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Distributional properties of JSE prices and returns

1. INTRODUCTION

Four decades after the introduction of the capital asset pricing model (CAPM), and close to three decades after that of the arbitrage pricing theory (APT) model, both models continue to attract the attention of academics, quantitatively inclined financial analysts, financial engineers and investors.

Within the South Africa context, many researchers believe that the APT model has potential to be the best description of returns on the JSE Securities Exchange (hereafter, JSE), while most investment analysts still report and use CAPM-based betas as measures of risk for individual stocks and stock portfolios. In particular, the two-factor return generating process (RGP) proposed by Page (1986, 1989) has motivated some researchers to propose a two-factor APT model for the JSE (see, for instance, van Rensburg and Slaney 1997). On the other hand, CAPM-based betas constitute the focal point of investment advice reported in the media and professional journals.

From a theoretical viewpoint, both the CAPM and the APT are linear and static (single period) models of security returns, and the traditional methodologies for investigating their empirical validity are premised on the assumption that prices follow a normal strong random walk process (i.e., that returns are normally, independently and identically distributed, or iid normal; see Campbell, *et al.*, 1997). Consistent with the efficient markets hypothesis (EMH), this assumption implies that security prices, hence returns, are not predictable, and that it is not possible to earn excess returns on the market as a reward for the shrewd use of information.

However, empirical evidence on the time series properties of security prices documented for most markets is strikingly against the normal strong random walk property, suggesting that static linear asset pricing models might not represent the best framework for modelling returns. Instead, these observations, which have been confirmed in some emerging markets as well (see, for instance, Kasch-Haroutounian and Price, 2001), may indicate that returns are probably predictable, and that conditional versions of the standard asset pricing models may be more appropriate. Therefore, continued application of the traditional methodologies could lead to inappropriate decision making among investors.

This paper appraises the distributional and time series features of JSE stock prices and returns, in order to validate the relevance of the traditional asset pricing methodologies on this emerging market. The specific issues investigated are threefold, namely the stationarity, normality and linearity properties in logarithmic prices and, mostly, logarithmic returns. A rejection of stationarity could imply that the series were, at least, weak random walk processes. Further, if log returns were normally and linearly distributed, then the underlying stock prices followed a log normal strong random walk process. Finally, a rejection of the assumption of linearity could connote many possibilities of non-linear dynamics, such as excess volatility and volatility clustering.

2. PREVIOUS RESEARCH

Since the pioneering work of Mandelbrot (1963), Fama (1965) and Taylor (1986), and contrary to the assumptions of the unconditional CAPM, the APT and the EMH, the international literature is now replete with a lot of evidence that stock market prices are non-normal, non-linear and partially predictable. The evidence of time-dependent predictability is buttressed by observations of volatility clustering, volatility smiles and mean reversion (Bollerslev *et al.*, 1994; Pagan, 1996; Blake, 2000), as well as numerous forms of seasonal effects. Although investigating the predictability of security prices and returns by taking into account the time series features of financial market data is an area of growing research interest internationally, and apart from traces of seasonal effects explored to validate the EMH (see Watson and Smit, 1994; Smit and Smit, 1998; Coutts and Sheikh, 2002 among others), not much has been done to explore these issues on the JSE.

Among the first of the limited studies that attempted to investigate the statistical properties of JSE stock prices and returns is one by Page (1993). Using a wide range of tests for normality, Page confirmed the presence of non-normalities in two hundred and forty-four JSE equity returns traded over the period from February 1973 to March 1992. Forty-five of the securities in his sample were quite frequently traded. Using non-parametric runs tests, he also found evidence suggesting that the security returns were non-stationary processes. Since it is common that (logarithmic) stock prices are integrated of order one (see Campbell *et al.*, 1997:8), this suspicious result could have been influenced by the methodology employed, and lends itself for validation using the now popularized and relatively more reliable unit root testing methodologies. In addition to the foregoing, while confirming the superiority of the APT model over the CAPM further, Page noted that non-normalities had no significant effect on his APT estimation results.

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In a study to test the APT, van Rensburg and Slaney (1997) attempted to address the problem of non-linearities in data by adopting the non-linear seemingly unrelated regression (SUR) technique of Gibbons (1982), and Burmeister and McElroy (1988). This technique was also employed in the pre-specified variables approach to factor identification in van Rensburg (1996), based on the work of Chen *et al.* (1986) and Burmeister and Wall (1986).

It is apparent from a review of the South African literature, therefore, that the time series properties of JSE data have not been fully investigated. In particular, it is apparent that the possible violation of the iid normal assumptions has not been fully acknowledged in modelling JSE prices and returns. The potential to model returns on this emerging market correctly and profitably could be enhanced through an understanding of such properties.

3. RESEARCH METHODOLOGIES

3.1 Sampling and data

Our determination and choice of sample size and study period was based on two major considerations. The first consideration was the trade-off between a long study period and a reasonably large number of securities to be included. The second consideration was based on the fact that, on 24 June 2002, the JSE implemented the FTSE global classification system, and introduced the free float criterion which recognises that equity held for control purposes does not trade and "may as well not be listed" (Profile Media, 2002). These developments resulted in major changes to JSE sectors, the most notable being a significant decline in the number of stocks constituting the JSE All Share index from over four hundred and fifty to only one hundred and sixty as at 4 June 2002. Therefore, by studying only a few appropriately selected companies in the new All Share index, it became possible to capture a significant proportion of the truly trading segment of the JSE. In particular, this study randomly sampled forty-two stocks in the new All Share index for which continuous data were available since February 1973.

The forty-two stocks constituting the study sample are shown in Appendix 1. In addition to capturing as much as 45 percent of the FTSE/JSE All Share index, the selected stocks were fairly well distributed across the Safex indices. Specifically, at the time, the sample captured about 48 percent of the Top 40 index, and about 52 percent of the Resi index. Further, the sample respectively captured about 48 percent, 35 percent and 42 percent of the Indi, Fini and Findi indices. On account of the free float criterion, five of the stocks in the final sample had zero investibility factors, hence a zero weighting in all the indices.

In addition to the individual stocks, two stock portfolios were used to capture the aggregate behaviour of the market. The first was the new JSE All Share index whose data were spliced back to 1983 at source. This is denoted ALSI in the ensuing analysis. Further, we constructed an equally weighted portfolio of the forty-two stocks described above, denoted PORT hereafter, in order to mitigate the effects of value-weighting in ALSI. Because ALSI is dominated by resources stocks, the use of the equally-weighted portfolio provided a measure of aggregate market dynamics that was not significantly influenced by the dynamics of the resources stocks *per se*.

