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# Do CAPM Anomaly Variables Provide Real-Time Tradable Opportunities on the JSE?

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## Abstract

There is an abundance of research, both international and South African, which suggests that certain empirically determined variables are able to predict the cross-section of stock returns. These results beg the question as to whether actual investors could use these empirically determined anomaly variables to make profitable predictions? This study applies the recursive out-of-sample methodology of Cooper *et al.* (2005) to determine whether CAPM anomaly variables provide real-time tradable opportunities on the Johannesburg Stock Exchange (JSE). The three predictor variables selected on the basis of the South African literature (size, earnings yield and one-year lagged returns) fail to show any statistical evidence of predictability in real-time.

## INTRODUCTION

There is an abundance of research, both international<sup>1</sup> and South African<sup>2</sup>, which suggests that certain empirically determined variables are able to predict the cross-section of stock returns. Despite these 'CAPM anomaly variables' having no concrete theoretical underpinnings, they have gained mainstream acceptance. These results beg the question as to whether actual investors could use these empirically determined anomaly variables to make profitable predictions? The real-world evidence seems to suggest the answer is 'NO'.

Perhaps the difference lies in the *ex post* nature of the empirical results; there is a significant inherent hindsight bias. Real investors do not have the luxury of implementing their decisions once market movements are already known, and there is nothing to suggest that the *ex post* predictive phenomenon can be extrapolated *ex ante*. Cooper, Gutierrez Jr., and Marcum (2005) have developed a recursive out-of-sample methodology to determine whether the anomaly variables do provide real-time tradable opportunities. This methodology attempts to determine whether investors would have employed the *ex post* successful anomaly variables for their investment decisions in real-time, and whether this would result in a profitable outcome.

Their study seeks to ascertain whether the hypothetical investor would have chosen the *ex post* successful predictor variables given the multitude of available alternatives. Cooper *et al.* (2005), following Pesaran and Timmerman (1995) and Bossaerts and Hillion (1999), note that this is achieved by allowing competing variables in the simulation. However, Cooper *et al.*

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<sup>1</sup> For a comprehensive review of the international literature review, see Shleifer (2000). See also Basu (1977), Banz (1981), De Bondt and Thaler (1985), Chan, Hamao, and Lakonishok (1991), Fama and French (1992, 1993), Jegadeesh and Titman (1993), Lakonishok, Shleifer, and Vishny (1994), Daniel and Titman (1997).

<sup>2</sup> See *inter alia* De Villiers, Lowings, Pettit, and Affleck-Graves (1986), Bradfield, Barr, and Affleck-Graves (1988), Page and Palmer (1991), Page (1996), Fraser and Page (2000), van Rensburg (2001), van Rensburg and Robertson (2003a), van Rensburg and Robertson (2003b).

(2005) confine their universe of variables to just four: three of the foremost predictor variables (as determined in the *ex post* literature) and beta. As a consequence, their results are biased in favour of finding predictability.

The predictor variables are determined by reference to historical data, therefore, the simulation allows a hypothetical investor to analyse a fixed historical period to determine the best performing investment strategy (the trading rules are characterised as "cross-sectional sorts of all stocks based on each of the four variables" (Cooper *et al.* (2005) p.3). The *ex post* successful trading rules are applied *ex ante*, and the historical performance of said rules is compared with the extrapolated performance. Cooper *et al.* (2005) allow for diverse investor preferences by utilising three criteria to determine the best performing trading rules (requiring three separate simulations).

Despite the outcome being biased in the favour of finding predictability, two of the three simulations fail to produce real-time profitable portfolios. Furthermore, the single simulation that does result in profits yields a best-performing portfolio that produces only a fraction of the profits generated by a "hindsight" portfolio (Cooper *et al.* (2005) p.3).

This paper employs the recursive out-of-sample methodology of Cooper *et al.* (2005) and finds similar results. The universe of variables differs, and in this case is determined with reference to the South African empirical literature. The methodology was also adapted slightly in some instances, due either to limitations imposed by the available South African data (which is not as comprehensive as the US data used by Cooper *et al.* (2005)), or where this author deemed alternative assumptions more appropriate (most notably the length of the in-sample window).

## LITERATURE REVIEW

De Villiers, Lowings, Pettit, and Affleck-Graves (1986) investigate the existence of a size effect on the JSE over the period 1973 to 1982. Three measures of firm size are considered (market capitalization, asset base, and marketability) and these are tested on a sample of JSE industrial shares. The authors conclude, contrary to international evidence, that there does not appear to be a small firm effect on the JSE (in fact, the results support the notion that large firms tend to outperform small firms on a risk-adjusted basis, but the findings are not statistically significant.)

Bradfield, Barr, and Affleck-Graves (1988) test the applicability of the one-parameter CAPM for the JSE, as well as the existence of three hypothesized CAPM anomalies: dividend yield, size and liquidity. The authors use a sample of listed shares over the period 1973 to 1984, but also separately test a sample of gold shares. They find that the one-parameter CAPM performs admirably for the JSE as a whole, but less well for gold stocks. In addition, their results, using both gold as well as non-gold stocks, indicate that none of the hypothesized anomalies are significant for the JSE.

The size effect is revisited by Page and Palmer (1991), who also consider the possibility of an earnings yield effect. Their sample consists of stocks listed on the JSE during the period 1978 to 1988. The authors do find evidence of an earnings yield effect on the JSE, with high E/P securities tending to outperform low E/P securities. However, there is no evidence to support the notion of a size effect.

Page (1996) again considers the size and earnings anomalies, but extends the work of Page and Palmer (1991) by introducing APT benchmarks (in addition to the CAPM benchmarks used previously). A sample of JSE industrial shares over the period 1973 to 1992 is considered. Page (1996) again finds evidence of a positive earnings yield effect and similar to De Villiers *et al.* (1986), the author finds positive, but statistically insignificant, size coefficients.

Value and momentum strategies are found to be significant by Fraser and Page (2000). They use a dataset consisting of JSE industrial stocks spanning the period 1973 to 1997 and find abnormal returns demonstrated by all the variables considered. The authors find dividend yield, book-to-market equity (value), and average past 12 months' returns (momentum) to be positively related to returns.

Van Rensburg (2001) considers 23 possible anomaly variables over the period 1983 to 1999, using JSE industrial shares. On a CAPM risk-adjusted basis, the following variables (listed in descending order of significance) exhibit abnormal returns: earnings yield, past 12 months' positive returns, size, dividend yield, past 6 months' returns, assets-to-debt, cash-flow-to-debt, turnover, past 3 months' positive returns, and past 6 months' positive returns. Given the large number of variables, cluster analysis is utilized to determine whether some of these variables displayed similar characteristics and could thus be grouped together. Van Rensburg (2001) identifies 3 clusters, namely, momentum, value and quality. Based on their individual performances, the variables past 12 months' positive returns, earnings yield and size respectively were chosen to represent the aforementioned clusters. The results indicate positive momentum and earnings yield effects, and a negative size effect.

A similar number of candidate anomaly variables are investigated by van Rensburg and Robertson (2003a). In total, 24 variables are considered over the period 1990 to 2000. This study differs from much of the previously published JSE anomaly variables literature in that the dataset is not restricted solely to industrial stocks. The results indicate that five variables display abnormal returns on a CAPM risk-adjusted basis; listed in descending order of significance they are: price-to-net-asset-value, market capitalization, earnings yield, dividend yield and cash-flow-to-price. Based on the results, the authors advocate a multifactor model comprised of size and earnings yield<sup>3</sup>.

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<sup>3</sup> The multivariate regression results show size and earnings yield to be the only jointly significant factor pairing, despite price-to-net-asset-value being the most significant on a univariate basis.

Having identified size and earnings yield as the significant variables in their previous study, van Rensburg and Robertson (2003b) examine these two variables (using the same sample period) in further detail. The authors find a negative relationship between size and returns, and a positive relationship between earnings yield and returns.

## DATA AND METHODOLOGY

### Variables

This study applies the recursive out-of-sample methodology of Cooper *et al.* (2005) to determine whether CAPM anomaly variables provide real-time tradable opportunities on the Johannesburg Stock Exchange (JSE). The South African literature, in particular the more recent work, motivated the selection of three candidate anomaly variables: size<sup>4</sup>, earnings yield<sup>5</sup> and one-year lagged returns<sup>6</sup>. Following Cooper *et al.* (2005), the fourth variable under consideration is beta. Cooper *et al.* (2005) note that by including only those variables that have been found to be significant in the *ex post* literature, one introduces a degree of hindsight advantage to the hypothetical investor. To alleviate this (albeit marginally), they include beta. These four variables, from which the trading rules are derived, constitute the universe of variables available to the hypothetical real-time investor. The limitation to merely four variables vastly understates the options available to actual investors. However, both for reasons of computational simplicity, as well as for the primary purpose of determining the significance, or otherwise, of the purportedly successful CAPM anomaly variables, the restriction is imposed. When interpreting the results, it should be noted that this restriction would bias the results in favour of predictability (Cooper *et al.* (2005)).

