University of Cape Town

FACULTY OF COMMERCE

THE IMPACT OF FIRM-SPECIFIC FACTORS ON THE CROSS-SECTIONAL VARIATION IN JOHANNESBURG SECURITY EXCHANGE LISTED EQUITY RETURNS

BY

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Thesis prepared under the supervision of Professor Paul van Rensburg and submitted in full fulfilment of the requirements for the Degree of Doctor of Philosophy in Finance in the Department of Finance and Tax of the Faculty of Commerce at the University of Cape Town.

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Declaration

I, J.D. van Heerden, hereby declare that the work on which this thesis is based is entirely my own work, except for the assistance which is acknowledged and the quotations specifically referenced in the text and bibliography. This thesis is not being submitted for degree purposes at any other university.

JD van Heerden

February 2014

Dedication

Dedicated to my wife, Lydia, and my two children, Mikal and Giann. Thank you so much for your continuous support and the sacrifices you made so that I could work on this thesis.

Soli Deo gloria

Acknowledgement

I would like to acknowledge and thank my supervisor, Professor Paul van Rensburg, for his unconditional guidance and assistance during the entire time I worked on this thesis. His timely comments and suggestions were invaluable. It was a great privilege to be supervised by him. I cannot describe the significant learning experience during this time.

My heartfelt thanks to Professor Willie Conradie and Professor Tertius de Wet of the Department of Statistics and Actuarial Sciences at the University of Stellenbosch for their support and encouragement during this time.

All of the mistakes are mine.

Abstract

The aim of this study is to examine the impact of technical and fundamental (referred to as firm-specific) factors on the cross-sectional variation in equity returns on the Johannesburg Securities Exchange (JSE). Three approaches to address this objective were identified through an extensive literature study covering more than half a century's research, namely a cross-sectional regression approach, a factor portfolio approach and an extreme performer approach. All three approaches are applied in this study, allowing for comparison and robustness- tests to be performed on the JSE for the first time.

In addition to factors identified through the literature review, factors that make economic sense from a South African point of view have also been included in the dataset, resulting in a total of fifty firm-specific factors to be examined. A fresh data set was created by collecting monthly data through numerous data sources on all shares listed on the JSE for the period January 1994 through May 2011, for these factors. The seventeen and a half year period is the longest period used to date (to the author's knowledge) for the kind of research conducted in this thesis. Furthermore, the data has been prepared to correct for potential statistical biases that may affect the results, including data snooping, infrequent trading, survivorship bias, look-ahead bias and outliers. This lengthy period further allows for the formation of two independent subsamples, each covering a full investment cycle, enabling in- and out of- sample empirical research and testing to be conducted on the JSE for the first time.

A number of sub-questions were formulated to further contribute to the existing body of knowledge. Specifically, the effect that time, holding (or payoff) period and liquidity may have on the identity and explanatory power of factors on the cross-section of equity returns is examined. Furthermore, identified factors are used in portfolio construction to examine whether abnormal returns can be generated, both on a raw and risk-adjusted basis.

The results of the three approaches are strongly correlated. It suggests that a strong value effect is present and robust on the JSE, and that this effect is best captured by cash-flow to price (CFTP). Although the presence of a value effect is in line with most prior research results, the firm-specific factor found to best capture this effect is contrary to most prior literature, which suggests that it is best captured by either the book-value to market (BVTMLOG) or earnings yield (EY) factor instead of CFTP.

The size effect found to be present in most prior literature is shown to be sensitive to time, liquidity and payoff period in this thesis. However, if a payoff period of at least 3-months is considered, the size effect seems to become significant across all time periods and remains significant if at least the largest 68 shares in terms of market capitalisation are included. Contrary to most literature it is found that the size effect is best captured by the natural log of share price (LNP) rather than market cap.

A momentum effect, suggested but not confirmed by most prior literature, is found to be present on the JSE mainly over a 1-month payoff period, and captured best by the prior 6 month (MOM6) or prior 12 month (MOM12) return. As soon as the payoff period is increased, the momentum effect becomes sensitive to time and liquidity.

Although a price reversal effect is suggested by a number of studies, it is found to be highly sensitive to time, liquidity and payoff period on the JSE. It appears that a price reversal effect may exist over both a short- term (represented by prior 1-month returns (MOM1)) and longer term (prior 60-month (MOM60) returns), but this observation is dependent on the subsample, level of sample liquidity and payoff period used when conducting the analysis.

Multifactor analyses show that when the factors found to be significant in explaining the cross-section of returns are combined, value and momentum factors are collectively significant in explaining the cross-section of returns across all time periods and level of liquidity. Considering only the largest shares in terms of market cap, a third factor, MOM1, can be added to create a three factor model that is robust across all time periods.

Compared to the cross-sectional regression and single-factor portfolio construction approaches, the extreme performer approach is relatively unexplored within a South African context. The extreme performer methodology followed in this thesis is, globally speaking, the first of its kind. Specifically, a combination of cross-sectional regression and logistic regression (logit) methods are used. Based on the cross-sectional regression, factors that differ significantly between winner and loser shares are identified, where a winner refers to a share that increased by at least 6% (100%) and a loser to a share that decreased by at least 5% (50%) over a 1-month (12-month) holding period. Using the results of the cross-sectional regressions, a logistic regression approach is applied to formulate ‘filter rules’ which may be used to filter potential future extreme performers. The results suggest that three factor categories, namely value, size and momentum, can collectively be used to distinguish between winners and losers over a 1-month and 12-month payoff period, indicating that these are insensitive to the payoff period within the logistic regression framework. Furthermore the factors best capturing the specific effects are similar to those identified in the other two approaches, namely CFTP, LNP and MOM6 (for a 12-month payoff period) and MOM12 (for a 1-month payoff period). In addition to these three factor categories, volatility (captured by CAPM Beta and 12-month volatility or RETVAR12), growth (captured by the change in 24-month dividend per share to price or C24MDPSP) and short- term price reversal factors (MOM1) contribute further in discriminating between potential winner and loser shares over a 1-month payoff period.

To determine whether the factors included in the logit models are robust, the logit models are applied using an independent sample to filter potential winner and loser shares and using these shares to construct potential winner and loser portfolios. The results suggest that such a logit filtering process can be applied to create winner (loser) portfolios that offer significant outperformance (underperformance) over a 1-month and 12-month payoff period.

The excess returns created by any of the portfolios based on the single factor approach or extreme performer approach cannot be explained by either the CAPM or Van Rensburg (2002) 2-factor APT models. The results contradict capital market theory, and instead suggest that anomalies exist and can be exploited profitably on the JSE. Furthermore, due to the finding that some technical and fundamental factors can be used to create profitable portfolios but are sensitive to at least one of the effects of time, liquidity or payoff period, it seems that a single market model would not be efficient to capture the cross-section of returns on the JSE. Hence, the findings of this thesis lead to the rejection of the efficient market and CAPM joint hypothesis, at least within the South African context.

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INTRODUCTION

1.1 Background

According to the assumptions underlying Modern Portfolio Theory (MPT), pioneered by Markowitz (1952), investors act rationally, are risk averse, have homogeneous expectations regarding the mean, variance and covariance of asset returns and base their investment decisions on maximising their expected utility. These assumptions underpin what is known as the Efficient Market Hypothesis (EMH), which states that investors should not be able to outperform their peers or the market in a consistent fashion as security prices already reflect historic price, volume, firm- specific and even insider information.

Behavioural finance on the other hand, takes into consideration how various psychological qualities affect the actions that investors, analysts and portfolio managers take, individually as well as in groups. These psychological qualities could lead to irrational behaviour in contrast to that assumed by MPT and cause markets to be less efficient than that proposed by the EMH.

Over half a century's literature concerning tests and results of the EMH and behavioural aspects is readily available to investors and researchers. From the literature review (Chapter 3) it is seen that the debate surrounding capital market efficiency is an on-going one and a definitive conclusion is yet to be made. The different approaches followed in conducting the tests have resulted in the ramification of the overarching debate surrounding capital market efficiency into a number of different topics. An in-depth study of this literature made it possible to not only formulate a comprehensive view of the EMH debate, but also identify areas in which additional research can make a valuable contribution to this field of study.

This thesis aims to determine the impact of firm-specific factors on the cross-sectional variation in Johannesburg Securities Exchange (JSE) listed equity returns. Three approaches are followed in reaching this goal, namely a cross-sectional regression approach, a factor-portfolio approach and an extreme performer approach. The different areas identified to make a valuable contribution to this field of study are addressed for each of the respective approaches followed.

1.2 Overview

Chapter 2 provides an overview of the theory relevant to this thesis. It begins with the concepts concerning market efficiency, namely the Efficient Market Hypothesis, capital allocation and asset pricing under conditions of market efficiency. Behavioural finance is discussed as well, focusing on the main behavioural theories and biases.

