	0.119	-2.498	0.288	-2.620
	4	0.551	-0.268	0.117	-2.507	0.279	-2.638
TOP40	*0*	0.507	-0.389	0.250	-2.106	0.520	-2.143
	1	0.414	-0.645	0.106	-2.555	0.285	-2.626
	2	0.436	-0.585	0.125	-2.473	0.316	-2.562
	3	0.503	-0.402	0.103	-2.568	0.271	-2.654
	4	0.535	-0.313	0.095	-2.602	0.251	-2.697
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.887 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

Table 26: Dickey-Fuller Test: Price

		Closing Price					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.960	1.408	0.917	-0.324	0.762	-1.646
	1	0.944	1.231	0.900	-0.426	0.719	-1.732
	2	0.920	1.035	0.865	-0.597	0.650	-1.874
	3	0.888	0.829	0.834	-0.728	0.532	-2.118
	4	0.859	0.671	0.769	-0.921	0.408	-2.373
TOP40	*0*	0.946	1.254	0.901	-0.419	0.756	-1.658
	1	0.929	1.105	0.881	-0.525	0.716	-1.740
	2	0.903	0.916	0.841	-0.700	0.630	-1.916
	3	0.867	0.712	0.805	-0.833	0.494	-2.197
	4	0.841	0.587	0.733	-1.005	0.380	-2.431
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.887 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

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Table 27: Dickey-Fuller Test: Adjusted Price for Total Return

		Adjusted Closing Price					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.982	1.785	0.950	-0.060	0.734	-1.703
	1	0.970	1.553	0.937	-0.177	0.692	-1.788
	2	0.950	1.294	0.912	-0.353	0.623	-1.930
	3	0.923	1.055	0.888	-0.487	0.511	-2.161
	4	0.892	0.849	0.847	-0.675	0.380	-2.430
TOP40	*0*	0.972	1.591	0.936	-0.181	0.732	-1.707
	1	0.959	1.394	0.921	-0.297	0.692	-1.789
	2	0.934	1.147	0.891	-0.474	0.606	-1.966
	3	0.903	0.916	0.863	-0.606	0.476	-2.232
	4	0.875	0.754	0.823	-0.769	0.358	-2.476
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.887 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

Period 1

Table 28: Dickey-Fuller Test: P/E Ratio

		P/E ratio					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.807	0.443	0.297	-2.002	0.549	-2.080
	1	0.786	0.376	0.186	-2.266	0.404	-2.382
	2	0.739	0.246	0.155	-2.366	0.359	-2.475
	3	0.690	0.113	0.135	-2.438	0.354	-2.485
	4	0.700	0.140	0.084	-2.673	0.229	-2.747
TOP40	*0*	0.789	0.385	0.263	-2.078	0.508	-2.166
	1	0.774	0.344	0.149	-2.388	0.334	-2.526
	2	0.725	0.209	0.131	-2.456	0.302	-2.593
	3	0.676	0.075	0.116	-2.517	0.300	-2.598
	4	0.682	0.092	0.064	-2.797	0.168	-2.905
SWIX ALSI	*0*	0.809	0.450	0.319	-1.950	0.612	-1.949
	1	0.796	0.402	0.203	-2.217	0.473	-2.239
	2	0.748	0.273	0.200	-2.224	0.467	-2.251
	3	0.702	0.146	0.140	-2.422	0.384	-2.423
	4	0.714	0.180	0.110	-2.544	0.319	-2.558
SWIX TOP40	*0*	0.804	0.429	0.273	-2.055	0.565	-2.048
	1	0.796	0.403	0.161	-2.347	0.412	-2.366
	2	0.747	0.268	0.157	-2.358	0.401	-2.387
	3	0.697	0.132	0.103	-2.574	0.306	-2.584
	4	0.701	0.144	0.067	-2.773	0.208	-2.790
Test-Stat Critical Value		**-1.945 (0.05 P-val)**		**-2.900 (0.05 P-val)**		**-3.470 (0.05 P-val)**	

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Table 29: Dickey-Fuller Test: Price