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<sup>4</sup> Van Rensburg (2001), Van Rensburg and Robertson (2003a)

<sup>5</sup> Van Rensburg (2001), Van Rensburg and Robertson (2003a)

<sup>6</sup> Fraser and Page (2000), Van Rensburg (2001), Van Rensburg and Robertson (2003a)

Data for the period July 1987 to June 2004 was extracted from the Datastream database available at the commerce section of UCT's main library. The JSE's dichotomous nature stems from the peculiarity of the resource sector which is subject to different forces (predominantly international) relative to the non-resource sector. As a result of this dichotomy, only industrial stocks were considered in this study<sup>7</sup>. Great, but ultimately futile, attempts were made to include both listed and delisted shares in the analysis (as required by a real-time simulation). Unfortunately delisted share data is not freely available for JSE stocks; the sample is thus confined exclusively to listed stocks. The survivorship bias thus introduced is regrettable, but unavoidable.

The majority of stocks are recorded as of January 1990 on Datastream, irrespective of whether these stocks were listed on the JSE prior to this date. For those few stocks where pre-1990 data is available, said additional data was extracted to ensure that Beta estimation was as comprehensive as possible. Datastream's total return index<sup>8</sup> was used as the proxy for stock price. This index is adjusted for capital events as well as dividends. The 91-day t-bill tender rate is the proxy for the risk-free rate, and the JSE All Share Index is used as a proxy for the market index. The frequent reclassifications of the JSE

<sup>7</sup> This is consistent with similar empirical work relating to the JSE.

<sup>8</sup> The return index (RI) is calculated assuming dividends are reinvested to purchase additional units of the stock at the closing price applicable on the ex-dividend date:

$$RI_t = RI_{t-1} * \frac{P_t}{P_{t-1}}$$

where:

$RI_t$  =return index at  $t$

$P_t$  =price at  $t$

except where  $t$  is the ex-dividend date, in this case:

$$RI_t = RI_{t-1} * \frac{P_t + D_t}{P_{t-1}}$$

where:

$P_t$  =price on ex-dividend date  $t$

$D_t$  =dividend associated with period  $t$

(Datastream help file)

in recent years necessitated the use of both the CI01 and J203 indices as market proxies (both were extracted from the INet Bridge database available at the commerce IT laboratories). The J203 index is not available prior to June 1995, hence the use of the CI01 index pre-June 1995.<sup>9</sup> Returns<sup>10</sup> were calculated individually for these two indices, and the return series were simply dovetailed to form a single market return series.

SIZE for June  $t$  is defined as the market capitalization at the end of June  $t$ . One-year lagged returns (LAGRET) for June  $t$  is defined as the arithmetic average of the prior 12 month's returns (following Fraser and Page (2000)).<sup>11</sup> Earnings yield (ERNYLD) for June  $t$  is defined as earnings per share for the financial year-end  $t-1$ , divided by price as at calendar year end  $t-1$ . The variables are calculated in such a way as to ensure that any accounting information used in their construction is dated between 6 and 18 months prior to June  $t$ . This conservative lag ensures that the hypothetical investor would have had access to the accounting data at the end of June  $t$ , the date of portfolio formation. These measures are implemented to prevent the introduction of look-ahead bias.

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<sup>9</sup> The return series for the two indices are both available for the period July 1995 to June 2002. A comparison of means test was conducted to determine if the series differed significantly. The result (p-value = 0.7589) indicates that the series are not statistically significantly different.

<sup>10</sup> Returns throughout this paper are calculated as continuously compounded:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}).$$

This representation has the advantage of allowing one to calculate mean monthly returns as:

$$\bar{r}_i = \frac{1}{n} \sum_{t=1}^n r_{i,t}.$$

It also allows one to express terminal wealth as:

$$P_{i,n} = P_{i,0} e^{\sum_{t=1}^n r_{i,t}} \quad (\text{Benninga (2000)})$$

<sup>11</sup> Cooper *et al* (2005), following Fama and French (1996), calculate one-year lagged returns from July  $t-1$  to May  $t$ , excluding June  $t$  to mitigate bid-ask bounce. The calculation thus allows comparisons between the aforementioned studies. Similarly, it was deemed appropriate to follow the methodology of Fraser and Page (2000) in this paper, despite the possible introduction bid-ask bounce.

BETA is assigned in June  $t$ , and estimated using simple OLS regressions, employing between 24 and 60 months of historic data:

$$(r_{i,t} - r_{f,t}) = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (1)$$

where:

$r_{i,t}$  = return for stock  $i$  in month  $t$

$r_{f,t}$  = risk-free return in month  $t$

$r_{m,t}$  = market return in month  $t$ .

The JSE is subject to thin trading, which results in a downward bias for OLS beta estimation (Bradfield (1990)). Several correction procedures are available, the foremost of which are the 'trade-to-trade' approach and the Cohen-type estimators (Bowie and Bradfield (1993)). Bowie and Bradfield (1993) find the trade-to-trade approach to be superior in terms of both efficiency and unbiasedness. However, the trade-to-trade approach is restrictive in terms of its data requirements<sup>12</sup> and is thus difficult to implement in practice (Bowie and Bradfield (1993)). The majority of practitioners use the Cohen-type estimator for the thinly-traded JSE (including Fraser and Page (2000)). The suggested form of the multivariate regression employed when using this estimation technique for the JSE uses leading, lagged and contemporaneous market return terms as independent variables. However, the inclusion of the lead market return term makes this form of beta estimation inappropriate for this particular study. Real-time simulation precludes the use of lead terms since this information would not be available to the hypothetical investor, hence the utilization of simple OLS regression for BETA estimation. The use of a market capitalisation weighted market proxy results in a smaller bias relative to equally weighted indices (Bradfield and Barr (1989)). In addition, the exclusion of delisted stocks, which are likely to be less well traded compared to listed stocks, tends to reduce the bias of the OLS Beta estimates. Whilst the bias introduced via the use of OLS for Beta estimation is acknowledged, the ranking procedure employed in this study reduces the importance of this bias since less emphasis is placed on the actual magnitude

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<sup>12</sup> One of the more restrictive requirements is the need for the time that each trade occurred.

of the Beta estimates. As previously mentioned, pricing data is predominantly available as of mid-1990, resulting in initial beta estimates for June 1992 (owing to the minimum 24 months of historic pricing data used in estimation).

### **Out-of-sample methodology**

Four variables are to be tested to determine whether the cross-section of share returns can be profitably predicted. Cross-sectional sorts of the variables are used to determine the trading rules. In other words, the shares are ranked according to each of the four variables, and split into a specified number of groups based on the rankings. The trading rules are derived either from the groups themselves (where the trading rule is based on a single variable), or from combinations of groups (where the trading rules are based on more than one variable<sup>13</sup>). Cooper *et al.* (2005) employ the sorting procedure in preference to a regression-based method since the latter implies a linear relationship between the variables and returns (p.9). The key to this simulation is an investor with no *a priori* beliefs<sup>14</sup>. The universe of trading rules is evaluated over a sample with full information (the in-sample period). The best (and worst) performing trading rules are selected to form active portfolios, which represent the investment strategy that has been *ex post* identified as the most successful. These successful strategies are then evaluated out-of-sample. Since the rules are identified empirically (and not on the basis of any theoretical foundation), they may change over time. The methodology allows for this by employing a rolling window; the best (worst) performing rules are identified in-sample, and then employed in the immediately following out-of-sample period. The in-sample window is shifted forward to identify a new set of trading rules, which are used in the following out-of-sample period. This process is repeated and results in a series of out-of-

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<sup>13</sup> It is possible to combine different groups of the same variable, but this particular type of trading rule is not considered here.

<sup>14</sup> The fact that only four variables have been included in the investor's rule universe implicitly assumes that he/she has prior beliefs vis-à-vis the efficacy of these variables, but the restriction is imposed for the express purpose of investigating the predictive nature, or otherwise, of these variables.

sample periods for which we have empirically determined portfolios. The out-of-sample performance of these portfolios is compared with a passive benchmark to determine whether the cross-section of returns is predictable.

At the end of June of each year  $t$ , stocks are ranked in ascending order according to each of the four variables, and subsequently split into three groups per variable. For a stock to be considered in a particular year, it must have data for all four variables in that year. This results in a minimum of 90 stocks in June 1992, and a maximum of 170 stocks in June 2003.<sup>15</sup> There are a total of 12 groups across the four variables (3 groups per variable), and it is from these groups that the trading rules are derived. Two different kinds of trading rules are considered, namely, one-way and two-way trading rules.

One-way rules are defined as the directive to purchase all stocks that occur in a single group of a particular variable. Examples of one-way trading rules include: 'purchase all stocks that occur in the small SIZE group', or 'purchase all stocks that occur in the middle ERNYLD group'. Since there are 12 groups in total, there are 12 one-way trading rules.

Two-way trading rules are defined as the directive to purchase all stocks that occur *simultaneously* in two groups. However, it is only those rules that combine two groups from *different* variables that are considered, those that combine two groups of the *same* variable are ignored since it is impossible for any stock to fall into the latter category.<sup>16</sup> Examples of two-way trading rules include: 'purchase all stocks that occur simultaneously in the middle BETA group and the small ERNYLD group', or 'purchase all stocks that occur simultaneously in the large LAGRET group and the small SIZE group'. Given the definition of two-way trading rules, which excludes those rules that incorporate two groups from the same variable, there are 54 two-way rules.<sup>17</sup>

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<sup>15</sup> Table I in the appendix contains a complete list of the 170 stocks considered in this study.

<sup>16</sup> For example: 'purchase all stocks that occur simultaneously in the small and large SIZE groups'.

<sup>17</sup> Each of the 3 BETA groups is individually paired with each of the 3 groups of the remaining 3 variables, resulting in 27 two-way rules. Each of the 3 ERNYLD groups are then individually

Two-way rules generally have fewer stocks than one-way rules due to the unlikelihood of two groups from different variables being comprised of exactly the same stocks. The total number of rules considered in each period is 66 (12 one-way and 54 two-way rules).