A review of relevant literature is provided in Chapter 3. An overview of tests concerning the Efficient Market Hypothesis is provided, with the focus on identifying potential technical and fundamental factors that may help explain the cross- sectional variation in equity returns, both from an international as well as a South African point of view. Additionally, an overview of how some of these factors have been used in the investment decision- making and portfolio formation process is provided.

Chapter 4 provides a detailed discussion of the problem statement and research objectives, the data period selected and the process followed to select and categorise the variables to be employed. An overview of possible statistical biases and the approach followed to control for these biases are also provided in Chapter 4. Descriptive statistics of the final list of variables are provided, and lastly an overview of the methodology to be followed within each respective chapter is discussed.

A one-factor cross-sectional regression approach is applied in Chapter 5 to determine which factors are significant in explaining the cross-sectional variation in returns. The approach is applied over three sample periods for different market cap samples over a number of payoff periods to examine the impact that time, liquidity and payoff period may have on the results.

The second approach, namely the single-factor portfolio approach, is applied in Chapter 6. Through this approach portfolios are constructed based on the respective factors under review to determine which factors could offer a portfolio construction approach that may present significant abnormal returns. The process is conducted over three sample periods for two market-cap samples (an all-share sample and a large-cap sample) and two payoff periods (1-month and 3-months) to once again examine the effect that time, liquidity and payoff period may have on the results.

In Chapter 7 the factors identified in Chapter 5 and Chapter 6 are used in multifactor analyses to examine the impact of combined factors on the cross-section of returns. Multifactor models are developed for each sample period for each of the two market-cap samples.

The third approach, the extreme performer approach, is applied in Chapter 8 and Chapter 9. Two samples are created to allow for in-sample analysis and out of sample testing. A combination of cross-sectional regression and logistic regression is used to determine which factors discriminate between extreme performing shares and the rest, and to subsequently formulate filter rules to filter potential extreme performer shares for portfolio construction purposes. The process is conducted over a 1-month payoff period (Chapter 8) as well as a 12-month payoff period (Chapter 9).

The consolidated findings of all tests conducted in this thesis are summarised in Chapter 10.

1.3 Contributions

A number of possible factors explaining the cross-sectional variation of share returns have been proposed throughout the literature (refer to Chapter 3). However, it is seen from the literature that the latest research (especially during the last decade) has focused more on investigating aspects of previously identified factors (e.g. the correct order of importance, the existence thereof in non-US markets, the effect on the explanatory power when correcting the database for statistical biases etc.) rather than investigating whether alternative factors may present stronger explanatory power of cross-sectional variation in returns. As a great number of South African and global events have occurred since 1994 (e.g. the South African political transformation in 1994, the 1998 Asian crisis, the 2000/2001 technological industry bubble, the sub-prime crisis of 2007/2008 and the current European debt-crisis) that could potentially have a significant impact on the mechanics of financial markets, it is essential to investigate the robustness of these previously identified factors and at the same time examine the impact that potential alternative factors may have on the cross-section of equity returns.

The first contribution to be made by this thesis is the use of a database that is bias-free, that has not been used before, that provides information gathered over an extensive period, and that is comprehensive in terms of variables used. The database to be employed covers a 17.5 year period, the longest period to be used for this type of research on the South African market to date. As this period allows for the formation of two independent subsamples, each covering a full investment cycle as well as extreme events, it is for the first time possible to empirically examine the technical and fundamental factors that explain the cross-sectional variation in returns and independently test for the robustness of the results.

To the author’s knowledge no study has conducted related research by employing and comparing different approaches. In this thesis three approaches are employed: a cross-sectional regression approach, a factor-portfolio construction approach and an extreme performer approach. Results are compared across the three approaches to determine whether the findings of this thesis and those of previous studies may be a function of the specific approach followed.

As the data set includes as many variables identified through prior research as possible as well as new variables that make economic sense from a South African point of view, it will not only allow for robustness tests of previously documented factors but also for the identification of possible alternative factors that may be superior candidates for explaining the cross-section of returns. The latter has not received much attention, especially during the last decade.

To date all related South African research has documented findings based on a specific, relatively short period used to perform the analysis. Therefore the question of whether there is a change in the identity and explanatory power of the factors when different periods are employed has not yet been answered. The comprehensive data set to be employed in this thesis allows for the tests to be performed and results to be compared over three periods, namely January 1994 through December 2002, January 2003 through May 2011 as well as over the entire sample of 17.5 years.

Related South African studies have either ignored the effect liquidity may have on the results (by including all listed shares) or specified a specific liquidity filter to adjust for thin trading to examine the possible effect it may have on results. It is well- known that the South African equity market is a highly concentrated market, dominated by only a few firms. Therefore, even when allowing for some sort of predefined liquidity filter, it is still possible to include shares in the analysis that will not be considered by portfolio managers due to low levels of liquidity, voiding the practical application potential of its results. The potential effect of different liquidity levels on the results is examined for the first time in this thesis.

The majority of research is based on a specific payoff period. According to the author’s knowledge, to date no study has examined the effect different payoff periods may have on the results. In this thesis a number of periods are used to compare the results across different payoff periods.

The approach followed in this thesis in conducting the extreme performer analysis is, globally speaking, unique. A cross-sectional regression technique is combined with a logistic regression technique to determine which factors discriminate between extreme performer shares and the rest. Additionally the logistic regression approach is employed to derive filter rules to filter potential extreme performer shares from an independent sample and subsequently construct portfolios to examine whether such a filter-rule approach could present the opportunity to create portfolios that may offer abnormal returns. This approach, together with the derivation of filter rules and application thereof in the portfolio construction process, is examined in this thesis for the first time.

The effect that time, liquidity and/or payoff period may have on the results (as described above) is examined for each of the three respective approaches applied in this thesis, making it one of the most comprehensive studies regarding the impact of firm-specific factors on the cross -section of returns on the JSE to date.

1.4 Summary of findings.

The results of the three approaches are strongly correlated. It suggests that a strong value effect is present and robust while a momentum, size and price reversal effect are present but sensitive to time, liquidity and/or payoff period. Multifactor analyses suggest that value and momentum factors are collectively significant in explaining the cross-section of returns across all time periods and level of liquidity, while three factor categories, namely value, size and momentum, can collectively be used to distinguish between potential winners and losers.

2

THEORETICAL OVERVIEW

2.1 Introduction

The theoretical framework on which this thesis is based, is reviewed in this chapter. Specifically, the review focuses on the various forms of the efficient market hypothesis (EMH), the allocation of capital under the assumption of an efficient market, the two equilibrium models developed to price assets in an efficient market (i.e. the Capital Asset Pricing Model and Arbitrage Pricing Theory), and lastly behavioural finance, the theory that attempts to explain investor behaviour and decision- making in an imperfect capital market.

The high level of competition in financial markets has, inter alia, two major implications (Bodie, Kane & Marcus, 2001:9). First, investors requiring a higher level of return should have to bear higher risk, known as the risk-return trade-off. The effect of diversification on portfolio risk, implications for the proper measurement of risk and the risk-return relation are topics subject to Modern Portfolio Theory (MPT), pioneered by Markowitz (1952). Second, investors should rarely expect to find bargains in a security market as the price of a security will quickly adjust with the arrival of new information about the security. The latter implication is the underlying theory of the EMH.

In accordance with the assumptions underlying MPT, the Capital Asset Pricing Model (CAPM) is developed to price assets in an efficient market. The CAPM is based on the notion that a completely diversified portfolio exists, known as the market portfolio. The implication is that investors should be compensated only for the risk of their portfolios relative to that of the market portfolio (i.e. systematic risk), as all other risk can be diversified away by holding the market portfolio. Deviating from the market portfolio introduces additional, diversifiable risk (also known as unsystematic or firm-specific risk) to a portfolio, but should not be compensated as this increase in portfolio risk is purely due to investor choice. Due to critique regarding the concept of a market portfolio, a second model is developed to price assets in an efficient market. This multi-factor model is based on the law of one price, which states that two assets that bear the same risk must trade at the same price, and is termed Arbitrage Pricing Theory (APT).

In contrast to the assumptions underpinning MPT and the EMH, behavioural finance takes into consideration how various psychological qualities affect the actions investors, analysts and portfolio managers take. Behavioural finance researchers are continuously investigating these psychological traits to develop theories that could help explain portfolio discrepancies, thereby adding significant value in deriving more accurate investment theories.

2.2 The Efficient Market Hypothesis

“The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time "fully reflect" all available information. A market in which prices always "fully reflect" available information is called "efficient."” Fama (1970: 383)

Fama’s definition of an efficient market suggests that an investor should not be able to consistently outperform his peers on a risk-adjusted basis. This is known as the efficient market hypothesis (EMH) in portfolio management literature.

Fama (1970) divides the hypotheses of how information is reflected in asset prices into three subsets, namely a weak form, semi-strong form and strong form of efficient markets. Due to the vast amount of literature that appeared on the subject of efficient markets since 1970, Fama (1991) reclassified the three subsets in 1991 to reflect more current titles and associated tests of the EMH.