INDEX	Lags	Closing Price: None P-value	None T-Stat	Intercept P-value	Intercept T-Stat	Intercept & Trend P-value	Intercept & Trend T-Stat
ALSI	0	0.948	1.285	0.602	-1.300	0.920	-1.112
	1	0.927	1.091	0.612	-1.277	0.903	-1.200
	2	0.892	0.853	0.614	-1.273	0.846	-1.423
	3	0.860	0.679	0.550	-1.419	0.735	-1.692
	4	0.815	0.475	0.554	-1.410	0.573	-2.030
TOP40	0	0.936	1.169	0.604	-1.296	0.913	-1.150
	1	0.914	0.996	0.611	-1.280	0.894	-1.243
	2	0.877	0.766	0.607	-1.288	0.823	-1.494
	3	0.844	0.602	0.539	-1.444	0.691	-1.785
	4	0.803	0.427	0.543	-1.435	0.543	-2.092
SWIX ALSI	0	0.956	1.368	0.568	-1.379	0.928	-1.063
	1	0.934	1.146	0.577	-1.358	0.912	-1.157
	2	0.912	0.980	0.577	-1.357	0.889	-1.263
	3	0.876	0.763	0.523	-1.482	0.813	-1.520
	4	0.822	0.504	0.527	-1.471	0.632	-1.906
SWIX TOP40	0	0.944	1.236	0.568	-1.378	0.924	-1.087
	1	0.921	1.046	0.573	-1.366	0.907	-1.182
	2	0.899	0.893	0.571	-1.371	0.880	-1.298
	3	0.854	0.650	0.507	-1.518	0.763	-1.635
	4	0.803	0.428	0.508	-1.517	0.583	-2.009
Test-Stat Critical Value		-1.945 (0.05 P-val)		-2.900 (0.05 P-val)		-3.470 (0.05 P-val)	

Table 30: Dickey-Fuller Test: Adjusted Price

INDEX	Lags	Adjusted Closing Price: None P-value	None T-Stat	Intercept P-value	Intercept T-Stat	Intercept & Trend P-value	Intercept & Trend T-Stat
ALSI	0	0.968	1.536	0.683	-1.113	0.901	-1.211
	1	0.951	1.309	0.686	-1.108	0.879	-1.305
	2	0.921	1.041	0.683	-1.113	0.810	-1.530
	3	0.890	0.844	0.625	-1.247	0.691	-1.785
	4	0.848	0.621	0.627	-1.243	0.516	-2.149
TOP40	0	0.957	1.387	0.674	-1.135	0.894	-1.240
	1	0.938	1.187	0.675	-1.133	0.870	-1.338
	2	0.905	0.931	0.669	-1.146	0.784	-1.592
	3	0.873	0.745	0.607	-1.288	0.649	-1.871
	4	0.834	0.560	0.609	-1.283	0.493	-2.197
SWIX ALSI	0	0.975	1.654	0.661	-1.165	0.907	-1.183
	1	0.958	1.394	0.661	-1.165	0.884	-1.281
	2	0.941	1.211	0.658	-1.172	0.859	-1.378
	3	0.910	0.966	0.607	-1.288	0.772	-1.616
	4	0.857	0.667	0.608	-1.286	0.564	-2.048
SWIX TOP40	0	0.964	1.478	0.645	-1.201	0.904	-1.197
	1	0.946	1.260	0.644	-1.204	0.881	-1.295
	2	0.927	1.092	0.639	-1.214	0.852	-1.404
	3	0.887	0.823	0.581	-1.347	0.723	-1.719
	4	0.837	0.572	0.580	-1.351	0.525	-2.129
Test-Stat Critical Value		-1.945 (0.05 P-val)		-2.900 (0.05 P-val)		-3.470 (0.05 P-val)	

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Period 2

Cointegration Testing - Stationarity of Regression Residuals

The complete preliminary cointegration tests for the OLS regression relationships are detailed.

Period 1

Table 31: Dickey-Fuller Test: Residuals - Price regressed on P/E ratio

		Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
	0	0.195	-1.245	0.632	-1.236	0.328	-2.538
	1	0.192	-1.254	0.623	-1.254	0.742	-1.687
ALSI	*2*	0.170	-1.326	0.577	-1.360	0.866	-1.364
	3	0.228	-1.152	0.643	-1.209	0.883	-1.295
	4	0.228	-1.152	0.647	-1.201	0.837	-1.459
	0	0.212	-1.197	0.653	-1.187	0.354	-2.484
	1	0.224	-1.164	0.665	-1.160	0.766	-1.637
TOP40	*2*	0.202	-1.224	0.626	-1.248	0.880	-1.308
	3	0.251	-1.090	0.676	-1.134	0.886	-1.282
	4	0.237	-1.127	0.662	-1.166	0.825	-1.496
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.887 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

Table 32: Phillips-Perron Test: Residuals - Price regressed on P/E ratio

		Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
	0	0.195	-1.245	0.632	-1.236	0.328	-2.538
	1	0.246	-1.103	0.698	-1.085	0.510	-2.163
ALSI	*2*	0.266	-1.048	0.725	-1.023	0.570	-2.039
	3	0.270	-1.038	0.733	-1.005	0.566	-2.049
	4	0.264	-1.054	0.729	-1.014	0.524	-2.134
	0	0.212	-1.197	0.653	-1.187	0.354	-2.484
	1	0.271	-1.034	0.728	-1.015	0.532	-2.118
TOP40	*2*	0.295	-0.969	0.761	-0.941	0.590	-1.998
	3	0.298	-0.961	0.768	-0.924	0.581	-2.017
	4	0.290	-0.983	0.762	-0.939	0.538	-2.105
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.886 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