The in-sample period is used to determine the investment strategy applicable in the out-of-sample period. Cooper *et al.* (2005) "employ a ten-year in-sample window as a reasonable trade-off between reducing error in the estimation of the relations between stock returns and (their) choice variables and permitting regime switches in those relations" (p.7). However, the ten-year window affords very little weight to the 'new' period included at each iteration, and the result is investment strategies that change very little from one out-of-sample period to the next. In addition, the limited available data prevents the use of a ten-year window in this particular study. For these reasons, a five-year window was selected. As with Cooper *et al.* (2005), the out-of-sample period is the 12-month period immediately following the in-sample window.

Once the stocks comprising each rule have been identified<sup>18</sup>, the hypothetical investor formulates the active portfolios based on the in-sample performance of the trading rules. The seven best performing rules during the in-sample window (approximately 10%) are selected to form the investor's LONG portfolio for the associated out-of-sample period. Similarly, the 7 worst performing rules form the investor's chosen SHORT portfolio. However,

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paired with each of the 3 LAGRET and SIZE groups (the two-way trading rules formed by combining the BETA and ERNYLD groups have been accounted for when the BETA groups were paired with the groups of the other variables), resulting in a further 18 two-way rules. Finally, the 3 LAGRET groups are individually paired with the 3 SIZE groups, resulting in 9 two-way rules. Thus, in total there are 54 two-way trading rules.

<sup>18</sup> The one-way trading rule constituents are easily identified: ranking the stocks according to each of the 4 variables and then inserting breakpoints to give 3 groups per variable (and thus 12 groups in total) gives the constituents of the 12 one-way rules. The two-way rules are identified using an array formula in Microsoft Excel that combines the 12 groups in the manner described previously, identifying those stocks that occur simultaneously in two groups, resulting in the two-way rule constituents.

numerous criteria may be used to gauge the in-sample performance of said trading rules. In a bid to cater for diverse investor preferences, Cooper *et al.* (2005) select three performance criteria and run a separate simulation for each. Consistent with previous assumptions, the authors do not assert which criterion the investor would have preferred *a priori* (pp.7-8).

Following Cooper *et al.* (2005), this study considers the same three measures, namely, mean monthly returns, Sharpe ratio and terminal wealth. The three performance criteria are used for each of the rules from the beginning of July  $t$  to the end of June  $t+1$ .

The mean monthly return is calculated as:

$$\bar{r}_i = \frac{1}{12} \sum_{t=1}^{12} r_{i,t} \quad (2)$$

where:

$\bar{r}_i$  = mean monthly return to rule  $i$

$r_{i,t}$  = monthly equally-weighted return to rule  $i$  in month  $t$ .

The Sharpe ratio is calculated as:

$$SR_i = \frac{\bar{r}_i - \bar{r}_f}{\sigma_i} \quad (3)$$

where:

$SR_i$  = Sharpe ratio for rule  $i$

$\bar{r}_i$  = mean monthly return to rule  $i$

$\bar{r}_f$  = mean monthly risk-free return

$\sigma_i$  = standard deviation of monthly returns to rule  $i$ .

Terminal wealth is calculated as:

$$P_i = e^{\sum_{t=1}^{12} r_{i,t}} \quad (4)$$

where:

$P_i$  = terminal value at the end of June  $t+1$  of ZAR 1.00 invested at the beginning of July  $t$

$r_{i,t}$  = monthly equally-weighted return to rule  $i$  in month  $t$ .

At the end of each year  $t$  of the in-sample window, the rules are ranked in descending order according to the performance criterion in question. The entire in-sample performance determines selection or otherwise for the active portfolios, therefore, each rule's ranks are summed over the five-year window. These cumulative in-sample ranks are used to determine the constituents of the active portfolios.

An alternative to the ranking procedure is a comparison of the cumulative underlying values of the criterion. However, the former should afford a better indication of consistent performance since outliers may appreciably affect the underlying values.

The rules that comprise the chosen LONG portfolio for the mean-return criterion are those that have the 7 smallest cumulative ranks<sup>19</sup> for this criterion over the 5-year in-sample window, whilst those with the 7 greatest cumulative ranks form the SHORT portfolio for the mean-return criterion.<sup>20</sup> Similarly, the LONG and SHORT portfolios corresponding to the Sharpe-ratio and terminal-wealth criteria, respectively, are formed.<sup>21</sup> It is possible that a particular stock occurs in more than one of the seven rules selected to form one of the out-of-sample portfolios; this stock does not receive additional weighting in the active portfolio.

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<sup>19</sup> The rules are ranked in *descending* order according to mean monthly returns. Thus, the rules with the greatest mean-monthly-return values (i.e. best performing) have the smallest rank. Similarly, the best performing rules over the entire in-sample window will have the smallest cumulative ranks, owing to the initial sort that ranked the rules in descending order.

<sup>20</sup> In the event that two rules, when ranked according to their cumulative ranks over the in-sample period, jointly achieve either 7<sup>th</sup> or 59<sup>th</sup> position, the underlying criteria are compared to determine which rule is included in the portfolio. That rule which achieves either the highest or lowest cumulative value for the underlying criterion over the in-sample period is consequently included in the LONG or SHORT portfolio, respectively, for that criterion. This situation arises on five separate occasions.

<sup>21</sup> Larger Sharpe-ratio and terminal-wealth values imply superior performance; hence the rules with the 7 smallest cumulative ranks form the LONG portfolio.

The in-sample window is rolled forward by one year and the process is repeated. An iterative application of this methodology results in a time-series of out-of-sample returns for the active portfolios.

To illustrate, consider the first in-sample window, which stretches from the beginning of July 1992 to the end of June 1997. The stocks are ranked at the end of June 1992 and split into three groups for each of the four variables. From the 12 groups derived at the end of June 1992, the 66 trading rules applicable from July 1992 to June 1993 are identified.<sup>22</sup> The returns for each of the 66 trading rules are calculated from the beginning of July 1992 to the end of June 1993. Once the monthly equally-weighted returns to each rule have been calculated, the mean return, Sharpe ratio and terminal wealth values associated with each rule are calculated for July 1992 to June 1993.

The stocks are ranked and split into groups again at the end of June 1993. Returns for the trading rules are calculated over the subsequent year, as well as values for each of the three performance criteria. This process is repeated for each of the five years in the in-sample window. The 7 best performing rules<sup>23</sup> over the entire period July 1992 to June 1997 are selected to form the LONG portfolio for July 1997 to June 1998. This is the first out-of-sample period. Similarly, the SHORT portfolio is also formed, and returns to the two portfolios are calculated for the first out-of-sample period.

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<sup>22</sup> The trading rules themselves remain unchanged from year to year, e.g. 'purchase all stocks that occur in the small SIZE group' (one-way rule). However, the constituent stocks are determined by the ranking and thus may change over time.

<sup>23</sup> The best and worst performing rules are derived from the ranking procedure described previously. The stocks are ranked in descending order for each year of the in-sample window according to each of the three performance criteria. The ranks associated with a performance criterion for a particular rule are summed over the five years of the relevant in-sample window. For example, the five mean-return ranks for rule 34 are summed over the in-sample window period to give a cumulative rank for rule 34's mean-return. These cumulative ranks determine the best and worst performing rules; the smaller the cumulative rank, the better the performance, and vice versa (owing to the descending sort employed to rank the performance criteria).

Once this process is complete, the in-sample window is moved forward by one year. It now stretches from July 1993 to June 1998, and the LONG and SHORT portfolios are selected for the second out-of-sample period (July 1998 to June 1999). The entire process is repeated iteratively until a time series of out-of-sample portfolio returns emerges for the period July 1997 to June 2004.

Three such simulations are performed, one simulation for each of the performance criteria, resulting in three sets of LONG and SHORT portfolio out-of-sample returns. The returns to the active portfolios are tested to determine whether predictability is evident.

Following Cooper *et al.* (2005), numerous tests are employed. The first test compares the performance of the LONG and SHORT portfolios to that of a passive benchmark. The benchmark is an equally-weighted portfolio (EW) comprised of all the stocks considered in the study. The performance of the portfolios is measured in three ways: mean monthly returns, Jensen's alpha and Sharpe ratio. Three measures are employed due to the lack of a definitive portfolio performance appraisal technique, and the three measures consider both raw (mean monthly returns) and risk-adjusted (Jensen's alpha, Sharpe ratio) returns.

Equally-weighted monthly returns for each of the LONG and SHORT portfolios are compared with those of the EW portfolio. Predictability is evident if the LONG portfolio's mean return exceeds that of the EW portfolio, or the return to the SHORT portfolio is less than that of the EW portfolio.

Jensen's alpha is estimated by independently regressing the excess returns of the LONG and SHORT portfolios against the excess returns of the EW portfolio. The OLS regression is of the following form:

$$(r_{A,t} - r_{f,t}) = \alpha_A + \beta_A(r_{EW,t} - r_{f,t}) + e_{A,t} \quad (5)$$

where:

$r_A$  = monthly equally-weighted return for active portfolio A

- $r_f$  = monthly risk-free return
- $r_{EW}$  = monthly return to the EW index
- $\alpha_A$  = Jensen's alpha for portfolio A.