The weak form originally stated that future prices cannot be predicted by historic prices and therefore follows a “random walk”, i.e. successive price changes are independent over time. If the weak form EMH cannot be rejected, technical analysts (analysts that use historic price patterns and volume data to assist in investment decision- making) will not be able to consistently outperform their rivals. According to Fama (1970), the weak form EMH was first argued based on empirical evidence by researchers such as Working (1934), Kendall and Hill (1953) and Roberts (1959), and was only later theoretically motivated in a mathematical approach by Samuelson (1965) and Mandelbrot (1966). Fama (1991) reclassified the weak form to cover a more general area of tests for return predictability. The new classification includes the use of variables such as dividend yields and interest rates to predict returns, tests of asset pricing models and anomalies as well as seasonality such as the January effect (refer to Chapter 3).

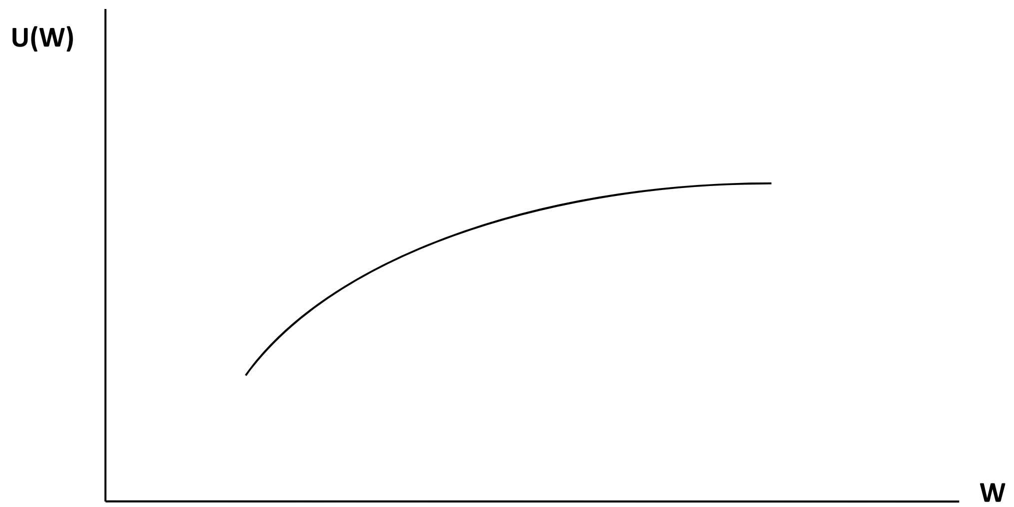
According to the semi-strong form of the EMH, stock prices adjust quickly to reflect publicly available data (e.g. announcements regarding earnings, share splits etc.). Ball and Brown (1968) found that only an insignificant portion of the information implicit in earnings announcements have not been anticipated by the announcement month. Fama, Fisher, Jensen and Roll (1969) found that markets are efficient with respect to the information implicit in a stock split. Waud (1970) concludes that the Federal Reserve Bank's announcement of changes in discount rates is either expected or the information is leaked beforehand. While the weak form of the EMH implies that technical analysts can't consistently outperform the market, the semi-strong form implies that fundamentalists (analysts basing their investment decisions on macro-economic forces and company performance) will also not be able to consistently outperform their rivals. Unlike the case for the weak form, the reclassification of the semi-strong form by Fama (1991) was merely a change in title rather than in coverage, and is now referred to as event studies.

The strong form of the EMH states that prices reflect all firm-relevant information, including private (or inside) information. Some of the earliest research done on this form of the EMH is that by Jensen (1969) who argued in favour of this form of EMH. If the strong form EMH cannot be rejected, it means that no investor (i.e. technical analysts, fundamentalists and not even company insiders) should be able to obtain above average returns in a consistent fashion. As with the semi-strong form, Fama's (1991) reclassification involved a change in title rather than coverage and is now known as tests for private information.

2.3 Allocation of Capital in an Efficient Market.

According to Fama (1970:383), "The primary role of the capital market is allocation of ownership of the economy's capital stock". Under the assumption of market efficiency, Markowitz (1952) assumes that investors consider return a desirable thing and variance (risk) of return an undesirable thing when allocating capital, introducing risk into the portfolio management process for the first time. Investors' attitude towards risk in Markowitz's (1952) modern portfolio theory (MPT) is based on the risk aversion concept according to the expected utility theory. Investors exhibit decreasing marginal utility (Bodie, Kane & Marcus, 1999), which means that although the utility function increases as wealth is higher, each extra unit of wealth should increase utility by progressively smaller amounts. Therefore the utility curve will be concave and can graphically be portrayed by figure 2.1. The implication of utility theory is that investors will reject risky investments without sufficient compensation for the risk.

Figure 2.1 Utility of wealth
Figure 2.1 is adopted from Bodie *et al*. (1999:175). The concave curve illustrates diminishing marginal utility (U(W)) of risk averse investors as wealth (W) increases.



According to Markowitz's theory (1952), investors will assign weights to securities to form a portfolio of *n* securities in such a way as to minimize their risk, subject to a given (or desired) return. Mathematically this can be expressed as follows:

$$\min_{w_i} \left[\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \right] \text{, subject to desired return } E(R_p) \qquad \ldots(2.1)$$

where σ_p^{2} = Variance of portfolio p

w_i = weight assigned to asset i, where i = 1, ..., n

σ_{ij} = Covariance between assets i and j

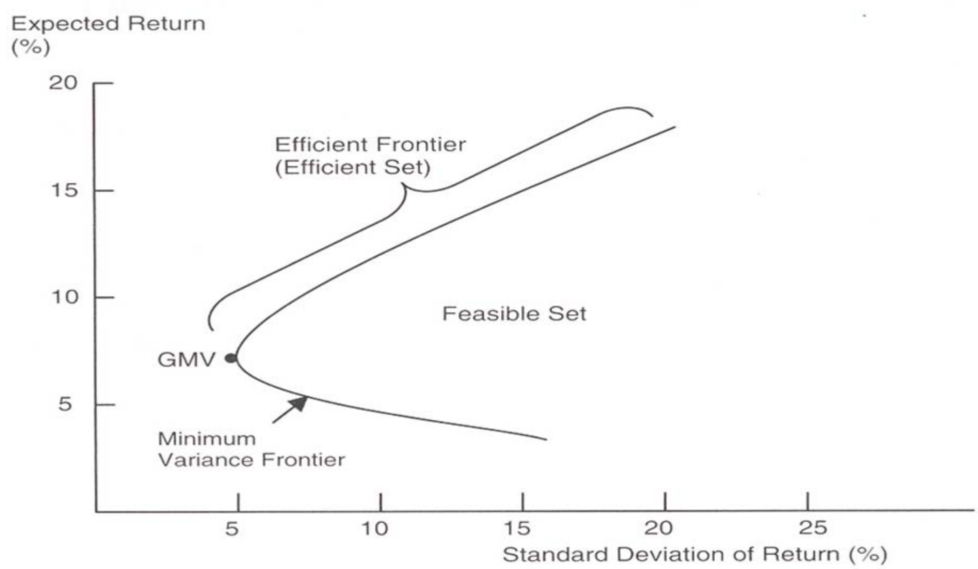
$E(R_p)$ = Expected return of portfolio p.

From equation (2.1) it is clear that the lower the average covariance (the degree to which two assets move together) between two assets, the lower the variance of the portfolio will be. The process of combining securities with low levels of covariance to decrease overall risk in terms of standard deviation (the square root of variance), is known as diversification. If diversification is done in such a manner as described by Markowitz, i.e. capital is allocated in such a way that the resulting portfolios offer the lowest possible risk (standard deviation) for every given level of expected return, it is referred to as efficient diversification (Bodie, Kane & Marcus, 1999).

A graphical presentation of effective diversification is presented in Figure 2.2

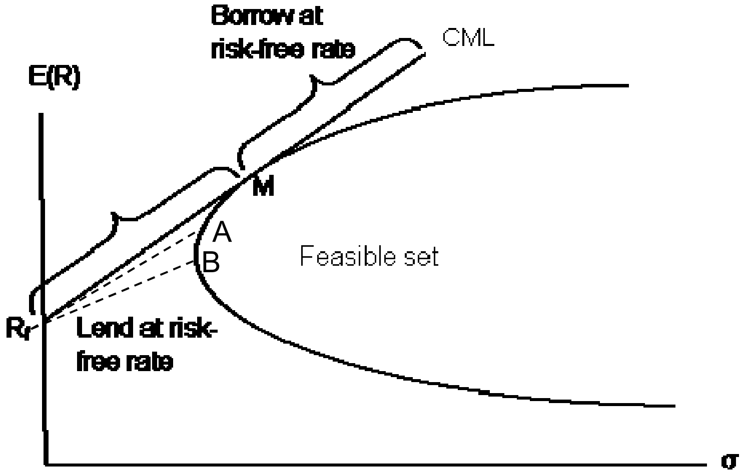
Figure 2.2 Markowitz Efficient Frontier

Figure 2.2 is adapted from Maginn, Tuttle, Pinto and McLeavey (2007). When capital is allocated towards risky assets in such a way that equation (2.1) is minimized, the global minimum variance (GMV) portfolio is obtained. The efficient frontier of risky assets originates at the GMV and presents all possible portfolios obtainable through different allocation of capital that will result in the highest expected return for a given level of risk.