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Table 33: Dickey-Fuller Test: Residuals - Adjusted Price regressed on P/E ratio

		Adjusted Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
	0	0.282	-1.006	0.738	-0.994	0.349	-2.495
	1	0.284	-0.999	0.739	-0.990	0.734	-1.702
ALSI	*2*	0.271	-1.034	0.713	-1.050	0.855	-1.401
	3	0.333	-0.865	0.782	-0.893	0.874	-1.335
	4	0.327	-0.881	0.782	-0.893	0.828	-1.488
	0	0.295	-0.969	0.754	-0.957	0.366	-2.458
	1	0.310	-0.929	0.771	-0.917	0.754	-1.662
TOP40	*2*	0.299	-0.959	0.749	-0.969	0.868	-1.356
	3	0.346	-0.830	0.800	-0.852	0.875	-1.332
	4	0.329	-0.875	0.784	-0.888	0.813	-1.530
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.887 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

Table 34: Phillips-Perron Test: Residuals - Adjusted price regressed on P/E ratio

		Adjusted Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
	0	0.282	-1.006	0.738	-0.994	0.349	-2.495
	1	0.333	-0.865	0.803	-0.840	0.514	-2.155
ALSI	*2*	0.354	-0.808	0.823	-0.770	0.570	-2.039
	3	0.358	-0.797	0.830	-0.746	0.571	-2.038
	4	0.351	-0.815	0.828	-0.753	0.536	-2.110
	0	0.295	-0.969	0.754	-0.957	0.366	-2.458
	1	0.353	-0.812	0.819	-0.786	0.529	-2.124
TOP40	*2*	0.377	-0.747	0.840	-0.706	0.584	-2.012
	3	0.380	-0.737	0.845	-0.684	0.579	-2.021
	4	0.371	-0.761	0.842	-0.697	0.542	-2.098
Test-Stat Critical Value		**-1.944 (0.05 P-val)**		**-2.886 (0.05 P-val)**		**-3.450 (0.05 P-val)**	

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Period 2

Table 35: Dickey-Fuller Test: Residuals - Price regressed on P/E ratio

		Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.258	-1.068	0.708	-1.058	0.609	-1.955
	1	0.365	-0.775	0.821	-0.770	0.894	-1.240
	2	0.382	-0.729	0.832	-0.730	0.930	-1.052
	3	0.330	-0.870	0.787	-0.874	0.950	-0.898
	4	0.292	-0.974	0.744	-0.973	0.908	-1.172
TOP40	*0*	0.253	-1.082	0.701	-1.072	0.614	-1.946
	1	0.365	-0.776	0.821	-0.771	0.884	-1.284
	2	0.381	-0.732	0.831	-0.733	0.922	-1.097
	3	0.330	-0.871	0.786	-0.876	0.940	-0.983
	4	0.290	-0.981	0.740	-0.983	0.879	-1.302
SWIX ALSI	*0*	0.230	-1.144	0.674	-1.134	0.178	-2.871
	1	0.374	-0.749	0.830	-0.740	0.581	-2.013
	2	0.414	-0.641	0.857	-0.629	0.790	-1.580
	3	0.385	-0.719	0.841	-0.694	0.889	-1.261
	4	0.349	-0.819	0.819	-0.777	0.852	-1.402
SWIX TOP40	*0*	0.216	-1.182	0.658	-1.172	0.226	-2.752
	1	0.368	-0.768	0.825	-0.759	0.618	-1.937
	2	0.414	-0.642	0.856	-0.633	0.831	-1.471
	3	0.388	-0.711	0.841	-0.695	0.905	-1.189
	4	0.339	-0.846	0.807	-0.820	0.862	-1.366
Test-Stat Critical Value		**-1.945 (0.05 P-val)**		**-2.900 (0.05 P-val)**		**-3.470 (0.05 P-val)**	