A Jensen's alpha figure is estimated for every LONG and SHORT portfolio, for each out-of-sample period. If the mean Jensen's alpha for the LONG portfolio is greater than zero, or that of the SHORT portfolio is less than zero, the implication is that the cross-section of stock returns on the JSE is predictable *ex ante*.

A Sharpe ratio is estimated for every LONG and SHORT portfolio in each out-of-sample period. The mean Sharpe ratio for the active portfolio is compared with the mean Sharpe ratio for the EW index. Out-of-sample predictability is manifest if the Sharpe ratio of the LONG portfolio exceeds that of the EW index, or the Sharpe ratio of the SHORT portfolio is less than that of the EW index.

A COMBINED portfolio is calculated by subtracting the returns of the SHORT portfolio from those of the LONG portfolio. The COMBINED portfolio is used to test for evidence of predictability by comparing its mean monthly return and Jensen's alpha with zero (a Sharpe ratio is not estimated). A positive value for either of these variables is indicative of predictability. It should be noted that the method of calculating Jensen's alpha for the COMBINED portfolio differs slightly from that used for the LONG and SHORT portfolios; the risk-free rate is not deducted from the returns of the COMBINED portfolio in (5). Cooper *et al.* (2005) warn that less emphasis be placed on the results of the tests involving the COMBINED portfolios. In practice, actual investors may face restrictions relating to the funding of long positions using the income from short sales, as well as other legislative limitations (Cooper *et al.* (2005)).

## RESULTS

### Rule Composition

With the exception of one period, the mean-return and terminal-wealth simulations yield identical portfolio rule compositions. In this period, two rules under consideration for both the mean-return and terminal-wealth SHORT portfolios were jointly ranked 59<sup>th</sup> based on their cumulative in-sample ranks. In the event of the ranking procedure failing to definitively select the best or worst performing rules, the underlying figures are used to differentiate between the jointly ranked rules. The two criteria differed with respect to the rule selected on the basis of the actual figures, however, in light of the extremely marginal difference for rule selection in this instance, it was deemed sufficient to consider the rule selections as identical. The statistics reported below do not give increased weighting to the rules selected by these two criteria, they are reported as if only two criteria were employed: mean-return and Sharpe-ratio.

Overwhelmingly, the active portfolios are comprised of two-way rules, with approximately 92% of total selected rules being of this type. Individually, the mean-return criterion dominated slightly in terms of two-way rule selection relative to the Sharpe-ratio criterion (93.88% vs. 89.80%).

The use of individual variables in portfolio construction was well diversified; ERNYLD and SIZE were most frequently employed, each featuring in approximately 52.55% of rules. LAGRET was utilised in approximately 47.96%, whilst BETA was accounted for in 38.78% of total rules. A priori, one would expect the predictor variables to feature most prominently since these variables have been empirically identified as those highly correlated with *ex post* returns. This expectation is evidenced in the above findings, however, BETA does account for a substantial portion of the rules used in active portfolio construction.

**Table II**  
**Mean Group Selected by Mean-Return and Sharpe-Ratio criteria for the**  
**Active Portfolios**

	Mean Groups Selected			
	BETA	ERNYLD	LAGRET	SIZE
LONG Portfolio				
Mean-return criterion	1.84 (0.93)	2.70 (0.60)	2.61 (0.49)	1.69 (0.82)
Sharpe-ratio criterion	1.35 (0.76)	2.90 (0.30)	2.32 (0.65)	1.55 (0.89)
SHORT Portfolio				
Mean-return criterion	2.16 (0.59)	1.52 (0.58)	1.41 (0.62)	2.12 (0.64)
Sharpe-ratio criterion	1.95 (0.72)	1.68 (0.55)	1.32 (0.47)	2.03 (0.61)

Table II shows the mean group selected by the performance criteria for the active portfolios<sup>24</sup>, where '1' is assigned to the small group and '3' to the large (standard deviations indicated in parentheses). The LONG portfolios for both performance criteria tend to be characterized by large ERNYLD and large LAGRET stocks. The nature of the portfolios is less clear with respect to the other two variables (given the average means and large standard deviations associated with BETA and SIZE). The Sharpe-ratio LONG portfolios show a more definite tendency towards large ERNYLD stocks, but are less conclusively typified by the large LAGRET stocks, relative to the mean-return LONG portfolios.

The chosen SHORT portfolios are characterised predominantly by small LAGRET stocks, particularly the Sharpe-ratio SHORT portfolios. The tendency towards small ERNYLD stocks is less distinct, but evident nonetheless for both performance criteria. A tentative conclusion of average BETA and SIZE stocks

<sup>24</sup> Tables III and IV in the appendix list the individual rules comprising the mean-return and Sharpe-ratio active portfolios, respectively.

for these SHORT portfolios is the best that one can make based on the figures in Table II, perhaps more convincingly in the case of the mean-return criterion.

Prior South African literature concerning anomaly variables advocates positive earnings yield and momentum effects; the portfolio composition above seems to correspond with these findings. The conclusions in the literature regarding a size effect differed, with some researchers construing the existence of a negative size effect, and others concluding that no such effect was evident on the JSE. The lack of a definitive tendency with respect to SIZE in portfolio construction here appears to be consistent with the latter findings. Interestingly however, SIZE does jointly account for the variable used most frequently in portfolio construction.

### **In-sample results**

Figures 1 and 2 show the market-adjusted in-sample returns to the mean-return LONG and SHORT portfolios, respectively. The return illustrated in a particular year is calculated over an entire five-year in-sample window, with the year on the horizontal axis reflecting the last year of the in-sample window. The monthly equally-weighted returns for the active portfolios are adjusted by subtracting the contemporaneous monthly equally-weighted returns to the EW index. For example, the return figure represented at 1997 in Figure 1 is the average of the monthly returns to the mean-return LONG portfolio, for the period July 1992 to June 1997, less the average of the monthly returns to the EW index, for that same period.

Market-Adjusted In-Sample Returns to the LONG Portfolio under the Mean-Return Criterion

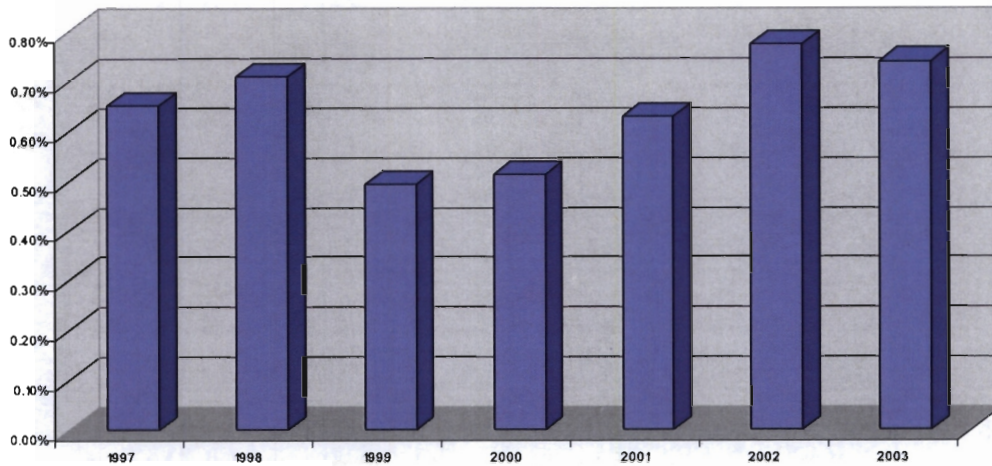


Figure 1

Market-Adjusted In-Sample Returns to the SHORT Portfolio under the Mean-Return Criterion

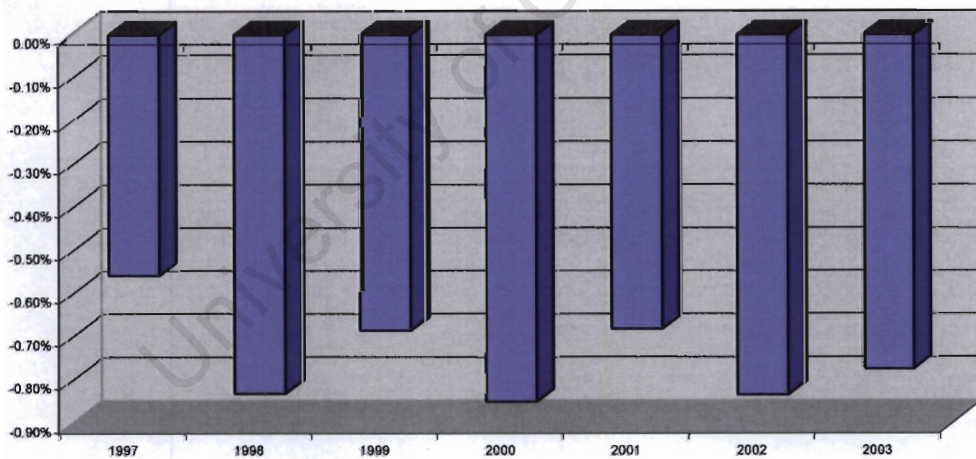
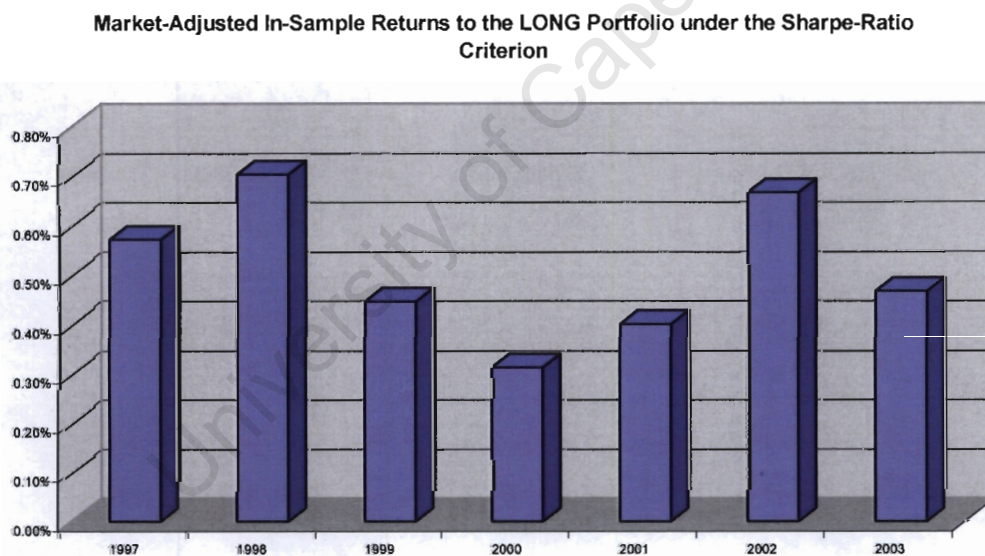