Markowitz's theory was extended when Tobin (1958) introduced a risk-free asset associated with an interest rate of zero. Sharpe (1964) argued that the risk-free asset should be associated with a positive interest rate at which investors could borrow and lend. Constructing a portfolio based on dividing capital between a risky portfolio and a risk-free asset as suggested by Tobin (1958) and Sharpe (1964), is known as the separation theorem. According to Sharpe's (1964) positive risk-free interest rate theory, the line connecting the risk- free rate with any risky portfolio on the risky asset efficient frontier represents all possible capital allocations between the risk- free asset and the specific risky portfolio. This line is therefore called the capital allocation line (CAL). As the covariance is zero between the risk-free asset and the risky asset (by definition), no diversification benefits are possible by combining the two, resulting in the CAL being a straight line (i.e. a linear relationship exists between the risk free asset and the risky portfolio) as opposed to the curved risky asset efficient frontier. Consider for a moment two CAL lines, say CAL_A (represented by the dashed line R_fA) and CAL_B (represented by the dashed line R_fB) on Figure 2.3. The portfolios represented by CAL_B offer a higher expected return for a specific level of risk with respect to the portfolios represented by CAL_A. Continuing to increase the slope of the CAL will result in more efficient portfolios being created by combining the risk- free asset with the risky portfolio on the efficient frontier. The slope is maximized at the point where the CAL is tangent to the risky asset efficient frontier, representing the optimal risky portfolio. According to the assumptions underlying MPT, all investors use the same mean-variance analysis on the same set of securities, have the same investment horizon, use the same security analyses and experience the same tax consequences. Therefore they must all arrive at the same efficient frontier and optimal risky portfolio. As the market is the aggregate of all individual portfolios, the optimal risky portfolio at the point of tangency of the CAL must therefore be the market portfolio (Bodie, Cane & Marcus, 2001:234), represented by M on Figure 2.3. Consequently the market portfolio represents a fully and completely diversified portfolio. As the CAL now represents all possible capital allocations between the risk-free asset and the market portfolio, the line is called the Capital Market Line (CML). The CML represents the new efficient frontier.

Figure 2.3 Capital Market Line
Figure 2.3 is adopted and modified from Brown and Reilly (2009: 210).



The relationship between the expected return and risk of a portfolio can now mathematically be expressed as the equation of the straight line representing the CML:

$$E(R_p) = R_f + \sigma_p{}^2 \left(\frac{E(R_M) - R_f}{\sigma_M{}^2} \right) \qquad \ldots(2.2)$$

where

$E(R_p)$	=	Expected return of portfolio p;
R_f	=	Risk-free rate
σ_p^2	=	Variance of portfolio p
$E(R_M)$	=	Expected return on market portfolio
σ_M^2	=	Market variance

It is furthermore assumed under MPT that investors can also borrow at the risk-free rate, which means that more than 100% of a portfolio manager's funds can be invested in the market portfolio, which is represented by the straight line to the right of the market portfolio (M) in Figure 2.3. An investor's decision with regards to the portion invested in the market portfolio is a function of the investor's attitude towards risk. Those investors that have a lower level of risk tolerance will typically allocate more of their capital towards the risk- free asset, while investors with higher risk appetite will allocate more towards the risky (market) portfolio, or even borrow at the risk- free rate and invest more than 100% of capital in the risky portfolio.

2.4 Asset pricing in an efficient market.

2.4.1 The Capital Asset Pricing Model (CAPM)

After the foundation of MPT has been laid by Markowitz (1952), the CAPM was developed over a period of 14 years in articles by Sharpe (1964), Lintner (1965) and Mossin (1966). According to the CAPM, investors should only be compensated for risk that cannot be diversified away, known as systematic risk. The relevant risk measure to use is therefore not the variance (or standard deviation) as this reflects both systematic and unsystematic (or diversifiable) risk, but rather a measure of systematic risk given by the covariance between a risky asset and the market portfolio. Substituting the variance of the portfolio (σ_p^2) in equation (2.2) by a measure of systematic risk, i.e. the covariance between asset i and the market portfolio M ($\sigma_{i,M}$), results in the following equation:

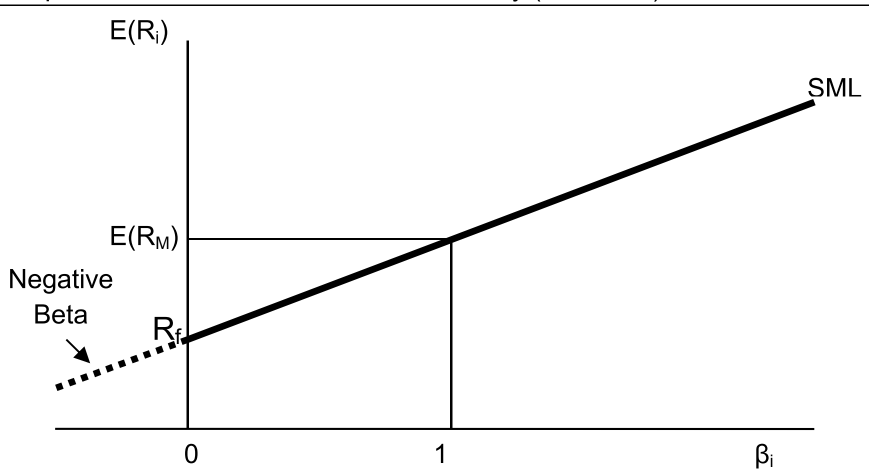
$$E(R_p) = R_f + \sigma_{i,M}\left(\frac{E(R_M) - R_f}{\sigma_M^{\ 2}}\right) = R_f + \beta_i\left(E(R_M) - R_f\right) \qquad \text{…(2.3)}$$

where

$\beta_i = \dfrac{\sigma_{i,M}}{\sigma_M^{\ 2}}$, a measure of the systematic risk of asset i relative to the market portfolio *M*.

Equation (2.3) is called the security market line, and is graphically presented in Figure 2.4:

Figure 2.4 The Security Market Line (SML)
Figure 2.4 is adopted and modified from Brown and Reilly (2009:216).



According to the definition of beta as presented in equation (2.3), the market's beta must be one. Therefore, if a security has a beta of more (less) than one, it is regarded as being more (less) volatile relative to the market, and the investor should be compensated accordingly. In an equilibrium market, assets should deliver an expected return as calculated by the CAPM and therefore plot on the SML to justify the level of systematic risk borne by the investor. An asset that plots above the SML (i.e. is expected to deliver a return higher than that associated with the CAPM) is regarded as undervalued in the market, while an asset plotting below the SML is regarded as overvalued. Investors' bidding activities will quickly cause the price of the overvalued (undervalued) asset to decrease (increase) until markets reach a state of equilibrium again.

The market portfolio as defined and used in the CAPM is impractical, as such a portfolio must contain all assets in the universe in proportion to their respective market values while being mean-variance efficient. A correct and unambiguous test for the validity of the CAPM is therefore, according to Roll (1977), impossible. The use of proxies for the market portfolio such as the Morgan Stanley Capital International World Index (MSCI) and Standard and Poor's 500 Index (S&P 500) is ambiguous, and may result in inaccurate conclusions. One way of addressing the unobservable market portfolio problem is to develop an equilibrium asset pricing model that does not need a theoretical market portfolio as input. Ross (1976) developed such a model, called the Arbitrage Pricing Theory (APT) model.

2.4.2 Arbitrage Pricing Theory (APT)

APT is built on the law of one price, which states that two assets that bear the same risk must trade at the same price. If this law is violated, arbitrage opportunities may arise in which investors can sell short an asset in the high-priced market while buying a similar asset in the low-priced market, effectively making a zero investment and riskless profit. Opposed to the single systematic risk factor (beta) used in the CAPM model, the APT model allows for more than one systematic risk factor (Roll & Ross, 1980). According to APT, there are a number of independent risk factors that influence the expected return on each asset. Mathematically, the APT model can be presented by equation (2.4):

$$E(R_i) = R_f + \sum_{k=1}^{K} b_{ik}\lambda_k \qquad \text{...(2.4)}$$

where $E(R_i)$ = Expected return of asset i

R_f = Risk-free rate

λ_k = Risk premium ($E(R_k) - R_f$) associated with risk factor k

b_{ik} = Sensitivity of asset i to risk factor k.