Table 36: Phillips-Perron Test: Residuals - Price regressed on P/E ratio

		Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	*0*	0.258	-1.068	0.708	-1.058	0.609	-1.955
	1	0.305	-0.940	0.767	-0.922	0.789	-1.582
	2	0.315	-0.912	0.781	-0.888	0.810	-1.530
	3	0.315	-0.912	0.784	-0.881	0.798	-1.563
	4	0.306	-0.936	0.777	-0.899	0.747	-1.669
TOP40	*0*	0.253	-1.082	0.701	-1.072	0.614	-1.946
	1	0.301	-0.949	0.763	-0.931	0.779	-1.602
	2	0.313	-0.918	0.779	-0.894	0.803	-1.551
	3	0.312	-0.919	0.781	-0.888	0.786	-1.587
	4	0.302	-0.946	0.772	-0.910	0.736	-1.693
SWIX ALSI	*0*	0.230	-1.144	0.674	-1.134	0.178	-2.871
	1	0.294	-0.970	0.754	-0.951	0.351	-2.492
	2	0.318	-0.903	0.786	-0.877	0.392	-2.407
	3	0.322	-0.892	0.794	-0.859	0.366	-2.459
	4	0.315	-0.913	0.788	-0.873	0.312	-2.572
SWIX TOP40	*0*	0.216	-1.182	0.658	-1.172	0.226	-2.752
	1	0.286	-0.992	0.744	-0.975	0.407	-2.376
	2	0.316	-0.910	0.783	-0.885	0.458	-2.269
	3	0.319	-0.900	0.790	-0.869	0.432	-2.323
	4	0.309	-0.929	0.779	-0.893	0.373	-2.446
Test-Stat Critical Value		**-1.945 (0.05 P-val)**		**-2.899 (0.05 P-val)**		**-3.469 (0.05 P-val)**	

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Table 37: Dickey-Fuller Test: Residuals - Adjusted Price regressed on P/E ratio

		Adjusted Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	0	0.318	-0.904	0.780	-0.891	0.576	-2.025
	1	0.414	-0.640	0.857	-0.628	0.849	-1.416
	2	0.426	-0.608	0.863	-0.601	0.887	-1.272
	3	0.372	-0.756	0.827	-0.749	0.913	-1.148
	4	0.333	-0.863	0.797	-0.852	0.842	-1.436
TOP40	0	0.307	-0.934	0.767	-0.921	0.590	-1.996
	1	0.407	-0.661	0.852	-0.650	0.846	-1.423
	2	0.417	-0.632	0.857	-0.627	0.884	-1.283
	3	0.364	-0.777	0.820	-0.775	0.903	-1.200
	4	0.326	-0.882	0.785	-0.879	0.811	-1.527
SWIX ALSI	0	0.307	-0.933	0.767	-0.920	0.143	-2.986
	1	0.444	-0.558	0.877	-0.539	0.470	-2.245
	2	0.482	-0.456	0.899	-0.422	0.651	-1.869
	3	0.451	-0.540	0.889	-0.473	0.795	-1.568
	4	0.405	-0.666	0.869	-0.571	0.732	-1.700
SWIX TOP40	0	0.285	-0.994	0.741	-0.982	0.183	-2.855
	1	0.427	-0.605	0.866	-0.590	0.523	-2.134
	2	0.470	-0.487	0.891	-0.464	0.722	-1.721
	3	0.443	-0.561	0.880	-0.520	0.837	-1.451
	4	0.388	-0.711	0.851	-0.655	0.774	-1.612
Test-Stat Critical Value		-1.945 (0.05 P-val)		-2.900 (0.05 P-val)		-3.470 (0.05 P-val)	

Table 38: Phillips-Perron Test: Adjusted Price regressed on P/E ratio

		Adjusted Closing Price Residuals					
		None		*Intercept*		*Intercept & Trend*	
INDEX	*Lags*	*P-value*	*T-Stat*	*P-value*	*T-Stat*	*P-value*	*T-Stat*
ALSI	0	0.318	-0.904	0.780	-0.891	0.576	-2.025
	1	0.359	-0.792	0.822	-0.767	0.726	-1.712
	2	0.367	-0.771	0.831	-0.735	0.746	-1.671
	3	0.366	-0.774	0.833	-0.728	0.732	-1.701
	4	0.355	-0.801	0.828	-0.746	0.685	-1.797
TOP40	0	0.307	-0.934	0.767	-0.921	0.590	-1.996
	1	0.349	-0.819	0.814	-0.795	0.730	-1.704
	2	0.358	-0.795	0.824	-0.761	0.749	-1.665
	3	0.356	-0.799	0.825	-0.756	0.732	-1.700
	4	0.345	-0.829	0.819	-0.777	0.686	-1.796
SWIX ALSI	0	0.307	-0.933	0.767	-0.920	0.143	-2.986
	1	0.366	-0.772	0.828	-0.746	0.275	-2.650
	2	0.390	-0.706	0.848	-0.667	0.316	-2.565
	3	0.395	-0.694	0.854	-0.641	0.300	-2.598
	4	0.386	-0.718	0.851	-0.654	0.253	-2.695
SWIX TOP40	0	0.285	-0.994	0.741	-0.982	0.183	-2.855
	1	0.349	-0.819	0.814	-0.796	0.339	-2.516
	2	0.378	-0.739	0.839	-0.704	0.389	-2.413
	3	0.383	-0.727	0.844	-0.682	0.371	-2.451
	4	0.372	-0.757	0.839	-0.703	0.318	-2.560
Test-Stat Critical Value		-1.945 (0.05 P-val)		-2.899 (0.05 P-val)		-3.469 (0.05 P-val)	

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Appendix B

The complete trading model performances are presented in this appendix.