Figure 2

The in-sample performance of the mean-return active portfolios is impressive: the LONG portfolio outperforms the market by an average of 65 basis points (bps) per month in terms of raw returns. This superior performance, as evidenced in Figure 1, is consistent throughout the in-sample period with the lowest mean monthly in-sample returns recorded in 1999 (49 bps above monthly market returns). Similarly impressive performance is apparent on a risk-adjusted basis; the average alpha of the mean-return LONG portfolio is

0.65% per month. The SHORT portfolio (Figure 2) underperforms by an average of 74 bps per month (minimum 56 bps in 1997) and records a mean alpha of -0.74%. These results indicate that the mean-return active portfolios easily outperform the market over the in-sample period, both in terms of raw returns, as well as on a risk-adjusted basis.

Figures 3 and 4 show the market-adjusted in-sample returns to the Sharpe-ratio LONG and SHORT portfolios, respectively. The LONG portfolio earns an average monthly return of 51 bps in excess of the EW index, and has an alpha of 0.54%. The SHORT portfolio earns on average 67 bps less than the EW index, whilst the Jensen's alpha for the SHORT portfolio is -0.69%. As with the mean-return simulation, the Sharpe-ratio active portfolios easily surpass the EW index both in terms of raw and risk-adjusted performance.



**Figure 3**

Market-Adjusted In-Sample Returns to the SHORT Portfolio under the Sharpe-Ratio Criterion

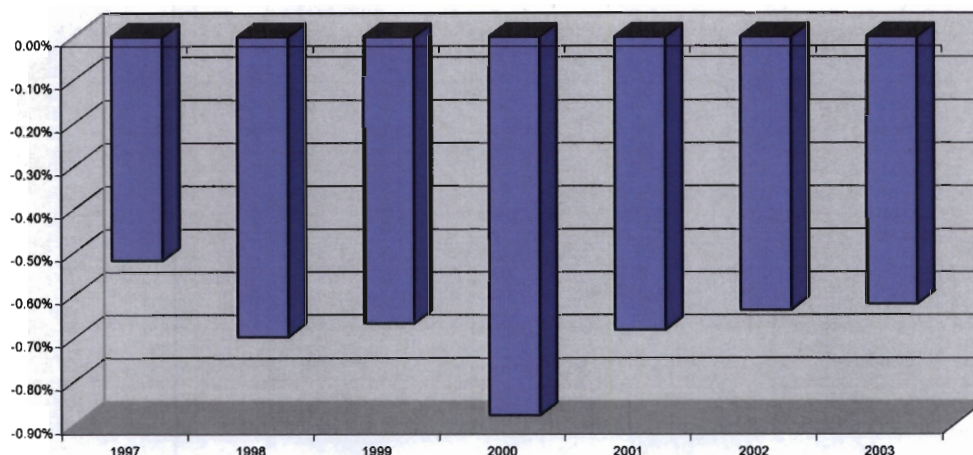


Figure 4

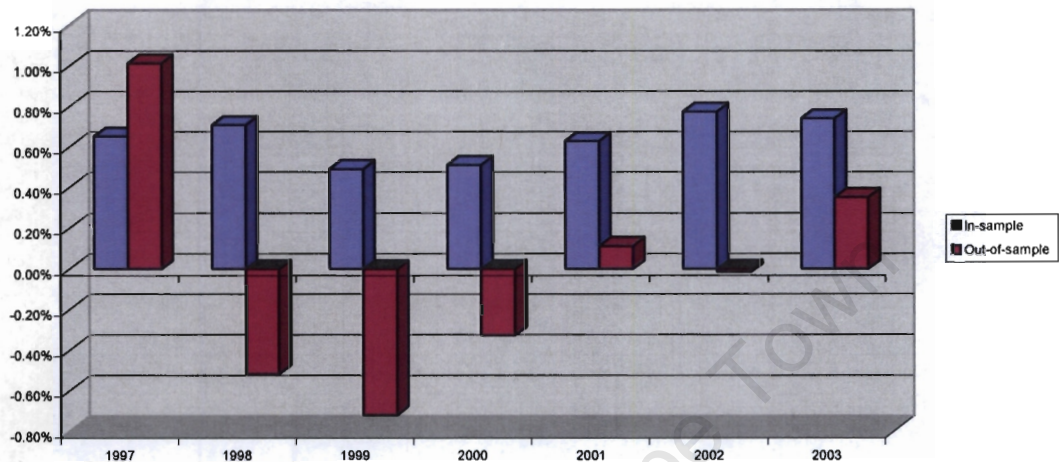
The performance differs marginally between the two simulations, with the mean-return portfolios recording better mean monthly returns and alphas. Despite the lesser in-sample performance figures of the two simulations, the performance of the Sharpe-ratio chosen portfolios is noteworthy nevertheless.

### Out-of-sample results

Figure 5 shows the in-sample and out-of-sample average monthly returns of the mean-return LONG portfolio plotted on the same set of axes. By construction, the in-sample returns should display less variability than the out-of-sample returns (the in-sample returns represent averages calculated over a five-year period whereas the out-of-sample returns represent averages calculated over a one-year period). Indeed the increased out-of-sample variability is graphically evident, but the general out-of-sample performance is in stark contrast with that exhibited in sample. In all but the first period, the returns to the LONG portfolio deteriorate out-of-sample. In fact, the passive index outperforms the active portfolio in 4 of the out-of-sample periods (the market-adjusted return in 2002 is marginally negative at -2 bps). The mean market adjusted out-of-sample return tells its own story; the average out-of-sample monthly return of the EW index exceeds that of the mean-return

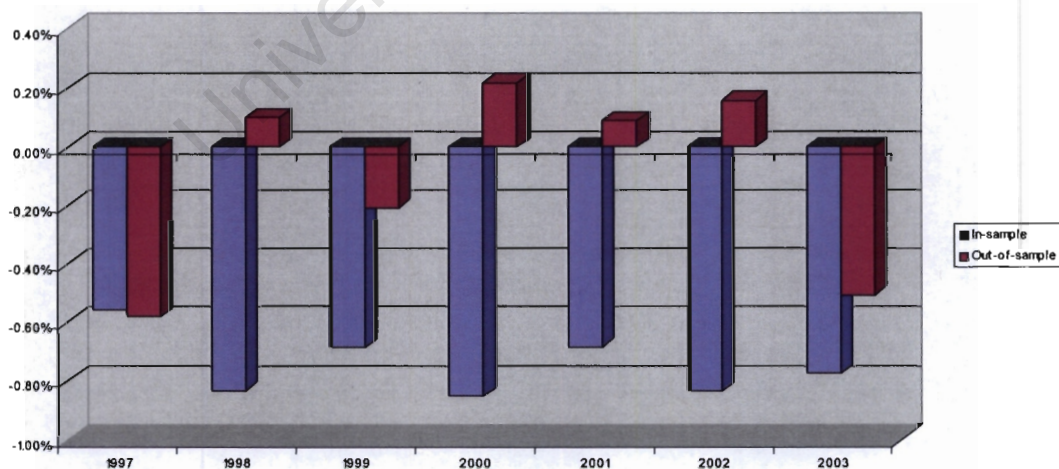
LONG portfolio by 1 basis point. If the first out-of-sample period is excluded, the average market-adjusted return drops to -18 bps, compared with an in-sample mean of 65 bps.

**Market-Adjusted In-Sample and Out-of-Sample Returns to the LONG Portfolio under the Mean-Return Criterion**



**Figure 5**

**Market-Adjusted In-Sample and Out-of-Sample Returns to the SHORT Portfolio under the Mean-Return Criterion**



**Figure 6**

The in-sample and out-of-sample returns to the mean-return SHORT portfolio are illustrated in Figure 6. As with the LONG portfolio, the first out-of-sample

period produces 'better' returns than the associated in-sample period (albeit the differential is not as large in the case of the SHORT portfolio) and increased variability is evident out-of-sample. The SHORT portfolio return exceeds that of the EW index in 4 of the 7 out-of-sample periods, but on average out-of-sample underperformance prevails (the average market-adjusted out-of-sample underperformance is 10 bps per month, falling to 2 bps with the exclusion of the first period, compared to an in-sample mean of -74 bps).