From equation (2.4) it is seen that APT is a multi-factor model that allows investors to identify various factors that contribute to asset returns and the sensitivity of assets to those factors (Modigliani & Pogue, 1988). Although the identity of these factors are not known, factors suggested by empirical research since 1976 are similar to the ones proposed by Chen, Roll and Ross (1986), namely the spread between long and short interest rates, expected and unexpected inflation, industrial production and the spread between high- and low-grade bonds.

Using APT as the equilibrium pricing model, it is possible to actively manage a portfolio by adjusting the portfolio's exposure to the different systematic risk factors (Roll & Ross, 1984 and Modigliani *et al*., 1988) as opposed to the CAPM where all investors are assumed to hold a portion of the market portfolio.

Irrespective of these desirable characteristics of the APT, the CAPM still remains the preferred pricing model in modern portfolio management.

2.5 Behavioural Finance

"*…financial markets often fail to act as predicted by fundamental factors such as expected corporate earnings and economic variables such as interest rates and inflation levels.*" (Olsen, 2006: 193)

Behavioural finance is a relatively new branch of financial economics, that came about in the 1990s (Brown & Reilly, 2009: 170). According to Olsen (1998), proponents of behavioural finance assert that the standard finance model is true only within certain limitations, which is based on the assumptions underpinning MPT. According to MPT, investors act rationally, are risk averse, have homogeneous expectations regarding the mean, variance and covariance of asset returns and base their investment decisions on maximising their expected utility. Behavioural finance on the other hand takes into consideration how various psychological qualities affect the actions that investors, analysts and portfolio managers take, individually as well as in groups. These psychological qualities could lead to irrational behaviour in contrast to that assumed by MPT and cause markets to be less efficient than that proposed by the EMH. For this reason behavioural finance research could add significant value in deriving more accurate investment theories.

Currently there is no single unified theory of behavioural finance, but the focus of most studies has been placed on identifying portfolio discrepancies which can be explained by the different psychological traits of individuals in the investing world (Brown & Reilly, 2009:170). These discrepancies in portfolio performance can be explained by a number of theories or biases which have been well documented to date. According to Scott, Stumpp and Xu (1999), behavioural finance theory and biases can mainly be grouped into two general categories, namely overconfidence and prospect theory.

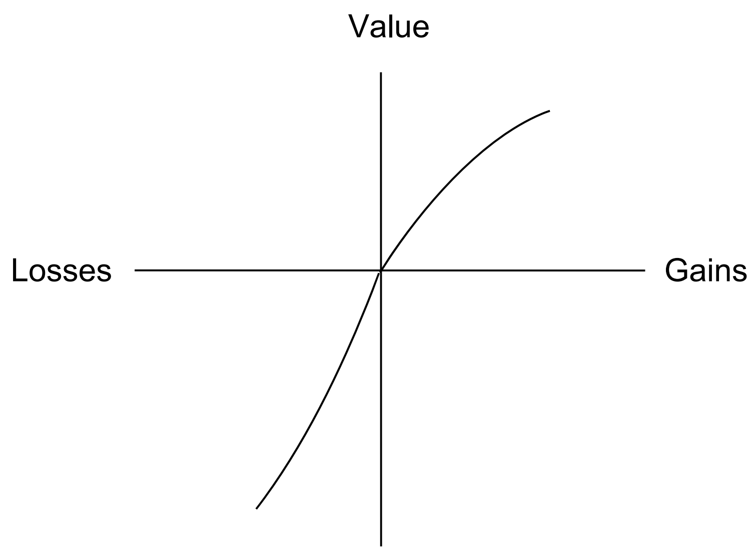
2.5.1 Overconfidence

Overconfidence refers to the phenomenon of humans assigning an excessively high probability of success to their own forecasts (Kahneman & Tversky, 1972). According to Scott *et al*. (1999) the consequences of overconfidence are multiple. Firstly, investors tend to look for information that confirms their findings relative to unbiased probabilities, a symptom known as *representativeness* or *confirmation bias* (Kahneman *et al*., 1972 and Grether, 1980). Secondly, investor preferences are a function of how an argument or situation is framed (Kahneman & Tversky, 1984). Thirdly, investors tend to overreact to dramatic events (e.g. stock market crashes), and consequently will assign a higher than justifiable probability to such an event happening again (De Bondt & Thaler, 1985). Finally, investors are slow to adjust their expectations (Daniel, Hirschleifer & Subrahmanyam, 1998). From the discussion it is clear that these four consequences may result in market inefficiency that may not be rectified by investor activities to quickly bring markets back to a state of equilibrium as suggested by the EMH.

2.5.2 Prospect Theory

Originally investigated by Kahneman and Tversky (1979), prospect theory argues that investor utility depends on deviations from moving reference points rather than absolute wealth as suggested by expected utility theory discussed in Section 2.3. This is indicative of a tendency towards loss aversion. To illustrate, Kahneman *et al*. (1979) uses an S-shaped value function, similar to figure 2.5.

Figure 2.5 S-shaped Value Function of Prospect Theory
Figure 2.5 is modified from Kahneman and Tversky (1979: 279).



Using the S-shaped value function, Kahneman *et al*. (1979) point out three aspects with regards to their prospect theory. Firstly, the value function is defined on deviations from the reference point. Secondly, the function is concave for gains, implying that the marginal utility from additional gains increases at a decreasing rate, while the function is convex for losses below the reference point, implying diminishing marginal disutility. Lastly, the function is steeper for losses than for gains, implying that the extent of disutility derived from making losses is larger than that of an equal amount of gains. Shefrin and Statman (1985) argue that the natural reference point for investors is the asset's purchase price, and a score of the gains and losses relative to this reference point is kept. This type of behaviour, referred to as the *disposition effect*, causes investors to hold on to losers for too long while selling winners too quickly, supporting the prospect theory of Kahneman *et al*. (1979). According to Shefrin *et al*. (1985), investors have a tendency to create such a reference point for every investment in their portfolio and keep score of their gains and losses for each investment separately, ignoring possible interaction. This process, known as *mental accounting*, ignores the importance of diversification (Thaler, 1985).

A number of behavioural biases that stem from prospect theory have been documented. These include *belief perseverance* (Lord, Ross & Lepper, 1979; Barberis & Thaler, 2003), *anchoring* (Kahneman & Tversky, 1979), *regret avoidance* (Shefrin & Statman, 1985) and *escalation bias* (Shefrin, 2001) to name but a few. The main argument however, is captured in prospect theory and a detailed review of the mentioned related biases therefore falls outside the scope of this thesis.

2.5.3 Other Behavioural Biases

As discussed above, the majority of behavioural theories can be categorised as either overconfidence- or prospect- theory (Scott *et al*., 1999). Some research however, propose behavioural aspects that are not categorised as either of the above categories.

Lee, Schleifer and Thaler (1991) argue that some owners of closed -end funds (funds that issue a fixed number of shares that trade on the stock market) are noise traders, causing the fund price to differ from the fund's net asset value (NAV), a phenomenon often referred to as the "closed-end fund puzzle". Noise traders are defined as irrational traders (Barberis *et al*., 2003) or non-professional traders with no special information (Brown *et al*., 2009: 171). Clarke and Statman (1998) argue that noise traders follow newsletter writers, who in turn follow the "herd", while Brown (1999) finds that noise traders tend to move together when there is a shift in sentiment, causing increases in the prices and volumes of the associated securities of closed-end mutual funds, supporting the findings of Lee *et al*. (1991). De Long, Shleifer, Summers and Waldmann (1990) and Schleifer and Vishny (1997) argue that the mispricing of securities caused by noise traders may be worsened, rather than being eliminated, by the actions of rational investors by means of arbitrage strategies. This "noise trader risk" may result in markets being much less efficient for longer periods of time.

2.6 Conclusion

Diversification, risk, expected return and risk-return trade-off are all topics subject to Modern Portfolio Theory (MPT), pioneered by Markowitz (1952). According to MPT, all investors attempt to maximise their economic utility while being risk averse, and therefore seek those portfolios that offer the highest level of return for any given level of risk, or the lowest risk for a given level of return (known as efficient portfolios). The search for these efficient portfolios results in fierce competition amongst investors, causing them to act quickly on new information. This leads to the notion that capital markets are efficient (the efficient market hypothesis or EMH), and as a result investors should not be able to outperform their peers in a consistent fashion. Tobin (1958) and Sharpe (1964) extended Markowitz's (1952) efficient frontier concept by introducing the risk-free asset which resulted in the separation theorem. According to the latter, capital should be allocated between the risky market portfolio and the risk-free asset in such a manner that it reflects the investor's risk appetite. Based on the foundations laid by Markowitz (1952) and Tobin (1958), Sharpe (1964), Lintner (1965) and Mossin (1966) developed the capital asset pricing model (CAPM) to price assets in an efficient market. According to the CAPM, the only risk that investors should be compensated for is that of the portfolio relative to the completely diversified market portfolio. Roll (1976) criticised the concept of an observable market portfolio that is completely diversified. This criticism led Ross (1976) to develop an alternative, multifactor asset pricing model which is based on the law of one price, i.e. securities bearing the same level of risk should sell at the same price (Arbitrage Pricing Theory).