Normal Model Performance

Period 1

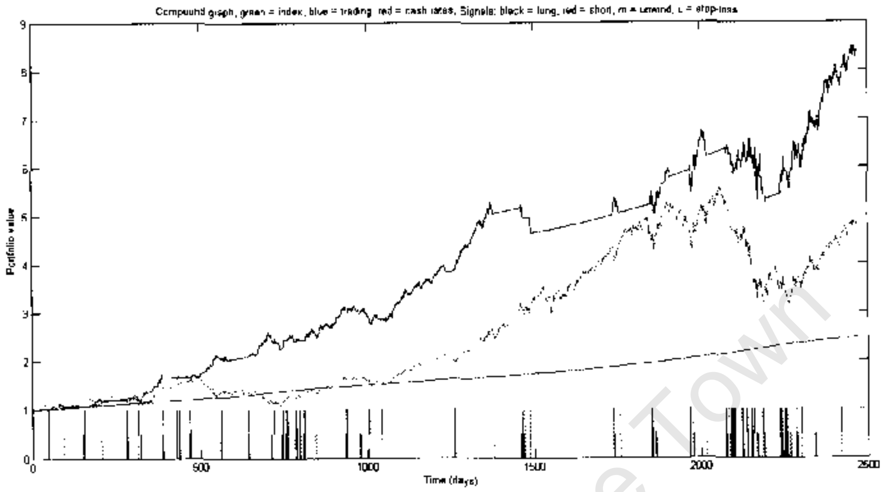

Figure 16: Normal Model Performance for ALSI (period 1)

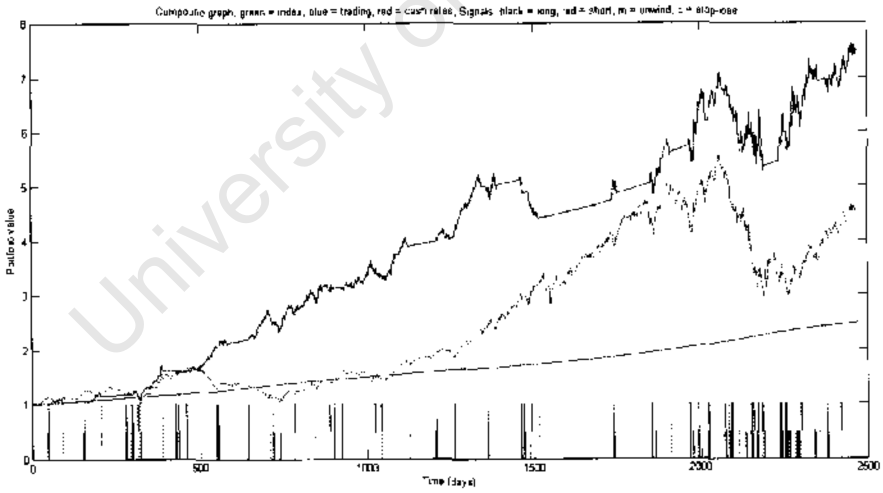

Figure 17: Normal Model Performance for TOP40 (period 1)

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Period 2

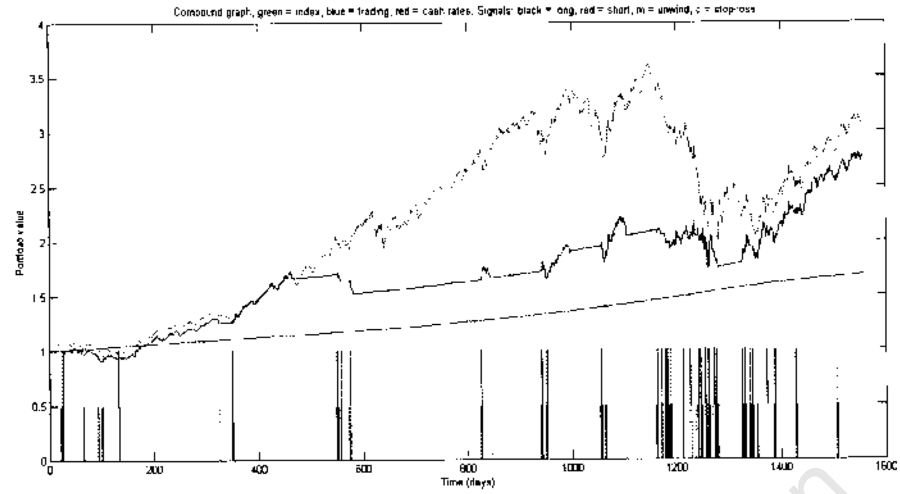

Figure 18: Normal Model Performance for ALSI (period 2)