Table V shows the out-of-sample performance of the chosen portfolios in the mean-return simulation. The apparent underperformance of the LONG portfolio in terms of raw returns is substantiated by a negative alpha (-5 bps), and a Sharpe-ratio (0.38) that is less than that of the passive index (0.45). The out-of-sample mean returns of the SHORT portfolio do underperform relative to the passive index, signifying the possibility of out-of-sample predictability. In absolute terms, the risk-adjusted measures corroborate the afore-mentioned suggestion of predictability with a negative alpha (-9 bps), and a Sharpe ratio of 0.36 compared with 0.45 for the passive index. However, not a single one of these results is remotely statistically significant (including the negative market-adjusted mean returns).

**Table V**  
**Out-of-Sample Performance under the Mean-Return Criterion**

	Mean Return (%) (std. dev.)	Monthly Jensen's Alpha	Sharpe Ratio
EW	0.27 (5.70)	-	0.45
LONG	0.25 (5.42)	-0.05	0.38
SHORT	0.16 (6.28)	-0.09	0.36
COMBINED	0.09 (3.38)	0.04	-

\* indicates statistical significance at the 10% level

\*\* indicates statistical significance at the 5% level

The comparative returns of the Sharpe-ratio LONG portfolio are illustrated in Figure 7. The out-of-sample performance is categorically inferior when compared with the allied in-sample periods. Four of the 7 out-of-sample periods are characterised by the chosen portfolio achieving returns less than those of the EW index. The average market-adjusted monthly return of -7 bps is lower than that obtained in the previous simulation. The risk-adjusted measures in Table VI correspond with the raw returns; the alpha is -13 bps and the Sharpe ratio is 0.37 (compared with a Sharpe ratio of 0.45 for the EW index).

Market-Adjusted In-Sample and Out-of-Sample Returns to the LONG Portfolio under the Sharpe-Ratio Criterion

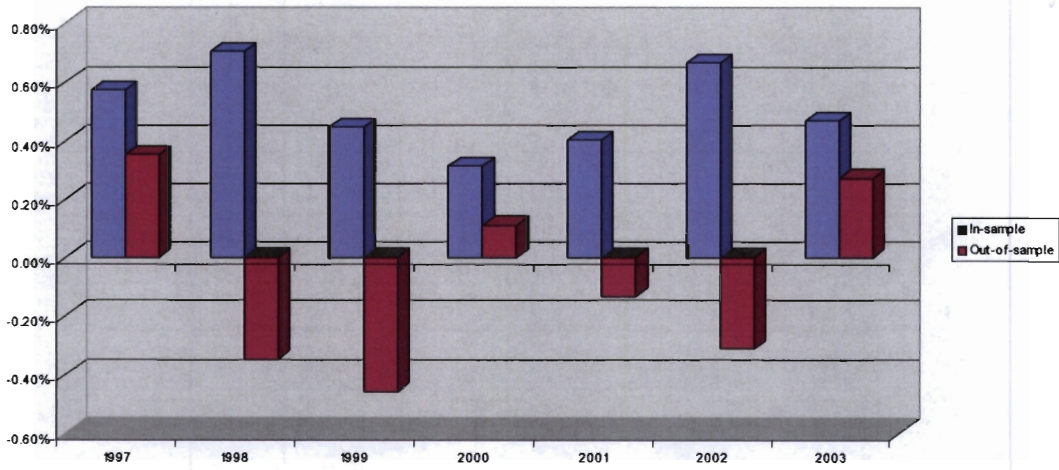


Figure 7

Market-Adjusted In-Sample and Out-of-Sample Returns to the SHORT Portfolio under the Sharpe-Ratio Criterion

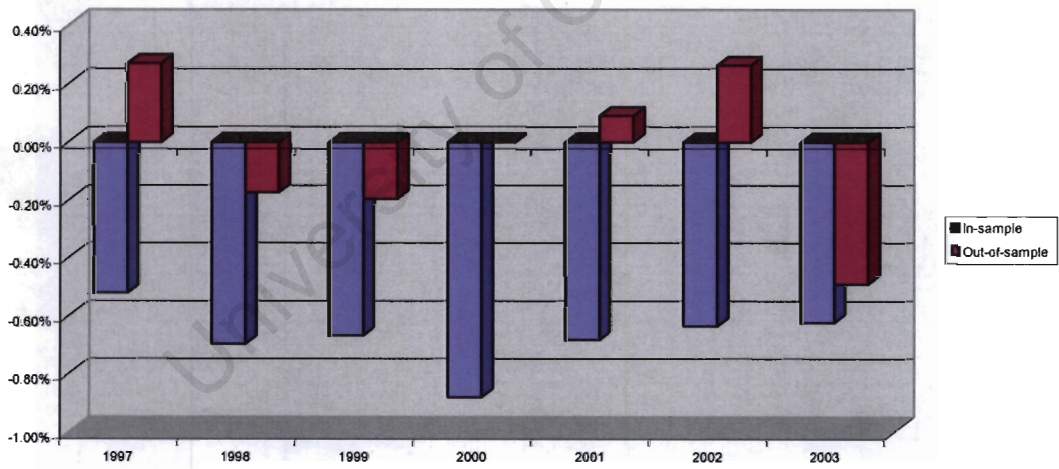


Figure 8

**Table VI**  
**Out-of-Sample Performance under the Sharpe-Ratio Criterion**

	Mean Monthly Return (%) (std. dev.)	Jensen's Alpha	Sharpe Ratio
EW	0.27 (5.70)	-	0.45
LONG	0.19 (5.31)	-0.13	0.37
SHORT	0.23 (6.27)	-0.10	0.40
COMBINED	-0.04 (3.34)	-0.03	-

\* indicates statistical significance at the 10% level

\*\* indicates statistical significance at the 5% level

As in the mean-return simulation, the Sharpe-ratio SHORT portfolio performs better than its counterpart. The results are, in absolute terms at least, indicative of predictability; the market-adjusted monthly mean return is negative (-3 bps), alpha is negative (-10 bps) and the Sharpe ratio of the index (0.45) exceeds that of the portfolio (0.40) (refer Figure 8 and Table VI). However, these figures are decisively statistically insignificant.

The in-sample and out-of-sample mean monthly returns for the mean-return COMBINED portfolio are illustrated in Figure 9. Following from the strong in-sample performance of the LONG and SHORT portfolios, the chosen COMBINED portfolio in this simulation records a positive mean monthly in-sample return of 139 bps, with a minimum of 118 bps in 1999. As with the mean-return LONG and SHORT portfolios, the first period is characterised by superior returns in the out-of-sample period. However, the subsequent performance is dismal; four of the seven periods produce negative returns. The mean monthly out-of-sample return and alpha of the COMBINED portfolio can be found in Table V; the mean return of 9 bps (this drops to -16 bps if the first period is excluded) and the mean alpha of 4 bps (reduces to -19 bps if

the first period is excluded) further demonstrate the reversal in performance experienced by the active portfolios. Whilst the overall mean return and alpha figures are positive (and thus indicative of predictability), they are not statistically significant.