The new JSE classification system partly provides a solution to the problems associated with non-synchronous trading and non-trading. Specifically, the Ground Rules that govern the FTSE/JSE Africa Index Series make a provision to ensure that illiquid securities will be excluded from the All Share index (see FTSE 2003a, Ground Rule 4.10). However, it is noted that our data could still exhibit some thin trading, particularly since they extended back to the 1970s. In the literature, it is recognised that a major effect of non-synchronous trading is to induce spurious autocorrelation (Atchison, Butler & Simonds, 1987), necessitating that corrective measures be employed to purify the data of linear dependencies. The present study applied such measures as discussed subsequently.

The primary data used in this analysis were weekly close prices for each of the individual stocks and portfolios. The study period extended from 23 February 1973 to 5 April 2002 for the individual stocks and PORT, and from 23 December 1983 to 5 April 2002 for ALSI. For the period up to 22 September 2001, close price data on the individual stocks were obtained from an online database maintained by the Statistical Sciences Department of the University of Cape Town, while the rest of the data up to April 2002 were obtained from the Inet-Bridge online database. The close price data on ALSI, spliced back to 1983, were also sourced from the Inet-Bridge.

Using the close prices, continuously compounded returns (i.e., logarithmic returns) at each time t, denoted R_t, were computed as logarithmic price differences:

$$R_t = \log P_t - \log P_{t-1} \qquad \ldots (1)$$

where P_t was the close price at time t; and log denotes the natural logarithm. In the ensuing discussions, we use the terms “returns”, logarithmic returns” and “log returns” interchangeably to mean continuously compounded returns. Similarly, we sometimes refer to “logarithmic prices” as simply “prices”.

Since the computation of logarithmic returns involved the loss of the first observation of price in the sample, we adjusted the price series to have the same start date as the log return series. Therefore, the final sample had 1519 observations of price and return series for each individual stock and PORT, and 954 observations for ALSI.

3.2 Testing for stationarity

In order to test for stationarity in each of the variables in our sample, we used the standard Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) tests, as well as the Perron test for stationarity in the presence of structural change.

The DF and ADF test equations have now become standard and will not be presented here (refer to Gujarati, 2003). In implementing these tests, the following procedure was adopted. Firstly, the DF test equation was run, and the presence of tenth order serial correlation in the residual estimates was investigated using the Breusch-Godfrey Lagrange Multiplier test. For series that did not exhibit such correlation, it was concluded that the residuals were not serially correlated, and that the DF test results were adequate. For each model with serially correlated errors, we included twenty-five augmentations in the test equation to account for such correlation.

In order to establish the appropriateness of the inclusion of intercept and trend terms, the approach used in the study was as follows. For each of the series, the least restrictive model (i.e., one with both intercept and trend terms) was initially estimated. For those series where the unit root hypothesis could not be rejected using this least restrictive model, we used the φ-statistic, provided by Dickey and Fuller (1981), to test the joint null hypothesis of a unit root when both the intercept and trend terms were insignificant. Under this null hypothesis, the φ-statistic was computed as in the standard subset *F*-test for linear restrictions. However, since the test statistic has a distribution that is different from the standard *F*-distribution, the critical values provided by Dickey and Fuller were used.

Since unit root tests are generally associated with low power to reject the null hypothesis, however, the foregoing procedure for resolving whether trend and intercept terms should be included was only applied where the hypothesis of a unit root could not be rejected in the appropriate least restrictive model used, following Enders (1995).

Eyeball inspections of the price series generally provided some evidence for the presence of unit roots, as well as some *prima facie* evidence that the test results could have been affected by the presence of structural breaks during the study period. Prior evidence that South African econometric models could exhibit structural instability due to changes in the economic and political environment was documented by Smit and Wesso (1988). As argued by Perron (1989), unit root tests that do not allow for the presence of structural breaks, such as the DF and ADF tests, are likely to have low power for rejecting the null hypothesis. In order to address this concern, we invoked Perron's (1989, 1994) procedure to test for stationarity in the presence of structural change. Among the available options, the following so-called innovational outlier model was used, in order to allow the intercept and trend terms to change simultaneously:

$$x_t = \alpha_1 + \alpha_2 T + \theta_1 DU_t + \theta_2 DT_t^* + \theta_3 D(T_b)_t + \gamma x_{t-1} + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \varepsilon_t \quad \ldots (2)$$

In (2), Δ is the first difference operator, x_t is the logarithmic price or logarithmic return series being tested for stationarity, T is a trend variable, α_j, θ_k, γ and β_i are coefficients, while the ε_t terms are (white noise) residuals. Subscript t denotes time, and the break date is identified as T_b. For all $t > T_b$, we set $DU_t = 1$ and $DT_t^* = t - T_b$, but zero otherwise. Lastly, we set $D(T_b)_t = 1$ if $t = T_b$ but zero otherwise. The hypothesis of a unit root was resolved using the *t*-statistic for testing the null hypothesis that $\gamma = 1$, using appropriate critical values as described subsequently. Since the autocorrelation structure in this framework was identical with that of the ADF model, the ADF augmentation structures were used.

The identification of potential permanent shocks and, hence, the selection of potential values for T_b, was primarily guided by the turbulent political history of South Africa, which had significantly influenced the country's economic policies and the pattern of its business cycle. In addition to these internal shocks, we also considered the likelihood of contagion effects from other international financial markets, in particular the Asian Crisis of 1997-98. Therefore, weeks inclusive of the following dates were considered as possible break points: 16 June 1976 (Soweto Uprising), 21 July 1985 (State of Emergency), 10 May 1994 (Majority Rule) and 17 August 1998 (Asian Crisis). For detailed political and economic characterisations of each of the break points, see van Rensburg (1999) and Barr and Sharp (2002).

In order to enhance the unit root test results in the foregoing procedure, the optimal value for T_b was selected as the value that maximised the (absolute) value of the *t*-statistic for testing the null hypothesis that $\theta_2 = 0$ in (2) (see Christiano, 1992). Compared with the alternative method of selecting T_b as the value that would minimise the *t*-statistic for testing the null hypothesis that $\gamma = 1$ (see Zivot and Andrews, 1992), the former approach was chosen because it generally allows greater power (Rao, 1994:136). Moreover, in order to avoid making the assumption of a one-sided change, the break date was selected by maximising the absolute value of the *t*-statistic constructed under the null hypothesis of $\theta_2 = 0$. The appropriate asymptotic critical values for resolving the unit root hypothesis under these conditions are provided by Perron and Vogelsang (1993, in Rao, 1994).

Since the calculation of continuously compounded returns inherently involved data de-trending and the differencing of typically non-stationary series, the test for stationarity in the presence of structural change was only applied to the logarithmic price series. A graphical inspection of the return series showed that it would be presumptuous to suspect permanent structural breaks in them.