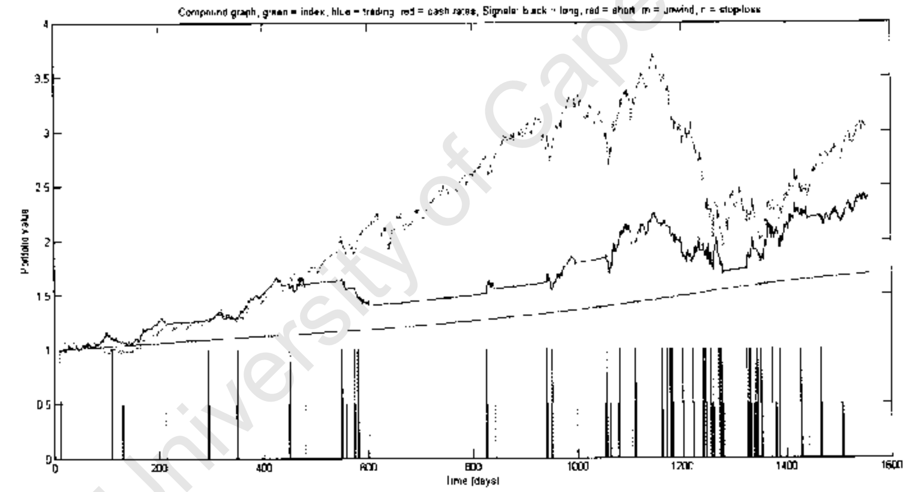

Figure 19: Normal Model Performance for TOP40 (period 2)

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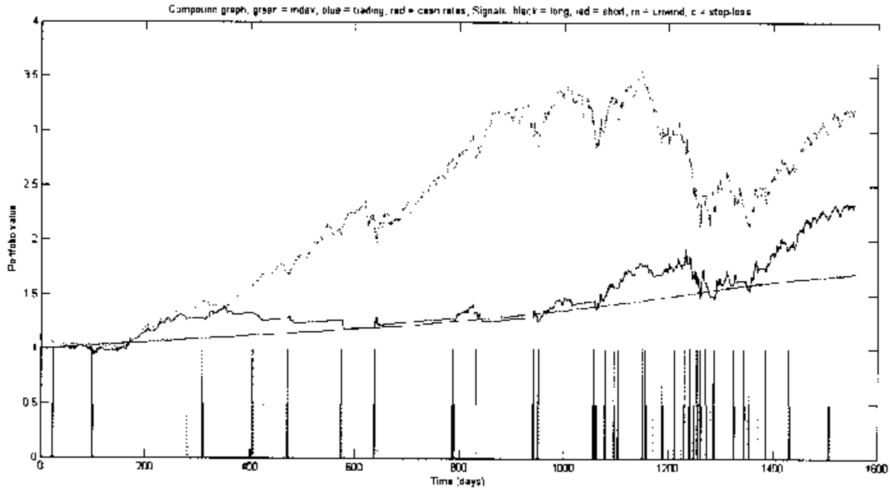

Figure 20: Normal Model Performance for SWIX ALSI (period 2)

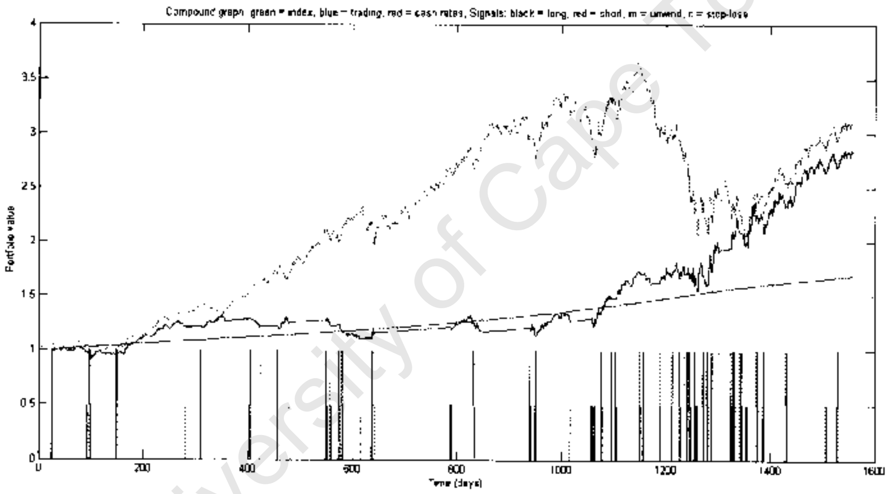

Figure 21: Normal Model Performance for SWIX TOP40 (period 2)