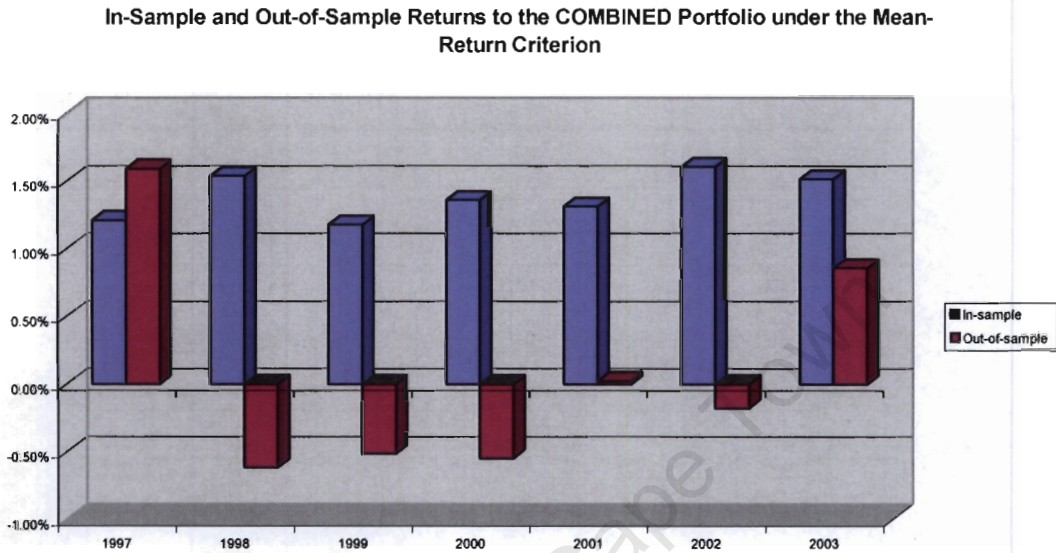


Figure 9

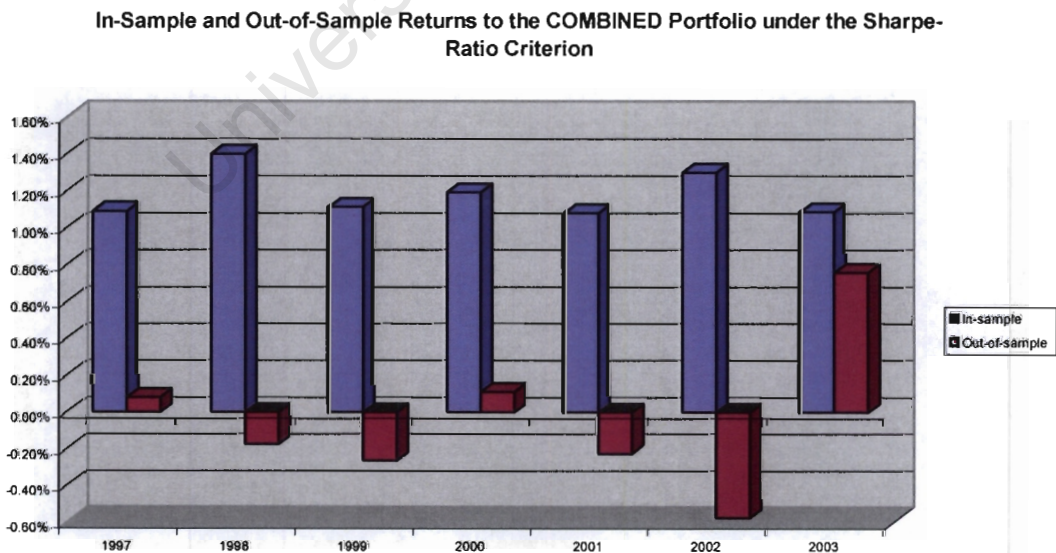


Figure 10

Figure 10 depicts the in-sample and out-of-sample performance of the COMBINED portfolio in the Sharpe-ratio simulation. The performance appears inferior when compared with that of the mean-return COMBINED portfolio (which is expected given the LONG and SHORT portfolios both fared worse in the Sharpe-ratio simulation). The portfolio records negative mean monthly returns in four of the out-of-sample periods, and two of the three positive mean returns are minor (8 and 11 bps in 1997 and 2000 respectively). This is compared with the strong in-sample performance, averaging 118 bps per month with a minimum of 108 bps in 2001. Table VI shows the mean monthly return for the entire out-of-sample period was -4 bps, and the risk-adjusted measure of alpha was -3 bps for the same period.

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## CONCLUSION

The in-sample performance of the active portfolios is striking: all of the chosen portfolios exhibit evidence of predictability. This is true for both simulations. The mean-return simulation produces superior performing in-sample portfolios, but the in-sample performance of the Sharpe-ratio portfolios is impressive nonetheless. The strong performance of the active portfolios corresponds with the empirical studies that have identified these CAPM anomaly variables. But, as mentioned at the outset, these impressive in-sample results lead to the obvious question – can these results be used to ‘beat’ the market in the real world? The performance of actual investors seems to suggest that the answer is ‘no’, but the aim of this study is to answer this question in a more systematic manner. The out-of-sample results seem to echo the real-world evidence.

The out-of-sample performance is remarkably different from that achieved in sample. The SHORT portfolio in both simulations, as well as the COMBINED portfolio in the mean-return simulation, display results which at face value are consistent with the conclusion of predictability. However, not a single one of these results holds when scrutinized from a statistical significance perspective. The results of the remaining portfolios do not even support the notion of predictability at the face value level: each of these portfolios underperforms relative to the passive index in the out-of-sample analysis. The conclusion would seem to be that real-time predictability is not evident.

This conclusion should also be examined in the context of some of the key assumptions of this study. The first of these is the selection of variables that constitute the universe of options available to the hypothetical investor. Three of the four variables have been empirically determined to be highly correlated with *ex post* returns. Whilst the selection of beta as the fourth variable somewhat mitigates the resulting bias in favour of predictability, it does not eradicate said bias.

The second key assumption is zero trading costs. Cooper *et al.* (2005) find some evidence of predictability using trading cost estimates based on the

findings of Keim and Madhavan (1997). However, when they adopted the assumption of 1.00% one-way trading costs (as part of their robustness checks), this completely eliminates any evidence of real-time predictability (p.21). In this study, there is no statistically significant evidence of real-time predictability to begin with, so the assumption of some degree of trading costs, whatever the magnitude, would only reinforce that conclusion. Had trading costs been assumed here, presumably the magnitude of the applicable trading costs would exceed those assumed by Cooper *et al.* (2005) since the South African market is less efficient than its US counterpart.

The conclusion of 'no real-time predictability' is thus strengthened when considered in the context of the simulated rule universe employed and the applicability of trading costs. A major shortcoming of this study is the exclusion of delisted stocks. As the South African market matures and the data available to researchers increases, the application of a recursive out-of-sample methodology such as that of Cooper *et al.* (2005) to a dataset including delisted stocks may prove an interesting avenue for future research.

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## APPENDICES

Table I

### List of Stocks Considered in the Paper

The detailed list of stocks considered in this paper are listed alphabetically below:

Amalgamated Beverage Industries Ltd  
Acuity Group Holdings Ltd  
Adcorp Holdings Ltd  
Admiral Leisure World Ltd  
Adonis Knitwear Holdings Ltd  
ADvTECH Ltd  
AECI Ltd  
African and Overseas Enterprises Ltd  
Afrgri Ltd  
African Oxygen Ltd  
AG Industries Ltd  
Afrox Healthcare Ltd  
Alex White Holdings Ltd  
Alliance Pharmaceuticals Ltd  
Allied Technologies Ltd  
Allied Electronics Corporation Ltd  
Amalgamated Appliance Holdings Ltd  
African Media Entertainment  
Anbeeco Investment Holdings Ltd  
Argent Industrial Ltd  
Aspen Pharmacare Holdings Ltd  
Astral Foods Ltd  
Astrapak Ltd  
Aveng Ltd  
AVI Ltd  
Awethu Breweries Ltd  
Barloworld Ltd  
Basil Read Holdings Ltd  
Bearing Man Ltd  
Bell Equipment Ltd  
Bicc Cafca Ltd

The Bidvest Group Ltd  
Bowler Metcalf Ltd  
Brandcorp Holdings Ltd  
Bridgestone Firestone Maxiprest Ltd  
Buildmax Ltd  
Burlington Industries Ltd  
The House of Busby Ltd  
Cargo Carriers Ltd  
Cashbuild Ltd  
Caxton and CTP Publishers and Printers Ltd  
The Cementation Company (Africa) Ltd  
Ceramic Industries Ltd  
City Lodge Hotels Ltd  
Combined Motor Holdings Ltd  
Comair Ltd  
Command Holdings Ltd  
Conafex Holdings Societe Anonyme  
Concor Ltd  
Connection Group Holdings Ltd  
Control Instruments Group Ltd  
Canadian Overseas Packaging Industries Ltd  
Crookes Brothers Ltd  
Cullinan Holdings Ltd  
Distribution and Warehousing Network Ltd  
Delta Electrical Industries Ltd  
Digicore Holdings Ltd  
Distell Group Ltd  
The Don Group Ltd  
Dorbyl Ltd  
Edgars Consolidated Stores Ltd  
ELB Group Ltd  
Ellerine Holdings Ltd  
EnviroServ Holdings Ltd  
Excellerate Holdings Ltd  
Famous Brands Ltd  
Forim Holdings Ltd

Foschini Ltd  
Glodina Holdings Ltd  
Global Village Holdings Ltd  
Gold Reef Casino Resorts Ltd  
Grindrod Ltd  
Grintek Ltd  
Group Five Ltd  
Heritage Collection Holdings Ltd  
Highveld Steel and Vanadium Corporation Ltd  
Howden Africa Holdings Ltd  
Hudaco Industries Ltd  
Iliad Africa Ltd  
Illovo Sugar Ltd  
Imperial Holdings Ltd  
Inmins Ltd  
Intertrading Ltd  
Invicta Holdings Ltd  
Iskor Ltd  
IST Group Ltd  
Italtile Ltd  
Jasco Electronics Holdings Ltd  
JD Group Ltd  
Johnnic Communications Ltd  
Johnnic Holdings Ltd  
Kagiso Media Ltd  
King Consolidated Holdings Ltd  
Kolossus Holdings Ltd  
KWV Investments Ltd  
LA Group Ltd  
Murray & Roberts Holdings Ltd  
Masonite (Africa) Ltd  
Massmart Holdings Ltd  
Medi-Clinic Corporation Ltd  
Metair Investments Ltd  
Metro Cash and Carry Ltd  
Mobile Industries Ltd

MoneyWeb Holdings Ltd  
Monteagle Holdings Societe Anonyme  
Moribo Leisure Ltd  
Mr Price Group Ltd  
MTN Group Ltd  
New Africa Investments Ltd  
Nampak Ltd  
Namibean Sea Products Ltd  
Naspers Ltd  
Network Healthcare Holdings Ltd  
Nictus Ltd  
New Clicks Holdings Ltd  
Nu-World Holdings Ltd  
Oceana Group Ltd  
Omnia Holdings Ltd  
OneLogix Group Ltd  
Pals Holdings Ltd  
Pasdec Resources SA Ltd  
Pick 'n Pay Stores Ltd  
Pick 'n Pay Holdings Ltd  
Pretoria Portland Cement Company  
Primedia Ltd  
Primeserv Group Ltd  
Putco Ltd  
Quyn Holdings Ltd  
Rainbow Chicken Ltd  
Rebserve Holdings Ltd  
Relyant Retail Ltd  
Reunert Ltd  
Rex Trueform Clothing Company Ltd  
Richemont Securities AG  
SABMiller plc  
SAIL Group Ltd  
Sappi Ltd  
Sasani Ltd  
Sear del Investment Corporation Ltd