According to the assumptions underlying MPT, EMH, CAPM and APT, investors act rational, are risk averse, have homogeneous expectations regarding the mean, variance and covariance of asset returns and base their investment decisions on maximising their expected utility. Behavioural finance on the other hand takes into consideration how various psychological qualities affect the actions that investors, analysts and portfolio managers take, individually as well as in groups. These psychological qualities could lead to irrational behaviour in contrast to that assumed by MPT and cause markets to be less efficient than that proposed by the EMH. Scott, Stumpp and Xu (1999), categorised behavioural finance -theory and -biases into two general categories, namely overconfidence and prospect theory. Overconfidence refers to the phenomenon of humans assigning an excessively high probability of success to their own forecasts (Kahneman & Tversky, 1972), while under prospect theory investor utility depends on deviations from moving reference points rather than absolute wealth as suggested by expected utility theory (Kahneman & Tversky, 1979). The latter is indicative of a tendency towards loss aversion, meaning that the extent of disutility derived from making losses is greater than that of an equal amount of gains.

As is clear from this chapter, the search for and formulation of accurate investment theories is a continuous process in which both proponents of market efficiency and behavioural finance are actively involved; an active process of which this thesis forms part.

3

LITERATURE REVIEW

3.1 Introduction

As discussed in Chapter 2, proponents of the efficient market hypothesis (EMH) believe that current security prices fully reflect all available information about a security (Brown & Reilly, 2009:152). The EMH is based on a number of assumptions: fierce competition exists amongst independent investors; information about securities arrive in a random, independent fashion; in an attempt to maximise their profits, investors' buy and sell decisions lead to the quick adjustment of prices to reflect any new information about the security. Combining these assumptions leads to the expectation that security price changes should be at random and independent, while reflecting all available information of a security including the associated risk. The implication of the EMH is therefore that the return implicit in the current price of a security should reflect its risk, in other words, investors' expected returns are consistent with their perceived risk. Investors are therefore believed to have rational expectations under EMH, and should not be able to outperform another in a consistent fashion. Based on modern portfolio theory (MPT) which is underpinned by the EMH, equilibrium models such as the capital asset pricing model (CAPM) and arbitrage pricing theory (APT) can be used to determine a security's expected return within an efficient market. Proponents of behavioural finance on the other hand believe that modern portfolio theory (MPT) (and by implication the CAPM and APT) is incomplete since it does not consider individual behaviour (Brown *et al*., 2009:170). Instead, it is believed that some financial phenomena can be better explained by models that reflect incomplete rational expectations and that it is not possible for arbitrageurs to offset all instances of mispricing (Brown *et al*., 2009:170; Barberis & Thaler, 2003).

The debate surrounding the EMH is an ongoing one, and researchers continue to investigate the validity of this hypothesis. Specifically, three forms of the EMH have been identified (see Chapter 2), and different research approaches have been followed to address each form.

As discussed in Brown and Reilly (2009: 154) the approaches followed to test the weak form EMH can be classified as a) statistical tests of independence between rates of return and b) a comparison of risk-return results for trading rules based on past market information relative to a simple buy-and-hold strategy. These include autocorrelation (or serial correlation) tests of independence of returns, tests of the overreaction theorem (see Chapter 2) and tests involving technical trading rules.

Tests concerning the semi-strong form EMH can be categorised into those that entail a) predicting future returns using available public information beyond market information such as prices and trading volume, e.g. firm- specific characteristics and b) event studies, i.e. the investigation of how fast stock prices adjust to significant economic events (Brown & Reilly, 2009: 156). Predicting future returns typically involve either time-series analysis of returns or cross-section distribution of returns for individual stocks. According to the semi-strong form EMH, it should not be possible to predict future returns. Investigating the subsequent abnormal returns obtained by investing in securities identified through screening of firm-specific characteristics and/or after a public announcement of significant events, e.g. company earnings, stock splits or economic data, are approaches followed to test the semi-strong form EMH.

Analysing returns over time for different identifiable investment groups to determine if any group consistently receive above-average risk-adjusted returns is an approach followed to test the strong form EMH (Brown & Reilly, 2009:166). The trading actions and subsequent returns of a) corporate insiders (e.g. corporate officers, members of the board of directors and owners of at least 10% of a firm's equities), b) stock exchange specialists, c) security analysts and d) professional money managers are followed and investigated. According to the strong form EMH, none of these groups should be able to consistently earn above-average risk-adjusted returns.

For the purposes of this study, the literature review will focus on the relevant studies concerning tests of the weak- and semi-strong form EMH.

The literature review starts off with a summary of traditional tests related to the weakform EMH, followed by those concerning the semi-strong form. From these studies, numerous potential factors, including technical and fundamental, are identified that, according to some of the researchers, could be used in the investment decision- making process to consistently provide above-average returns (commonly referred to as market anomalies), therefore rejecting the EMH. According to proponents of the EMH however, these same indicators are either not sustainable and could therefore not be used to create above-average returns in a consistent fashion, or it is nothing more than common risk factors that should form part of an APT multifactor model. The last part of this chapter discusses a relatively new and, especially from a South African point of view, an unexplored approach in testing the EMH. Similar to the more traditional approaches, this approach allows for the identification of potential factors that may affect the cross- sectional variation in equity returns, but the focus is to identify those factors that are associated with equities that experienced extreme return levels during a specific period. Hence, this approach is referred to as the extreme performer approach in this thesis.

3.2 Tests concerning the weak form EMH

3.2.1 Technical Indicators

In the literature the effect of momentum and price reversal has mainly been studied by examining the way past returns have influenced future returns, with the focus on serial (or auto) correlation. Positive serial correlation is an indication of price momentum as price increases (decreases) are followed by more price increases (decreases), meaning that trends in prices can be recognised. Negative serial correlation on the other hand is an indication of a price reversal effect, in other words price increases (decreases) are followed by price decreases (increases), indicating a mean-reverting effect. Momentum-motivated technical analysts will argue that momentum strategies could result in excess returns if securities are bought after a period of price increases while they are sold after periods of price decreases, given that positive serial correlation is evident and the analyst has the ability to accurately predict the trend. In contrast, contrarian-motivated analysts argue that abnormal returns could be created by exploiting price reversal effects. Of course a combination of the two strategies is possible (and practised) as well, and a number of researchers have attempted to identify the correct timing and holding period for momentum versus contrarian strategies to form a profitable strategy based on the combination of the two effects. This section focuses on those studies concerning momentum strategies, price reversal (or contrarian) strategies and a combination of the two to identify possible momentum and/or contrarian indicators. The section is further subdivided to address those studies that focus on very short investment periods separately.

3.2.1.1 Momentum and price reversal: International studies

Fama (1970) summarises the findings of researchers like Kendall and Hill (1953), Granger and Morgenstern (1963), Godfrey, Granger and Morgenstern (1964) and Fama (1965) in which it is argued that no significant serial correlation is evident between lagged price changes or returns. Summers (1986) however, questions these findings and argues that the statistical tests used to derive these findings have very low power. He argues that if prices slowly oscillate around its fundamental value over the long- term, short- term serial correlation may, incorrectly, lead to the conclusion that the mean-reverting components of prices have no considerable consequence while it actually accounts for a significant portion of variation in returns. Fama and French (1988) respond by arguing conversely that the behaviour of long- term returns can in fact give a clearer impression of the importance of the mean-reverting price components. Fama et al. (1988) examine serial correlation for increasing holding periods for the period 1926 to 1985. A U-shaped serial-correlation pattern is found over increasing periods. Serial correlation becomes negative for 2-year returns, reaches a minimum for 3 to 5 year returns and then moves back towards zero for longer return periods. This is consistent with the hypothesis that prices oscillate slowly around its fundamental value. Furthermore, Fama *et al*. (1988) found that a significantly greater amount of 3 to 5 year return variation is explained by the negative serial correlation for larger firms compared to that of smaller firms. Serial correlation for the period 1940 to 1985 however, does not follow a U-shape and are closer to zero. Additionally it is found that the negative autocorrelation evident in portfolio returns for the period 1926 to 1985 is due to a common macro-economic phenomenon and not security specific. These results led Fama *et al*. (1988) to conclude that the weak form EMH cannot be rejected.