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Difference Model Performance

Period 1

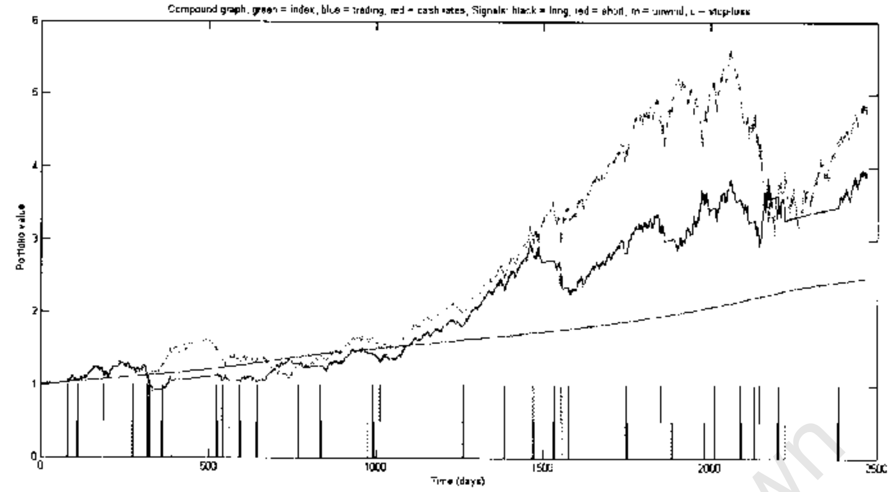

Figure 22: Difference Model Performance for ALSI (period 1)

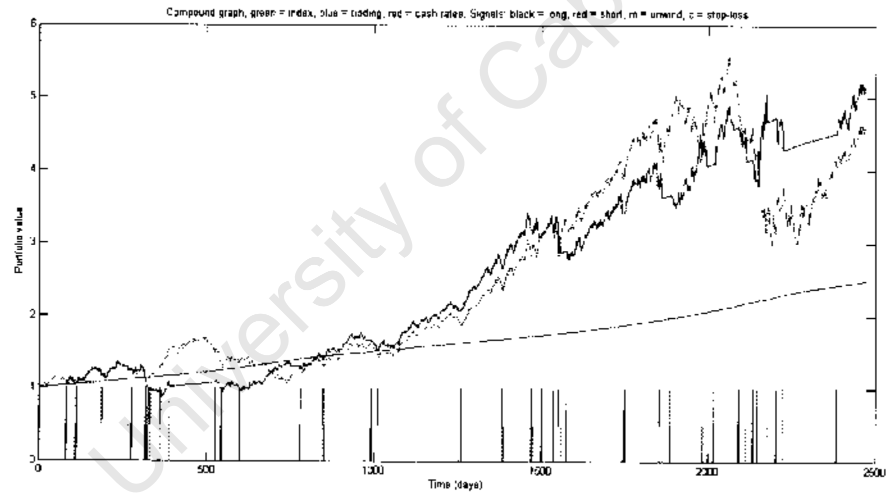

Figure 23: Difference Model Performance for TOP40 (period 1)

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Period 2

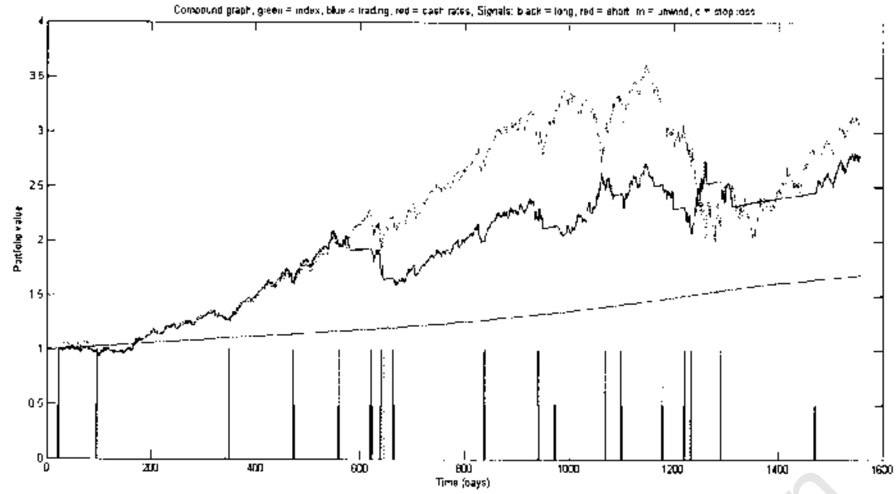

Figure 24: Difference Model Performance for ALSI (period 2)