3.3 Testing for normal strong random walk properties

In addition to the unit root hypothesis, two further aspects of random walk properties in stock market data have generally attracted the attention of researchers, namely normality and linearity. In general, data are said to satisfy the normality property if their probability density function is consistent with that of a normally distributed random variate: generally a symmetric (i.e., skewness equals zero) distribution with a kurtosis parameter of three. Further, a series is said to satisfy the linearity property if it is an independently and identically distributed (iid) process. When both the normality and linearity properties are satisfied in the return series, the underlying price series is said to follow a normal strong random walk process. Else, when the return series is non-normal but iid, price follows a strong random walk process. Our interest in these properties derives directly from static asset pricing theory, which assumes joint multivariate normality and linearity as characterising the distributions of returns.

Normality tests

Page (1993) provides compelling evidence that JSE security returns are not normally distributed, and this point did not belabour the present research beyond seeking to buttress the available evidence. The present study examined the descriptive statistics of the returns for each of the selected stocks and stock portfolios, in order to assess their conformity with the normal distribution. The normality hypothesis was more formally resolved by using the Jarque-Bera test. Note that normality of the individual returns is a necessary (but not sufficient) condition for the joint multivariate normality of all the returns.

In order to use the basic descriptive statistics for the purpose of resolving the normality hypothesis, note that skewness and kurtosis are the normalised third and forth moments of a random variable. Therefore, following Stuart and Ord, (1987), asymptotically standard normally distributed statistics for the sample skewness ($\hat{S}$) and sample kurtosis ($\hat{K}$) of each return series, respectively denoted $z_{\hat{S}}$ and $z_{\hat{K}}$, were computed in the study as:

$$z_{\hat{S}} = \frac{\sqrt{n}\hat{S}}{\sqrt{6}}, \text{ and} \qquad \ldots (3)$$

$$z_{\hat{K}} = \frac{\sqrt{n}\left(\hat{K} - 3\right)}{\sqrt{24}}, \qquad \ldots (4)$$

The Jarque-Bera test statistic (JB) is also based on a measure of the difference of the skewness and kurtosis of the series with those from the normal distribution. Under the null hypothesis that the series is normally distributed, the statistic is given by:

$$JB = \left[\hat{S}^2 + \tfrac{1}{4}\left(\hat{K} - 3\right)^2\right]\frac{n-k}{6}, \qquad \ldots (5)$$

where $\hat{S}$, $\hat{K}$ and n are as defined, and k is the number of estimated coefficients used to create the series. The JB statistic has a χ^2-distribution with 2 degrees of freedom.

Since three different test statistics were used in the normality investigation, 5 percent statistical significance could not be rejected for each individual test statistic with a probability value of less than 0,017, after correcting for multiple testing using a Bonferroni procedure.

Linearity tests

In order to investigate whether the variables satisfied the linearity assumption, we used two test: a simple test due to Engle (1982), as well as a test based on the procedure due to Brock *et al.* (1987), commonly referred to as the BDS test. Although other tests are proposed in the literature (see, for instance, Tsay, 1986; Hsieh, 1989), these two were chosen because they are known to have power against most non-linear models. For instance, while the Engel test was originally intended to detect the autoregressive conditional heteroscedasticity (ARCH) process, McLeod and Li (1983) as well as Brock *et al.* (1993) showed that this test was quite robust and could be used to identify many (but certainly not all) types of non-linearities. On the other hand, Hsieh (1991) also argued that the BDS test had power to detect many forms of chaotic and stochastic non-linearities in a random variable, including non-stationary, nonegordic, non-linear moving average (NMA) and threshold autoregressive (TAR) processes, as well as some ARCH-type models. Brock *et al.* (1993) further demonstrated that both the BDS test and the Engle test had power against the tent map, NMA, TAR and some ARCH-type models. They also showed that the BDS test had power against the generalised ARCH (GARCH) of Bollerslev (1986), but that the Engel test was not equally reliable in detecting this process. In contrast, the Tsay test exhibited lower power against Engle's (1982) original ARCH model in the Brock *et al.* (1993) illustration. The Tsay test is related to the Hsieh test, since both are based on higher moments of the data, and both have not been found useful in detecting complex non-linearities in time series.

The easier, but comparably powerful Lagrange Multiplier linearity test proposed by Engel is generally conducted as follows. Firstly, a linear model is fitted to the data, in order to obtain residual estimates. Secondly, an AR(k) process (with an intercept term) of the squared residuals from the linear model is estimated, to obtain the coefficient of determination, R^2, hence to computed the χ^2_k-distributed Lagrange Multiplier test statistic, nR^2, where n is the sample size of the original series.

To implement the Engle test in this study, the following autoregression was fitted to each logarithmic return series:

$$R_t = \alpha + \sum_{i=1}^{p} \rho_i R_{t-i} + e_t \,, \qquad \ldots (6)$$

where t was the current period, α was an intercept term, ρ_i were coefficients, e_t was an uncorrelated error term, and the AR structure was chosen such as to remove autocorrelation. The procedure used to choose the AR terms is described below in the context of the BDS test, since the same procedure was used in both tests. Where serial correlation could not be detected it was assumed that $\rho_i = 0$ for all i in (6). Finally, a tenth order autoregressive structure was fitted to squared residual terms.

The more reliable BDS test procedure culminates into the computation of an asymptotically standard normally distributed test statistic for resolving the iid hypothesis. As illustrated by Hsieh (1989, 1991) and Brock *et al.* (1993), the test is conducted as follows. Firstly the series are pre-filtered with an autoregression in order to remove autocorrelation, if it is detected. Secondly, the (pre-filtered) data are organised into non-overlapping m-histories, say x_t^m, where the parameter m is called the embedding dimension. The third step involves the calculation of correlation integrals, each of which is the limit, as the sample size increases, of the fraction of pairs of m-histories close to each other. Specifically, for a given number, l, the pair of m-histories, x_s^m and x_t^m, is said to be close to one another if the greatest absolute distance between the corresponding members of the pair is smaller than l. For a sample of size n, and given m and l as defined, the corresponding correlation integral may be denoted as $C_{m,n}(l)$. Finally, Brock *et al.* (1987) showed that, under the null hypothesis that a given series is iid, even when l is finite, the following statistic is asymptotically standard normally distributed:

$$W_{m,n}(l) = \sqrt{n}\,\frac{C_{m,n}(l) - [C_{1,n}(l)]^m}{\hat{\sigma}_{m,n}(l)} \,, \qquad \ldots (7)$$

where $\hat{\sigma}_{m,n}(l)$ is an estimator of the standard deviation under the null hypothesis, expressed as in Hsieh (1989).