Jegadeesh (1990) notes that although the results of Fama *et al*. (1988) suggest significant serial correlation over a 3 to 5 year period, their study doesn't state clearly whether these results suggest economically important deviations from the random walk model. To address the question of economic significance, Jegadeesh (1990) first tests for serial correlation in monthly returns using data of securities from the Center for Research in Security Prices (CRSP) database over the period 1929 to 1982. He finds that monthly returns exhibit significant negative first -order serial correlation while significant positive higher-order serial correlation is also evident, especially for 12-month lags. A number of studies have reported that stock returns in January are predictable while those for the remainder of the year are not (e.g. Branch, 1977; Reinganum, 1983). Jegadeesh (1990) tests for the "January effect" by repeating his previous tests outside the month of January and finds that the reported January anomaly does not affect the earlier conclusions drawn from his tests. In line with Fama *et al*. (1988), Jegadeesh (1990) also tests for the effect firm- size may have on serial correlation. He finds that the pattern of serial correlation is similar across all size-based quintiles and that it is not restricted to any isolated sub-period. Finally Jegadeesh (1990) tests whether the rejection of the random- walk hypothesis is of economic significance by means of a portfolio formation procedure for the period

1934 until 1987. He constructs ten portfolios based on predicted returns using ex ante estimates of the obtained regression parameters. The difference in risk-adjusted excess return of the extreme decile portfolios (the return of the portfolio predicted to perform the best minus the return of the portfolio predicted to perform worst, adjusted for risk) is found to be 2.49% per month. This difference decreases to 2.20% per month if January is excluded. Jegadeesh (1990) concludes that the degree to which returns can be predicted based on historical returns is therefore economically significant.

De Bondt and Thaler (1985) suggest two hypotheses: Firstly that extreme stock price movements will be followed by subsequent movements in the opposite direction (i.e. negative serial correlation), and secondly, the more extreme the first price movement, the greater the subsequent correction will be. Their hypotheses are motivated by a behavioural aspect, specifically, that investors tend to overreact to unexpected and dramatic news events (referred to as the overreaction phenomenon, discussed in Chapter 2). Using monthly return data for the NYSE between 1926 and 1982, De Bondt *et al*. (1985) find that loser portfolios outperform winner portfolios by as much as 25% over a 3-year period. This finding is in line with the negative serial correlation of 3 to 5 year holding period returns suggested by Fama *et al*. (1988).

Continuing with the overreaction phenomenon investigated by De Bondt *et al*. (1985), Lo and Mackinley (1990) find that negative serial correlation in individual stocks may indeed offer profitable strategies due to overreaction behaviour, but argue that such a contrarian strategy is not the major source of expected profits. Instead, positive cross- serial correlation is found to be the main explanatory variable. Lo *et al*. (1990) show that such a positive cross- serial correlation exists due to a specific pattern of size-sorted portfolios. Specifically, a lead-lag relation exists between large capitalisation and small capitalisation stocks, where the returns of larger firms generally lead those of smaller firms as information is usually first reflected in the prices of the more traded larger firms before it is captured in the prices of the less or thinly traded smaller firms.

Lehman (1990) examines the predictability of stock returns over weekly intervals. Using data on the New York and American Stock Exchanges since 1962, portfolios are formed on a weekly basis by shorting recent winners and going long recent losers, in such a way that the resulting portfolio is a zero-investment portfolio. Each portfolio has an investment time-horizon of 26 weeks. Lehman finds that applying such a strategy results in arbitrage profits for approximately 90% of the weeks under review, even after controlling for bid-ask spreads and transaction costs. This leads him to conclude that, at least over the short- term, markets are inefficient due to overreaction of stock prices.

In an attempt to solve the puzzle of conflicting results documented with regard to relative strength (or momentum) versus contrarian strategies, Jegadeesh and Titman (1993) investigate the return patterns of different portfolio formation strategies. They find that a short- term momentum strategy of buying stocks that has shown positive returns in the last 6 months while selling those that have shown negative returns during the same period and holding the portfolios for a 6-month period, result in an average annual compounded excess return of 12.01% for the period 1965 to 1989. Based on their methodology and results, Jegadeesh *et al*. (1993) argue that the profits observed following such a relative strength strategy cannot be ascribed to systematic risk or lead-lag effects as proposed by Lo *et al*. (1990), but instead to delayed price reactions to firm-specific information. Observing the return patterns of the portfolios formed over a longer period (than 6-months) shows that although past winners (losers) continued to outperform (underperform) over the short- term (up until seven months after formation), past losers significantly outperformed past winners during the thirteen months thereafter. Therefore, the longer term results are more indicative of profitable contrarian strategies. Jegadeesh *et al*. (1993) argue that their findings may be an indication that the market under-reacts to information regarding short- term firm prospects, while overreacting to information regarding longer term prospects. They do however mention that this hypothesis is not testable based on the evidence provided in their research. Their findings however, can serve as an indication of overreaction and correction patterns in stock prices.

Building on the 1993 study of Jegadeesh *et al*., Chan, Jegadeesh and Lakonishok (1996) seek to explain the results obtained from short- term profitable momentum strategies followed by price reversals over longer periods. They argue that the short-term profits offered may be due to markets responding gradually to new information, and therefore investigate the effect of the momentum strategies around earnings announcements. The results show that a big portion (41%) of the superior performance with regards to the momentum strategies occurs around the earnings announcement date, and that if the market is surprised by good or bad earnings-news it continues to be surprised in the same direction over at least the subsequent two announcements. Another argument put forward by Chan *et al*. (1996) supporting the slow reaction of markets to new information, is that of analysts adjusting their forecasts in a sluggish manner, especially for the worst performing companies. Possible reasons for this action by analysts may be to avoid alienating management and in the process decrease future business opportunities.

According to Chan *et al*. (1996), a possible reason for the contradicting results with regards to momentum versus contrarian strategies documented thus far is that the types of stocks selected under a momentum strategy may be very different to those selected under a contrarian strategy. Specifically, it is argued that investor perceptions differ under the two strategies. With regards to Chan *et al*.'s (1996) momentum strategy, shares that have shown good or poor performance over the immediate past (6-months) are identified. Over the longer term however, these shares have not performed much different from the average shares. Most contrarian strategies on the other hand focus on shares that have performed extremely poor over a longer period of time. This history of poor performance may create a mindset of excessive pessimism, and it may take a while for investors to change their opinions about such a company, causing price reversals or corrections to take place over a longer period of time.

The overreaction hypothesis is tested on the Frankfurt Stock Exchange (FSE) by Schiereck, De Bondt and Weber (1999) for the thirty year period from 1961 to 1991. Their findings are very much in line with that of Jegadeesh *et al*. (1993) and Chan *et al*. (1996) in that short- term momentum strategies and longer term contrarian strategies significantly outperform the DAX index. Similarly, Forner and Marhuenda (2003) test the hypothesis on the Spanish Stock Market for the period 1963 to 1997. Similar findings are obtained, namely that short- term (12-month) momentum and longer term (60-month) contrarian strategies offer significant excess returns relative to the market.

Chan, Hameed and Tong (2000) investigate the profitability of momentum strategies in international equity markets. The analysis is based on 23 sample countries from Asia, Europe, North America and Africa from 1980 to 1995. Based on five different holding periods (one-, two-, four-, twelve- and twenty-six weeks) they long the winner countries and short the loser countries. It is found that the momentum strategies are statistically and economically significant, especially over shorter periods (less than four weeks).

Motivated by prospect theory and mental accounting (discussed in Chapter 2), Grinblatt and Hang (2005) attempt to explain why momentum exists in the cross-section of stock returns. They suggest that prospect theory and mental accounting combined are perhaps the main reason for the disposition effect which leads to a spread between a stock's fundamental value and its equilibrium price. Grinblatt *et al*. (2005) argue that the random evolution of fundamental values and the updating of reference prices lead to spread convergence and therefore predictable equilibrium prices, which is interpretable as momentum. They find that when controlling for a variable that proxy for unrealised capital gains, past returns have no predictive power of future returns.

Avramov and Chordia (2006) develop a framework to test whether asset pricing models can explain, inter alia, the momentum anomaly. As part of their framework, they condition the CAPM systematic risk measure (or beta) of a security on the market capitalisation (the number of shares in issue multiplied by market price, used to classify a share as large, medium or small cap and referred to as the size style-factor) and the book-to-market ratio (or value style-factor) allowing this conditioning to vary over time with a macro-economic predictor (the size and value style-factors are discussed in detail in Section 3.3.1). Specifically, they model the conditional beta of security j as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1} + (\beta_{j3} + \beta_{j4} z_{t-1}) Size_{jt-1} + (\beta_{j5} + \beta_{j6} z_{t-1}) BM_{jt-1} \qquad \ldots(3.1)$$

where

z_{t-1} = a macro-economic predictor (specifically, the default spread which is the yield differential between low graded and high graded corporate bonds)

$Size_{jt-1}$ = market capitalisation of security j at time t-1

BM_{jt-1} = book-to-market ratio of security j at time t-1

In their empirical analysis, Avramov *et al*. (2006) model beta under four specifications: a) an unconditional beta where all βs except β_{j1} are restricted to be zero; b) $\beta_{j2} = \beta_{j4} = \beta_{j6} = 0$; c) $\beta_{j3} = \beta_{j4} = \beta_{j5} = \beta_{j6} = 0$; d) all βs are allowed to depart from zero. Applying their framework on data of listed companies on the NYSE, AMEX and NASDAQ for the period 1964 to 2001, led them to conclude that, even when β is allowed to vary with momentum, none of their models capture the momentum anomaly. In contrast to Grinblatt *et al*. (2005), they conclude that the search for a risk-based asset pricing model that captures the momentum anomaly is ongoing.