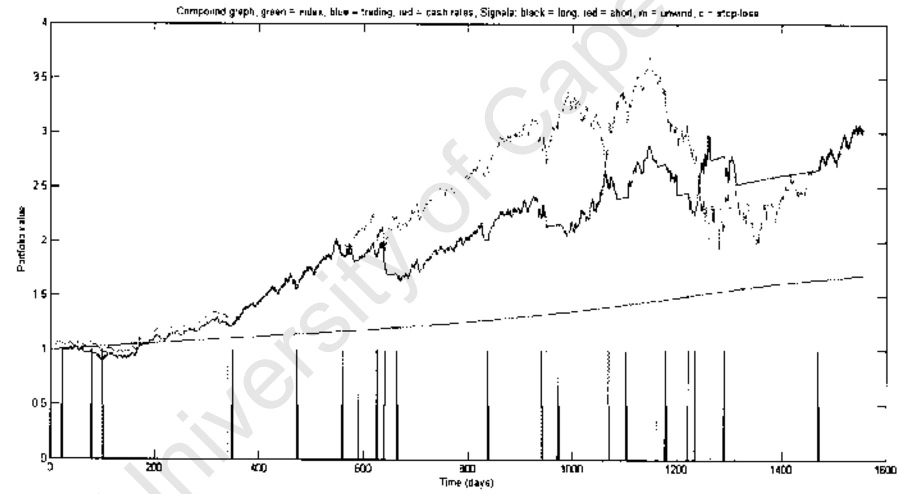

Figure 25: Difference Model Performance for TOP40 (period 2)

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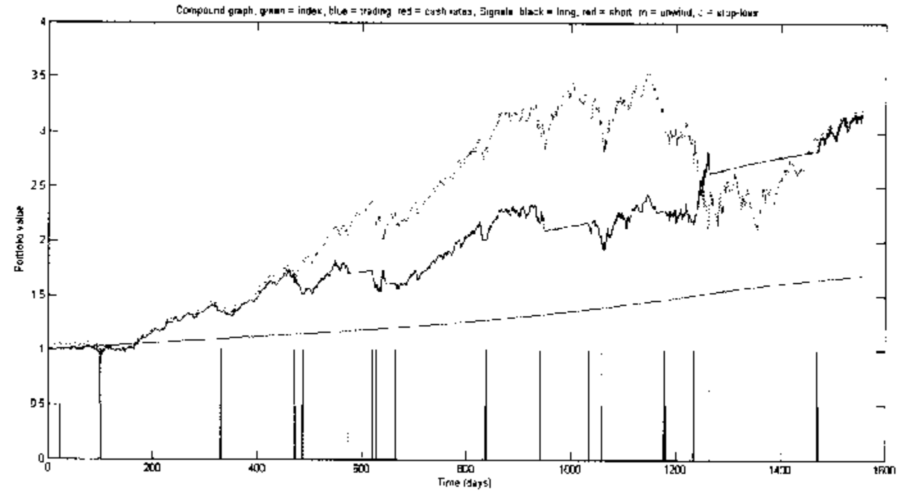

Figure 26: Difference Model Performance for SWIX ALSI (period 2)

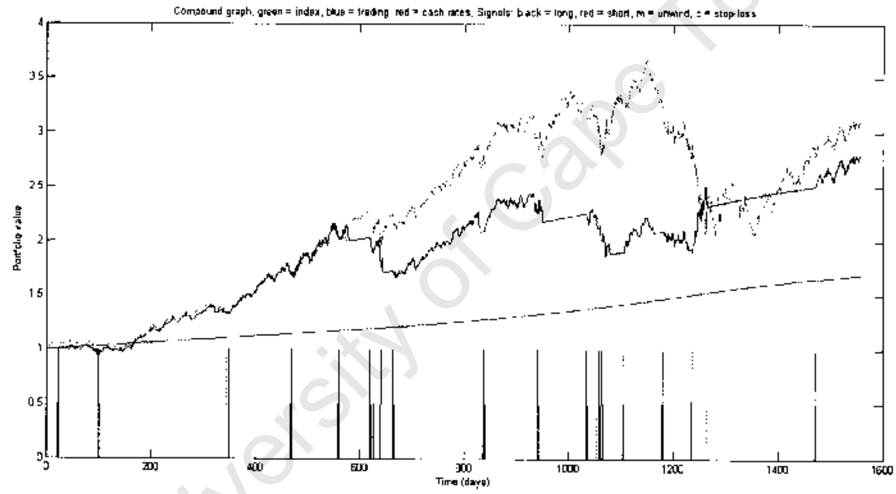

Figure 27: Difference Model Performance for SWIX TOP40 (period 2)

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