The calculation of the BDS test statistics in this study was facilitated by the use of a C-Source code developed by LeBaron (1991). However, three practical issues had to be addressed in the implementation of the test, namely potential serial correlation in the return series (which could arise from thin trading), the choice of values for m, and the choice of l.

Removing autocorrelation in the return series, if detected, was necessary in both the Engel test and the BDS test because the presence of linear dependencies could potentially affect some tests for non-linearities. In order to detect autocorrelation, we examined the correlograms of each of the series. In keeping with the Bonferroni correction for multiple testing, a series was considered as exhibiting some linear dependencies at the 5 percent significance level if the probability value for the Ljung-Box *Q*-statistic was less than 0,005, provided that the lag length for the *Q*-statistic was ten or less. The order of autocorrelation was precisely established as the lag length for the first significant *Q*-statistic. If the presence of such autocorrelation could not be established, the BDS test was applied to the raw return data, whereas the Engel test was based on squared residuals from a regression of return on a constant term, as already stated.

In order to filter autocorrelation if it was detected in a given series, autoregression (6) was fitted to the data, setting $p = 10$. The filtered data, which were precisely the sequence of estimates of e_t in (6), were tested for tenth order autocorrelation using the Breusch-Godfrey LM test to confirm the reliability of the filter. This procedure implies that the analysis focused on the linearly unpredictable components of the continuously compounded returns, since any predictable parts would have been removed using the autoregressive scheme.

Although there are no strict *a priori* values for the embedding dimension, m, Monte Carlo experiments reported in Brock *et al.* (1993) suggested that m should be chosen such that the number of non-overlapping data points (i.e., n/m for a series of sample size n) should be in excess of 200 in order for the asymptotic distributional properties of the test to remain reliable. The current study set $m = 2,3,4,5$ for all the series except ALSI, and $m = 2,3,4$ for ALSI.

As with the chosen values for m, there are no strict *a priori* values for l, but the test results are also sensitive to the choice made. The common procedure is to set l within the interval $0,5\sigma \le l \le 2,0\sigma$, where σ is the standard deviation of the data (Hsieh, 1989,1991; Scheinkman & LeBaron, 1989; Brock *et al.*, 1993). To remain consistent with the empirical literature, the present study chose $l = 0,5\sigma, 1,0\sigma, 1,5\sigma$.

Finally, since the BDS test was conducted nine times for ALSI and twelve times for every other series, the corresponding 5 percent two-tail critical values based on the z-distribution were adjusted to 2,773 and 2,865 respectively, using the Bonferroni correction for multiple testing.

4. RESULTS AND DISCUSSION

4.1 Stationarity and structural change

The DF/ADF test results for the logarithmic price series in levels and first differences are reported in Table 1. Notice that in twenty-three of the forty-two stocks, no tenth order serial correlation could be detected in the error terms of the DF test equations. Therefore, the unit root hypothesis was initially investigated using the DF test equation for such stocks, and the ADF equation for the remaining nineteen stocks, as well as the two aggregates. Focusing on column 3 of the table, it is evident that the hypothesis of a unit root could only be rejected for the logarithmic price series of SBK.

In Table 2, we report the computed φ-statistics for the logarithmic price series for which the unit root hypothesis could not be rejected using the least restrictive model, in order to verify the appropriateness of the inclusion of intercept and trend terms. Comparing the computed φ-statistics with the appropriate critical value, we could not reject the joint null hypothesis that the data contained a unit root and/or no intercept and/or no deterministic time trend, except for the case of stock REM. Even after controlling for the effects of intercept and trend terms, therefore, we could not reject the null hypothesis of a unit root in the logarithmic price series.

The investigation of the joint structural change-unit root hypothesis in the levels of logarithmic prices provided results very similar to the foregoing DF/ADF test results. As reported in Table 3, the joint hypothesis could not be rejected at the 5 percent level of significance in all cases except for PIK. Note that for ALSI and thirteen of the forty-two stocks, the absolute *t*-statistics for selecting the break point were less than 1,960, temptingly implying that the concerned series might not have experienced any statistically significant structural breaks during the sample period, and the joint hypothesis was potentially irrelevant. This result ought to be cautiously interpreted, however, since the general presence of a unit root in the series could imply that the selected optimal values for the break points might not have been consistent estimates. Moreover, the results showed that the framework could not be used to study the behaviour of the JSE in the turbulent times under investigation further, since the parameter estimates for the dummy variables might not have the desirable asymptotic properties. Further work could pursue the last matter.

In general, therefore, the results provided evidence that JSE stock prices were non-stationary processes, even after accounting for unnecessary deterministic regressors or potential structural changes. This observation was consistent with those found for other markets (Pagan, 1996; Kasch-Haroutounian and Price, 2001), as well as the JSE (van Rensburg, 1999). This general observation was also consistent with the hypothesis that logarithmic stock prices could contain a random walk component.

The results of the stationarity tests in the logarithmic return series (i.e., first differences of logarithmic prices) are reported in column 4 of Table 1, and sharply contrasted with those reported for the stock price series: the unit root hypothesis could unambiguously be rejected for all the return series.

From the reported findings, it could be concluded that continuously compounded JSE stock returns were stationary processes, or that logarithmic stock prices were integrated of order one. This result, too, was consistent with those reported for other markets (e.g., Pagan, 1996; Kasch-Haroutounian and Price, 2001), as well as, selectively, the JSE (van Rensburg, 1999). Incidentally, however, the finding was somewhat in contrast with Page (1993), arguably on account of the weaker testing tools he employed. The finding that returns did not contain a unit root could be inconsistent with the random walk hypothesis, but only crudely so (Campbell *et al.*, 1997:65). Since JSE logarithmic prices were confirmed to contain a unit root in the foregoing, the *prima facie* evidence against the (weak-form) random walk hypothesis in the logarithmic return series could mean that the JSE was not in continuous stochastic equilibrium, and that changes in returns could be profitably predictable.