Sekunjalo Investments Ltd  
Set Point Technology Holdings Ltd  
Shoprite Holdings Ltd  
Sun International (SA) Ltd  
Sovereign Food Investments Ltd  
Spanjaard Ltd  
Spur Coporation Ltd  
Steinhoff International Holdings Ltd  
Super Group Ltd  
Terexko Ltd  
Tiger Brands Ltd  
Tiger Wheels Ltd  
The Tongaat-Hulett Group Ltd  
Tourism Investment Corporation Ltd  
Tradehold Ltd  
Trencor Ltd  
Transpaco Ltd  
Truworhs International Ltd  
United Service Technologies Ltd  
Unitrans Ltd  
Vaalauto Ltd  
Vaaltrucar Ltd  
Value Group Ltd  
Venter Leisure and Commercial Trailers Ltd  
Wilson Bayly Holmes - Ovcon Ltd  
WB Holdings Ltd  
Wesco Investments Ltd  
Winhold Ltd  
Woolworths Holdings Ltd  
Wooltru Ltd  
The York Timber Organisation Ltd

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**Table III**

**Trading Rule Composition of LONG and SHORT Portfolios Selected by the Mean-Return Criterion**

The active portfolios for each year contain 7 trading rules each, with each row indicating the group(s) associated with that particular trading rule. One-way trading rules have only one entry per row, while two-way trading rules have two entries per row. The one-way trading rules select all stocks in one group for a particular variable; e.g. the first rule comprising the LONG portfolio in 1997: buy all stocks that occur in the small SIZE group. Two-way trading rules select all stocks that occur simultaneously in two groups (excluding those rules that select two groups from any one variable); e.g. the second rule comprising the LONG portfolio in 1997: buy all stocks that occur in the large BETA group and the large ERNYLD group simultaneously. The year indicates the last year of the in-sample window.

	LONG		SHORT	
1997	SIZE small	-	SIZE large	-
	BETA large	ERNYLD large	BETA small	SIZE large
	BETA large	SIZE small	BETA middle	LAGRET small
	BETA large	SIZE middle	BETA middle	SIZE middle
	ERNYLD small	SIZE small	ERNYLD small	SIZE middle
	ERNYLD large	LAGRET large	ERNYLD middle	LAGRET middle
	LAGRET large	SIZE middle	LAGRET small	SIZE large
1998	SIZE small	-	SIZE large	-
	BETA small	ERNYLD large	BETA middle	ERNYLD small
	BETA small	SIZE small	BETA large	ERNYLD middle
	BETA large	SIZE middle	BETA large	SIZE large
	ERNYLD large	LAGRET large	ERNYLD small	SIZE large
	ERNYLD large	SIZE small	ERNYLD middle	LAGRET middle
	LAGRET large	SIZE middle	LAGRET small	SIZE large
1999	SIZE small	-	BETA middle	ERNYLD small
	BETA small	ERNYLD large	BETA middle	LAGRET large
	BETA small	SIZE small	BETA middle	SIZE middle
	BETA large	SIZE middle	ERNYLD small	LAGRET small
	ERNYLD large	LAGRET large	ERNYLD small	SIZE middle
	ERNYLD large	SIZE small	ERNYLD middle	LAGRET middle
	LAGRET middle	SIZE small	LAGRET middle	SIZE middle

2000	BETA small	ERNYLD large	BETA middle	ERNYLD small
	BETA small	LAGRET large	BETA middle	LAGRET small
	ERNYLD small	LAGRET middle	BETA middle	LAGRET large
	ERNYLD large	LAGRET large	BETA middle	SIZE middle
	ERNYLD large	SIZE small	ERNYLD small	LAGRET small
	LAGRET middle	SIZE small	LAGRET small	SIZE middle
	LAGRET large	SIZE middle	LAGRET middle	SIZE middle
2001	BETA small	ERNYLD large	BETA middle	ERNYLD small
	BETA small	LAGRET large	BETA middle	SIZE middle
	BETA large	LAGRET large	ERNYLD small	SIZE middle
	ERNYLD middle	SIZE large	ERNYLD middle	LAGRET small
	ERNYLD large	LAGRET middle	ERNYLD middle	SIZE small
	ERNYLD large	LAGRET large	LAGRET small	SIZE small
	LAGRET middle	SIZE small	LAGRET middle	SIZE middle
2002	BETA small	LAGRET middle	LAGRET small	-
	BETA small	SIZE large	BETA large	LAGRET small
	BETA middle	ERNYLD large	BETA large	SIZE middle
	ERNYLD middle	SIZE large	ERNYLD middle	LAGRET small
	ERNYLD large	LAGRET middle	ERNYLD middle	SIZE small
	ERNYLD large	SIZE large	LAGRET small	SIZE middle
	LAGRET middle	SIZE small	BETA small	LAGRET small
2003	BETA middle	ERNYLD large	BETA large	LAGRET small
	BETA large	LAGRET large	ERNYLD small	LAGRET middle
	ERNYLD middle	LAGRET large	ERNYLD small	SIZE middle
	ERNYLD middle	SIZE large	ERNYLD middle	LAGRET small
	ERNYLD large	LAGRET middle	ERNYLD middle	SIZE small
	ERNYLD large	LAGRET large	ERNYLD large	LAGRET small
	ERNYLD large	SIZE large	LAGRET small	SIZE middle

Table IV

**Trading Rule Composition of LONG and SHORT Portfolios Selected by the Sharpe-Ratio Criterion**

The active portfolios for each year contain 7 trading rules each, with each row indicating the group(s) associated with that particular trading rule. One-way trading rules have only one entry per row, while two-way trading rules have two entries per row. The one-way trading rules select all stocks in one group for a particular variable; e.g. the first rule comprising the LONG portfolio in 1997: buy all stocks that occur in the large ERNYLD group. Two-way trading rules select all stocks that occur simultaneously in two groups (excluding those rules that select two groups from any one variable); e.g. the third rule comprising the LONG portfolio in 1997: buy all stocks that occur in the small BETA group and the large ERNYLD group simultaneously. The year indicates the last year of the in-sample window.

	LONG		SHORT	
1997	ERNYLD large	-	BETA small	LAGRET middle
	SIZE small	-	BETA small	SIZE middle
	BETA small	ERNYLD large	BETA small	SIZE large
	BETA small	LAGRET small	BETA middle	LAGRET small
	BETA small	SIZE small	ERNYLD small	SIZE middle
	BETA large	ERNYLD large	LAGRET small	SIZE large
	ERNYLD large	SIZE small	BETA large	SIZE large
1998	ERNYLD large	-	BETA middle	LAGRET small
	SIZE small	-	BETA middle	SIZE large
	BETA small	ERNYLD large	BETA large	ERNYLD middle
	BETA small	SIZE small	BETA large	LAGRET small
	ERNYLD large	LAGRET small	ERNYLD middle	LAGRET middle
	ERNYLD large	LAGRET large	ERNYLD middle	SIZE large
	ERNYLD large	SIZE small	LAGRET small	SIZE large
1999	ERNYLD large	-	BETA small	ERNYLD middle
	SIZE small	-	BETA small	SIZE middle
	BETA small	ERNYLD large	BETA middle	ERNYLD small
	BETA small	SIZE small	BETA middle	SIZE middle
	ERNYLD large	LAGRET large	ERNYLD middle	LAGRET middle
	ERNYLD large	SIZE small	ERNYLD middle	SIZE middle
	LAGRET middle	SIZE small	LAGRET middle	SIZE middle

2000	ERNYLD large	-	BETA small	ERNYLD middle
	BETA small	ERNYLD large	BETA middle	ERNYLD small
	BETA small	SIZE small	BETA middle	LAGRET small
	BETA large	LAGRET large	BETA middle	SIZE middle
	ERNYLD large	LAGRET large	ERNYLD small	LAGRET small
	ERNYLD large	SIZE small	LAGRET small	SIZE middle
	LAGRET middle	SIZE small	LAGRET middle	SIZE middle
2001	ERNYLD large	-	BETA middle	ERNYLD small
	BETA small	ERNYLD large	BETA middle	SIZE middle
	BETA small	LAGRET middle	ERNYLD small	SIZE middle
	BETA small	SIZE large	ERNYLD middle	LAGRET small
	ERNYLD large	LAGRET middle	ERNYLD middle	SIZE small
	ERNYLD large	LAGRET large	LAGRET small	SIZE small
	LAGRET middle	SIZE small	LAGRET middle	SIZE middle
2002	BETA small	LAGRET middle	LAGRET small	-
	BETA small	SIZE large	BETA large	SIZE middle
	ERNYLD middle	SIZE large	ERNYLD middle	LAGRET small
	ERNYLD large	LAGRET middle	ERNYLD middle	SIZE small
	ERNYLD large	SIZE small	ERNYLD middle	SIZE middle
	ERNYLD large	SIZE large	LAGRET small	SIZE middle
	LAGRET middle	SIZE small	LAGRET middle	SIZE middle
2003	ERNYLD large	-	BETA large	LAGRET small
	BETA large	LAGRET large	ERNYLD small	LAGRET middle
	ERNYLD middle	LAGRET large	ERNYLD small	SIZE middle
	ERNYLD middle	SIZE large	ERNYLD middle	SIZE small
	ERNYLD large	LAGRET middle	ERNYLD large	LAGRET small
	ERNYLD large	LAGRET large	LAGRET small	SIZE small
	ERNYLD large	SIZE large	LAGRET small	SIZE middle