Table 1 – DF and ADF tests for logarithmic stock prices and returns

*This table reports unit root test results for the logarithmic price series and returns. Column 2 shows Breusch-Godfrey correlation test statistics at the 10th order, based on the DF test equation, with p-values in parentheses. p>0.05 implies that no serial correlation was detected, otherwise 25 augmentations were included in the ADF tests. Respectively, columns 3 and 4 give the absolute test statistics for the levels and first differences of the series. Both intercept and trend terms were included in the test equations. At 5% significance level, the absolute critical values were 3,417 for ALSI and 3,415 for all others. * denotes a rejection of the null hypothesis.*

(a) Stock portfolios

#	1 Portfolio	2 nR^2 (p)	3 τ (Levels)	4 τ (1^{st} Differences)
1	ALSI	37,766 (0,000)	3,149	6,073*
2	PORT	30,673 (0,001)	2,594	7,893*

(b) Individual stocks

#	1 Security	2 nR^2 (p)	3 τ (Levels)	4 τ (1^{st} Differences)
1	AFE	23,007 (0,010)	2,612	7,465*
2	AFX	4,859 (0,900)	1,637	39,108*
3	AGL	15,471 (0,116)	2,557	38,148*
4	ALT	33,240 (0,000)	1,510	7,250*
5	ANG	5,148 (0,881)	2,223	38,271*
6	ASR	1,855 (0,997)	1,648	39,089*
7	AVI	23,157 (0,010)	0,954	9,079*
8	BAW	14,659 (0,145)	2,393	40,314*
9	BVT	10,159 (0,427)	2,824	37,080*
10	CHE	34,843 (0,000)	3,570	8,337*
11	CTP	9,317 (0,502)	2,615	38,965*
12	DEL	12,586 (0,248)	3,011	39,516*
13	DUR	61,425 (0,000)	2,716	7,775*
14	ECO	82,809 (0,000)	1,110	7,065*
15	ELH	51,657 (0,000)	2,800	7,770*
16	FOS	27,495 (0,002)	0,290	8,330*
17	GMF	10,351 (0,410)	2,812	38,934*
18	HAR	18,800 (0,042)	2,927	37,306*
19	HLH	8,720 (0,559)	1,957	37,840*
20	HVL	11,038 (0,355)	2,457	37,733*
21	IMP	15,896 (0,103)	2,355	37,662*
22	JCM	109,898 (0,000)	1,349	8,832*
23	JNC	111,273 (0,000)	1,037	8,882*
24	LGL	7,603 (0,667)	1,186	40,301*
25	MAF	33,043 (0,000)	3,385	7,143*
26	MLB	3,256 (0,975)	1,193	39,701*
27	NED	7,503 (0,677)	2,581	40,328*
28	NPK	6,895 (0,735)	1,671	39,232*
29	OCE	13,991 (0,173)	3,221	39,455*
30	PAM	5,540 (0852)	2,250	37,865*
31	PIK	5,043 (0,888)	2,085	39,855*
32	PPC	69,700 (0,000)	1,743	7,329*
33	REM	143,731 (0,000)	1,381	7,580*
34	RLO	36,855 (0,000)	2,529	7,887*
35	SAB	2,917 (0,983)	1,292	38,941*
36	SAP	8,411 (0,589)	2,167	39,739*
37	SBK	29,860 (0,001)	3,992*	8,263*
38	TBS	19,107 (0,039)	0,619	9,045*
39	TNT	3,346 (0,972)	2,759	39,552*
40	TRE	4,299 (0,933)	1,599	38,361*
41	WAR	18,658 (0,045)	2,755	6,832*
42	WLO	12,612 (0,246)	1,491	7,596*

Table 2- Intercept and trend terms in DF/ADF tests

This table shows the computed φ-statistics for the logarithmic price series for which the unit root hypothesis could not be rejected using the DF and ADF tests. The critical value at 5% significance level is 4,59 (see Enders, 1995). denotes a rejection of the joint hypothesis.*

a) Stock portfolios

#	*Portfolio*	φ
1	ALSI	2,035
2	PORT	3,262

b) Individual stocks

#	*Security*	φ
1	AFE	2,294
2	AFX	0,969
3	AGL	2,199
4	ALT	2,911
5	ANG	1,804
6	ASR	1,259
7	AVI	2,210
8	BAW	1,913
9	BVT	3,508
10	CHE	4,137
11	CTP	2,451
12	DEL	3,295
13	DUR	2,944
14	ECO	1,062
15	ELH	3,524
16	FOS	1,932
17	GMF	2,647
18	HAR	3,398
19	HLH	1,312
20	HVL	2,055
21	IMP	4,288
22	JCM	1,408
23	JNC	1,570
24	LGL	0,534
25	MAF	3,359
26	MLB	0,690
27	NED	2,575
28	NPK	1,081
30	PAM	1,691
31	PIK	1,572
32	PPC	2,700
33	REM	5,396*
34	RLO	3,566
35	SAB	0,595
36	SAP	1,577
38	TBS	3,629
39	TNT	2,596
40	TRE	0,902
41	WAR	2,353
42	WLO	1,566

Because logarithmic returns were scale-free stationary processes and contained all the necessary information to guide the investment decision-making process, financial analysts generally tended to prefer focusing attention on them as opposed to prices (Campbell *et al.*, 1997:9). The rest of this discussion follows suit.

4.2 Normality of returns

Table 4 refers. In conflict with the normality assumption, the standard normally distributed statistics computed using (3) and (4) showed that the sample skewness parameter was insignificant in only six of the forty-two individual stock return series (i.e., AFX, CHE, PPC, SAP, SBK, TNT) and in none of the two market aggregate series, while the sample kurtosis parameter was significantly greater than three in virtually all the cases, and generally enormous. Thus, there was unequivocal evidence of leptokurtosis on the JSE, a feature that is documented for most markets, and that renders no support for the assumption of normality in the distributions of security returns. Although both aggregates showed that the returns were negatively skewed, eighteen of the individual stocks showed that the returns could also be positively skewed on this market.

More formally, for all the series, the generally enormous Jarque-Bera test statistics reported in Table 4 led to an unambiguous rejection of the hypothesis of normality in all the series. This finding provided further evidence that the distribution of JSE security returns was consistent with observations made in developed markets (Mandelbrot, 1963; Fama, 1965), as well as the JSE (Page, 1993). Therefore, joint multivariate normality could not be a realistic assumption for modeling JSE returns.

4.3 Linearity of returns

Table 5 reports the autocorrelation structures for the raw return series, as well as the Engel linearity test results. Although ARCH and potentially other non-linear processes could not be detected in thirteen of the forty-two individual stocks under investigation, there was strong evidence of the prevalence of non-linearities in the remaining return series, including both of the market aggregates. The failure to reject the hypothesis of linearity in over a quarter of the individual stocks could provide justification for an investigation based on an alternative test, such as the BDS test. Furthermore, as asserted by Brock *et al.* (1993), the results implied that we could not use the ARCH model of Engel (1982) to explain the logarithmic return dynamics of the said thirteen stocks.

Table 3 – Perron's joint unit root-structural break tests

*This table shows results of the Perron test for the logarithmic prices. t_{θ_2} are t-statistics under the null hypothesis of $\theta_2 = 0$. t_γ are test statistics for resolving the unit root hypothesis. The Perron-Vogelsang critical value for t_γ is -4,91 at 5% significance levels. * denotes a rejection of the null hypothesis.*

a) Stock portfolios

#	Portfolio	Optimal Break Point	t_{θ_2}	t_γ
1	ALSI	1994	-1,790	-4,190
2	PORT	1985	-2,325	-3,462

b) Individual stocks

#	Security	Optimal Break Point	t_{θ_2}	t_γ
1	AFE	1985	-2,631	-3,602
2	AFX	1994	-3,090	-3,884
3	AGL	1994	-2,797	-4,035
4	ALT	1985	-4,047	-4,268
5	ANG	1985	-2,263	-3,184
6	ASR	1994	-3,577	-4,101
7	AVI	1985	-2,758	-2,467
8	BAW	1985	2,804	-3,954
9	BVT	1994	-1,665	-2,022
10	CHE	1994	-2,151	-4,559
11	CTP	1994	-1,935	-2,735
12	DEL	1985	3,565	-4,687
13	DUR	1985	-1,509	-3,276
14	ECO	1994	-2,960	-3,343
15	ELH	1994	-2,345	-3,361
16	FOS	1994	-4,374	-4,469
17	GMF	1985	-1,382	-3,322
18	HAR	1976	1,820	-3,092
19	HLH	1985	-2,250	-3,476
20	HVL	1985	-2,072	-3,277
21	IMP	1994	1,936	-3,325
22	JCM	1994	-3,507	-3,576
23	JNC	1985	-3,861	-4,013
24	LGL	1994	-4,396	-4,534
25	MAF	1994	-1,572	-3,157
26	MLB	1994	-2,176	-2,889
27	NED	1998	-1,588	-2,477
28	NPK	1994	-3,372	-3,762
29	OCE	1998	2,336	-3,713
30	PAM	1985	-1,541	-3,471
31	PIK	1985	-4,892	-5,172*
32	PPC	1994	-2,735	-3,888
33	REM	1985	-3,729	-3,640
34	RLO	1994	-0,776	-2,242
35	SAB	1994	-2,617	-3,267
36	SAP	1985	-1,385	-2,708
37	SBK	1994	-1,565	-4,011
38	TBS	1985	-2,875	-2,851
39	TNT	1976	1,164	-2,827
40	TRE	1994	-2,681	-3,551
41	WAR	1976	2,060	-2,689
42	WLO	1994	-3,613	-3,741

Table 4 – Descriptive statistics for security returns

In this table of selected descriptive statistics for logarithmic returns, $\hat{S}$ *and* $\hat{K}$ *are sample skewness and sample kurtosis,* $z_{\hat{S}}$ *and* $z_{\hat{K}}$ *are z-statistics for skewness and kurtosis.* JB *is the Jarque-Bera test statistic , and Prob(JB) is its p-value. The 5% critical value and corresponding probability value were adjusted using a Bonferroni procedure to 2,394 and 0,017, respectively.*
** denotes statistical insignificance.*

a) Stock portfolios

Portfolio	$\hat{S}$	$z_{\hat{S}}$	$\hat{K}$	$z_{\hat{K}}$	JB	***Prob (JB).***
ALSI	-1,042	-13,145	9,294	39,681	1747,335	0,000
PORT	-0,952	-15,307	8,632	43,146	2177,112	0,000

b) Individual stocks

Security	$\hat{S}$	$z_{\hat{S}}$	$\hat{K}$	$z_{\hat{K}}$	***JB***	***Prob (JB).***
AFE	-2,414	-38,408	43,571	322,770	105655,50	0,000
AFX	0,053	0,847*	6,531	28,091	789,83	0,000
AGL	-8,901	-141,618	216,060	1695,022	2893157,00	0,000
ALT	0,208	3,315	15,166	96,789	9379,04	0,000
ANG	0,222	3,529	4,251	9,949	111,44	0,000
ASR	-24,820	-394,910	845,913	6705,882	45124813,0	0,000
AVI	-2,408	-38,309	39,697	291,944	86699,02	0,000
BAW	-2,637	-41,964	43,189	319,731	103988,60	0,000
BVT	-0,305	-4,855	15,829	102,065	10440,79	0,000
CHE	0,063	1,000*	10,595	60,423	3651,90	0,000
CTP	0,222	3,536	12,732	77,427	6007,51	0,000
DEL	-5,935	-94,431	134,041	1042,509	1095742,00	0,000
DUR	0,342	5,442	7,623	36,780	1382,36	0,000
ECO	-0,322	-5,118	13,552	83,946	7073,10	0,000
ELH	0,275	4,383	9,882	54,748	3016,55	0,000
FOS	0,950	15,110	16,424	106,798	11634,06	0,000
GMF	-1,136	-18,077	17,367	114,296	13390,30	0,000
HAR	0,383	6,095	6,089	24,574	641,04	0,000
HLH	-1,137	-18,092	19,055	127,726	16641,11	0,000
HVL	0,156	2,484	6,346	26,619	714,73	0,000
IMP	0,187	2,972	6,024	24,062	587,80	0,000
JCM	-2,282	-36,317	245,745	1931,187	3730803,00	0,000
JNC	0,229	3,641	189,066	1480,270	2191213,00	0,000
LGL	-0,725	-11,535	14,740	93,400	8856,69	0,000
MAF	-20,658	-328,699	648,104	5132,189	26447408,0	0,000
MLB	-4,242	-67,496	80,998	620,519	389599,80	0,000
NED	-0,156	-2,476	6,164	25,170	639,64	0,000
NPK	-0,467	-7,430	8,993	47,677	2328,33	0,000
OCE	-0,286	-4,547	9,896	54,863	3030,67	0,000
PAM	0,500	7,963	7,446	35,373	1314,69	0,000
PIK	-0,220	-3,499	8,676	45,157	2051,41	0,000
PPC	0,142	2,262*	10,574	60,253	3635,56	0,000
REM	-0,702	-11,170	106,449	822,997	677448,80	0,000
RLO	0,421	6,698	18,337	122,018	14933,27	0,000
SAB	-1,217	-19,363	20,288	137,534	19290,45	0,000
SAP	0,024	0,385*	7,539	36,109	1304,02	0,000
SBK	-0,226	-3,589	9,904	54,924	3029,49	0,000
TBS	-0,124	-1,974*	8,924	47,127	2224,85	0,000
TNT	-0,044	-0,703*	5,979	23,702	562,28	0,000
TRE	2,683	42,683	348,565	2749,177	7559798,00	0,000
WAR	0,315	5,013	5,254	17,935	346,81	0,000
WLO	-0,399	-6,343	8,862	46,635	2215,06	0,000

Table 5 – Autocorrelation structures and Engel tests

*This table reports the autocorrelation structures of the logarithmic returns, as well as the Engle test results. The order of serial correlation is given in Column 2, where p is the p-value for the Q-statistic. By the Bonferroni correction, $p<0,005$ indicates the presence of serial correlation at 5% significance level. 'U' indicates that no correlation could be detected, hence the p-value relates to the Q-statistic at lag 10. Engel's ARCH(10) test statistics are given in Column 3, where p-values are also denoted as p. In the Engel test, the null hypothesis could be rejected if $p < 0,05$. * indicates the presence of non-linearity.*

a) Stock portfolios

1 Portfolio	*2* Corr. Order (p)	3 nR^2 (p)	
ALSI	1 (0,000)	61,605	(0,000)*
PORT	1 (0,000)	114,552	(0,000)*

b) Individual stocks

1 Security	*2* Corr. Order (p)	3 nR^2 (p)	
AFE	2 (0,0,001)	17,789	(0,057)
AFX	U (0,883)	44,821	(0,000)*
AGL	U (0,219)	0,102	(1,000)
ALT	1 (0,000)	25,020	(0,005)*
ANG	U (0,873)	61,392	(0,000)*
ASR	U (0,995)	0,013	(1,000)
AVI	1 (0,002)	5,559	(0,851)
BAW	U (0,085)	1,670	(0,998)
BVT	U (0,483)	29,226	(0,001)*
CHE	1 (0,000)	62,533	(0,000)*
CTP	U (0,412)	18,990	(0,040)*
DEL	U (0,164)	4,497	(0,922)
DUR	1 (0,000)	24,345	(0,007)*
ECO	1 (0,000)	92,534	(0,000)*
ELH	1 (0,000)	72,654	(0,000)*
FOS	1 (0,000)	15,180	(0,126)
GMF	U (0,320)	4,587	(0,917)
HAR	U (0,106)	48,068	(0,000)*
HLH	U (0,594)	7,759	(0,652)
HVL	1 (0,216)	33,716	(0,000)*
IMP	U (0,130)	54,110	(0,000)*
JCM	2 (0,000)	117,810	(0,000)*
JNC	1 (0,000)	247,100	(0,000)*
LGL	U (0,676)	24,180	(0,007)*
MAF	5 (0,000)	2,151	(0,995)
MLB	U (0,969)	0,135	(1,000)
NED	U (0,686)	124,583	(0,000)*
NPK	U (0,824)	226,487	(0,000)*
OCE	U (0,365)	22,955	(0,011)*
PAM	U (0,898)	57,280	(0,000)*
PIK	U (0,883)	44,865	(0,000)*
PPC	1 (0,000)	24,250	(0,001)*
REM	1 (0,000)	203,568	(0,000)*
RLO	1 (0,000)	21,461	(0,018)*
SAB	U (0,986)	5,955	(0,819)
SAP	U (0,654)	41,492	(0,000)*
SBK	7 (0,004)	320,550	(0,000)*
TBS	U (0,036)	48,119	(0,000)*
TNT	U (0,956)	69,291	(0,000)*
TRE	U (0,939)	0,103	(1,000)
WAR	U (0,075)	105,554	(0,000)*
WLO	U (0,413)	25,417	(0,005)*

Given the chosen values for m and l as described in the methodology, the BDS test was conducted nine times for ALSI, and twelve times for each of the remaining forty-three series, giving a total of 525 estimates of the test statistic. However, for want of space, Table 6 only shows the results for $l = 1{,}0\sigma$; the rest of the results are available from the author upon request. It was observed that the iid assumption could not be accepted in 504 (i.e., 96 percent) of the 525 experiments. Security ASR showed a linear deterministic distribution at all embedding dimensions when $l = 1{,}0\sigma$ and $l = 1{,}5\sigma$, but did not show linearity when $l = 0{,}5\sigma$. Thus, linearity could be confirmed in eight of the twelve test statistics for this single stock. Linearity was also scarcely detected at some few of the low embedding dimensions for CHE, IMP, and PIK, especially when $l = 1{,}0\sigma$ and when $l = 1{,}5\sigma$. Hence, apart from a total of twenty-one outlier cases from a possible 525, there was strong evidence that the stock returns did not follow an iid process.

As expected, it was noted that the evidence provided by the BDS test against the random iid assumption was unambiguously stronger than that provided by the Engle test. Finally, as stated earlier, the combined effect of the rejection of normality and iid implies that JSE logarithmic security prices did not follow a normal strong random walk process. This evidence could imply that continuously compounded JSE stock returns were profitably predictable over time, and could render suspicious the appropriateness of static asset pricing methodologies in analysing stock price movements on this emerging market.

Since the BDS approach tests for the null hypothesis of a random iid system, and since the test was applied to linearly unpredictable log return series which were also confirmed to be stationary, the results obtained in this investigation ruled out the possibility that the rejection of the iid hypothesis could be attributable to linear dependencies or to a linear stochastic return generating process. This further implies that the return generating process could be characterised by either non-linear stochastic dynamics or low complexity chaotic dynamics. The latter implies the presence of non-linearities in the conditional mean while, for the former, non-linearities would manifest in the conditional variance.

Most of the evidence in the literature does not seem to support the presence of chaotic dynamics as accounting for non-linearities in financial time series (e.g., Hsieh, 1991). If the iid hypothesis were rejected because returns were non-linear in variance, as would be the case if volatility clustering were evident, it would imply that JSE equity returns could be modelled as ARCH-type processes. Further research might explore this possibility.

5. SUMMARY AND CONCLUSION

This paper investigated the stationarity, normality and linearity properties of logarithmic stock prices and logarithmic returns on the JSE. The sample consisted of weekly data on forty-two individual JSE-listed stocks, the JSE All Share index, as well as an equally-weighted portfolio of the forty-two stocks. In order to investigate the unit root hypothesis, Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) tests were initially used. Further, the innovational outlier model proposed by Perron (1994) was used to investigate the joint unit root-structural change hypothesis, where the selection of potential break dates was guided by South Africa's largely interrelated social, political and economic developments. Secondly, by examining relevant descriptive statistics and invoking the Jarque-Bera test, the study investigated the normality property in the returns. Joint multivariate normality was evaluated by noting that the normality of individual returns was a necessary (but not sufficient) condition. Finally, the hypothesis of linearity was resolved by using both Engel's Lagrange Multiplier test and the BDS test due to Brock *et al.* (1987). Due attention was paid to the problem of autocorrelation which could arise from non-synchronous trading or non-trading. Moreover, the Bonferroni correction for multiple testing was accordingly invoked where appropriate.

The major findings of this analysis were consistent with stylised facts documented in the literature. Specifically, the results validated the use of returns as opposed to prices as the basis for the analysis of JSE stock price behaviour, since logarithmic returns were confirmed to be stationary processes, while logarithmic prices were largely non-stationary. Further, the results of the investigations of normal strong random walk properties in the log return series showed that both the assumptions of normality and linearity were inapt: return distributions were highly leptokurtic, generally displayed excess skewness (which could be positive or negative), and were far from being iid. These findings disputed the empirical applicability of standard two-date (single period) asset pricing methodologies in describing movements in prices and returns on this market. Importantly, they showed that changes in JSE returns could be non-linearly predictable over time, more so on account of the potential presence of volatility in linearly filtered returns.

Table 6 – BDS test statistics for returns

This table presents the BDS test statistics for the logarithmic returns, for $l = 1{,}0\sigma$. *Results for* $l = 0{,}5\sigma$ *and* $l = 1{,}5\sigma$ *are available from the author upon request. The Bonferroni-adjusted critical values at 5 percent significance levels were 2,773 for ALSI and 2,865 for all other series.* * indicates evidence of linearity.

a) Stock portfolios

#	*Portfolio*	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	ALSI	3,306	5,339	6,742	n.a.
2	PORT	6,168	7,275	7,348	7,892

b) Individual stocks

#	*Security*	$m = 2$	$m = 3$	$m = 4$	$m = 5$
1	AFE	6,095	7,692	8,894	9,417
2	AFX	5,282	6,170	6,802	7,480
3	AGL	4,316	5,096	5,929	6,988
4	ALT	4,990	5,659	6,418	6,723
5	ANG	5,479	6,969	7,635	8,254
6	ASR	0,805*	0,769*	0,761*	1,190*
7	AVI	7,579	8,744	9,467	10,380
8	BAW	6,525	7,261	7,782	8,075
9	BVT	5,539	6,963	7,029	7,437
10	CHE	1,394*	3,001	3,589	4,060
11	CTP	7,492	9,280	10,403	11,603
12	DEL	7,052	7,210	7,460	7,972
13	DUR	6,058	7,321	7,887	8,211
14	ECO	4,518	6,875	7,892	8,468
15	ELH	8,122	8,839	8,975	9,198
16	FOS	6,805	7,475	7,874	8,404
17	GMF	3,787	4,445	5,038	5,608
18	HAR	5,085	5,610	6,137	6,804
19	HLH	5,391	7,338	8,010	8,955
20	HVL	6,869	6,873	6,989	7,026
21	IMP	2,609*	3,693	4,105	4,651
22	JCM	2,210*	8,122	10,136	10,900
23	JNC	19,541	21,578	22,865	23,529
24	LGL	7,076	6,772	6,374	6,813
25	MAF	2,695*	4,155	4,853	5,348
26	MLB	6,369	7,050	7,261	7,665
27	NED	4,685	6,069	6,363	6,563
28	NPK	8,633	9,053	9,322	9,656
29	OCE	5,252	6,787	8,068	9,403
30	PAM	5,592	7,420	8,464	8,913
31	PIK	2,859*	3,405	3,527	3,514
32	PPC	6,364	7,193	7,716	8,062
33	REM	4,428	4,924	4,861	4,847
34	RLO	6,980	8,418	10,043	11,010
35	SAB	4,700	6,898	7,479	7,573
36	SAP	5,276	6,898	7,478	7,900
37	SBK	4,897	6,072	7,421	8,196
38	TBS	4,041	4,403	5,341	5,504
39	TNT	7,007	7,544	7,920	8,084
40	TRE	4,771	5,236	5,541	5,555
41	WAR	3,927	5,395	6,240	7,190
42	WLO	7,753	8,906	9,533	9,980

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Appendix 1 – Stocks in the study sample

This appendix shows the 42 stocks selected to constitute the final sample. UMC is the market capitalisation, before the application of the investibility weighting, while the WMC is the market capitalisation, after this application. UMC and WMC are in million rands, as at June 2002.

#	JSE Code	Company Name	UMC (Rm)	WMC (Rm)	% of All Share Index
1	AFE	AECI Ltd	2346	2346	0,16
2	AFX	African Oxygen Ltd	4558	2279	0,15
3	AGL	Anglo American Plc	273677	273677	18,11
4	ALT	Allied Technologies Ltd	2383	1191	0,08
5	ANG	Anglogold Ltd	74176	37088	2,45
6	ASR	Assore Ltd	1820	0	0
7	AVI	Anglovaal Industries Ltd	4581	4581	0,3
8	BAW	Barloworld Ltd	14680	14680	0,97
9	BVT	The Bidvest Group Ltd	15415	15415	1,02
10	CHE	Chemical Services Ltd	1427	571	0,04
11	CTP	CTP Holdings Ltd	1930	579	0,04
12	DEL	Delta Electrical Industries Ltd	2409	2409	0,16
13	DUR	Durban Roodepoort Deep Ltd	9724	9724	0,64
14	ECO	Edgers Consolidated Stores Ltd	2039	2039	0,13
15	ELH	Ellerine Holdings Ltd	1255	1255	0,08
16	FOS	Foschini Ltd	2073	1555	0,1
17	GMF	Gencor Ltd	16802	0	0
18	HAR	Harmony Gold Mining Co Ltd	28572	28572	1,89
19	HLH	Hunt Leuchars & Hepburn Holdings Ltd	1824	0	0
20	HVL	Highveld Steel Steel & Vanadium Corp. Ltd	1612	484	0,03
21	IMP	Impala Platinum Holdings Ltd	38649	28986	1,92
22	JCM	Johncom Communications Ltd	1354	0	0
23	JNC	Johnnic Holdings Ltd	7309	7309	0,48
24	LGL	Liberty Group Ltd	16526	8263	0.55
25	MAF	Mutual & Federal Insurance Co Ltd	4432	0	0
26	MLB	Malbak Ltd	2333	1166	0,08
27	NED	Nedcor Ltd	32370	16185	1,07
28	NPK	Nampak Ltd	7405	7405	0,49
29	OCE	Oceana Group Ltd	1536	614	0,04
30	PAM	Palabora Mining Company Ltd	1699	680	0,04
31	PIK	Pik n Pay Stores Ltd	6736	3368	0,22
32	PPC	Pretoria Portland Cement Co Ltd	3918	1567	0,1
33	REM	Remgro Ltd	34541	34541	2,29
34	RLO	Reunert Ltd	3999	3999	0,26
35	SAB	South African Breweries plc	71864	71864	4,76
36	SAP	Sappi Ltd	34068	34068	2,25
37	SBK	Standard Bank Group Ltd	47001	47001	3,11
38	TBS	Tiger Brands Ltd	12058	12058	0,8
39	TNT	The Tongaat-Hulett Group Ltd	4789	2394	0,16
40	TRE	Trencor Ltd	1383	0	0
41	WAR	Western Areas Ltd	4315	3236.25	0,21
42	WLO	Wooltru Ltd	1792	1792	0,12
		Sample	**803380**	**684941**	**45,30**

(Source: Adapted from Profile Media, 2002).