In addition to the momentum anomaly tested by Avramov *et al*. (2006), Boynton and Oppenheimer (2006) also investigate the contrarian anomaly. They control for survivorship bias (discussed in Chapter 4) as well as for microstructure distortions from the bid-ask spread bounce. After controlling for these two biases, they find that the premium offered by the contrarian anomaly is significantly decreased, while the premium associated with the momentum anomaly is increased. Although the premium for the contrarian anomaly is substantially reduced, they fail to conclude that the anomaly is not valid.

Similar to the studies of Avramov *et al*. (2006); Boynton *et al*. (2006), Lewellen and Nagel (2006) test whether the conditional CAPM in which betas are allowed to vary over time, can explain market anomalies like momentum. They find that for the conditional CAPM to hold, the variation in betas and the equity premium will have to be implausibly large, and conclude therefore that momentum remains a capital market anomaly.

Bauer, Cosemans and Schotman (2010) perform a similar study to that of Lewellen *et al*. (2006), on the European market. A conditional three-factor model of Fama and French (1993) is applied to a sample of 2 503 shares from 16 European countries covering approximately 80% of the European stock market capitalisation. The conditional three-factor model used is described as:

$$E_t(R_{it+1}) = \alpha_{it} + \sum_{k=1}^{3} \beta_{ikt} E_t\left(FF_{kt+1}\right) \qquad \ldots(3.2)$$

where

α_{it} = conditional alpha = $\alpha_{i0} + \alpha_{i1} W_{it}$ where W_{it} = a vector of instruments for alpha.

R_i = excess return on asset i

FF = vector of three Fama and French factors (market return, market capitalisation and a value factor namely the book-to-market ratio)

$E_t(.)$ = conditional expectation, given the public information set at time t

β_{ikt} = conditional beta with respect to factor k = $\gamma_{ik0} + \gamma_{ik1} Z_{it}$

where γ_{ik0} = scalar

γ_{ik1} = vector of N parameters

Z_{it} = vector of N instruments

They find that the conditional three-factor model outperforms the static version, but that it still fails to completely capture cross- section of returns. In an attempt to identify the sources of mispricing, Bauer *et al*. (2010) apply the framework of Avramov *et al*. (2006) to their data, and find that although the model captures the size effect (market capitalisation) it fails to capture the cross-sectional predictive power of the momentum effect.

Using the monthly largest 300 constituents of the Dow Jones Sector Titans Composite Index, Hsieh (2010) constructs size, value and momentum indices for the period 1991 to 2008. Momentum indices are based on 1-month lagged prior 11-month returns (excluding the immediate prior 1-month return), and it is found that these momentum indices earn significant abnormal returns relative to the MSCI World index.

Fama and French (2010) add the momentum factor to their three-factor model (1993) and test the traditional three and new four-factor model on four regions, namely North America, Europe, Japan and Asia Pacific. Although their tests do not support integrated pricing across regions, they do find that the three- and four-factor models support integrated pricing within the regions. Specifically, they conclude that size, value and momentum are common risk factors on the local front of North America (given that portfolios aren't tilted towards microcap shares) and that the cross-section of returns can therefore be explained by the four-factor model. With regards to Japan, they find that momentum is not an issue and that the three-factor model can therefore be used to explain cross- section of returns in the Japanese market. While the three-factor model is found to be acceptable for size and value- tilted portfolios in Europe, momentum-tilted portfolios are found to be more of a challenge. To address the problem they construct a six-factor model by splitting the big and small components of the value and momentum factors and using these as separate explanatory variables. They find that the six-factor model is acceptable for the European momentum-tilted portfolios, but note that the case is not strong. Lastly, they find that the three and six-factor models are statistically acceptable for the Asian- specific size and value portfolios, but that none of their models are acceptable for momentum-tilted portfolios in this region.

3.2.1.2 Momentum and price reversal: South African studies

Page and Way (1992) find that portfolios constructed using prior winners on the Johannesburg Securities Exchange (JSE) outperform those using prior losers over a 36-month period.

For the period 1985 to 1998 Muller (1999) finds that an optimised momentum strategy (optimised relative to starting date of portfolio formation, formation period, number of shares and holding period) resulted in excess return relative to the market. However, the optimised contrarian strategy outperformed the momentum strategy, and Muller therefore concludes that there is clear evidence of market overreaction on the JSE which could be exploited profitably.

Investigating factors that explain expected returns on the industrial sector of the JSE, Van Rensburg (2001) finds that portfolios formed on 3-, 6-, 12- and 24-month momentum deliver excess return relative to the market for the period 1983 to 1999. Based on a cluster analysis approach, Van Rensburg concludes that three style factors, namely earnings to price (a value cluster), market capitalisation (a quality cluster) and 12-month positive returns (a momentum cluster) form a parsimonious representation of style-based risk on the JSE. Kornik (2006) however, finds that no momentum variables show any level of significance for distinguishing winner shares from loser shares for the period 1995 to 2005 on the JSE.

Hsieh and Hodnett (2011) construct 12-month, 36-month and 60-month equally weighted momentum portfolios based on the top and bottom 20 shares (ranked according to their prior 12-, 36- and 60-month period returns respectively) to investigate the price reversal effect on the JSE for the period 1993 to 2009. It is found that the loser portfolios outperform the winner counterparts, and that mean reversal is most significant for the portfolios formed, based on a 60-month momentum period. The 12- and 36-month momentum winner portfolios continue to accumulate excess return, while the average cumulative abnormal return of the 36-

month momentum winner portfolios turns negative 20 months after formation. Furthermore it is found that price reversal is stronger for loser portfolios, and that reversals are more likely during times of economic turmoil, making a contrarian strategy a safe haven during times of financial uncertainty.

3.2.1.3 Momentum and price reversal over very short periods: International studies.

Since the phenomenon of market overreaction has been suggested by De Bondt *et al*. (1985), a number of studies have tried to explain (or disprove) this phenomenon over all investment periods, including weekly and even intra-day horizons.

Lo and Mackinley (1988) test the random walk model using weekly stock market returns over the period 1962 to 1985. Based on different weekly sub-periods, they find significant positive serial correlation present in equally weighted as well as value-weighted CRSP NYSE-AMEX indices. This leads them to reject the random- walk model. It is commonly argued that new information is firstly reflected in the prices of large capitalisation companies and by means of a lag effect in the price of smaller capitalisation companies that trade less frequently, resulting in positive serial correlation for the latter. Lo *et al*. (1988) therefore adjust their data for the effect that size and infrequent trading may have on their results, and find that, although the serial correlation for larger companies is lower than that of smaller firms, it is still statistically significant. For individual securities however, Lo *et al*. (1988) find the presence of negative serial correlation although not statistically significant.

Brown and Harlow (1988) investigate De Bondt *et al*.'s (1985) overreaction hypothesis by means of three subtests: firstly whether market overreaction is indeed present over the long (one-, two- and three-year) and short (one month) terms, secondly whether the extent of the original price movement has an effect on the subsequent price movement (called the magnitude effect) and finally whether the duration of the initial price change has an effect on the size of the subsequent change (called the intensity effect). Evidence of overreaction, magnitude and intensity are found over the short- term (monthly investment periods). Furthermore, in line with prospect theory, an asymmetry is apparent in that the tendency to overreact is stronger and more predictable based on a negative stimulus. Over the longer term however, Brown *et al*. find that prices tend to keep moving in the same direction as the initial change, creating more of a momentum effect. Their results lead them to conclude that the tendency for the market to overreact is an asymmetric, short- term phenomenon.

Atkins and Dyl (1990) use data from the New York Stock Exchange for the period 1975 to 1984. They find that the price of stocks experiencing large declines in one day is followed by significant abnormal increases in subsequent days (measured over a 60-day period, starting 31 days from the loss), while large price increases are followed by negative abnormal declines in subsequent days, although the magnitude of the price reversal effect of the latter is much less than that of the former. However, after controlling for the size of the bid-ask spread, Atkins *et al*. (1990) find that traders cannot profit from a short- term price-reversal strategy, and conclude that markets are efficient when transaction costs are considered.

In a similar study, Cox and Peterson (1994) investigate the price reversal effect of stocks that experienced a price decline of at least ten percent in one day. The subsequent return of the stock is measured over different periods. In line with prior studies they find evidence of a short-term price reversal effect (they used a period of 1 through 3 days after the price decline), and furthermore that smaller firms reverse more than larger firms. Similar to the findings of Atkins *et al*. (1990) they find that the bid-ask spread accounts for a substantial part of the reversal and conclude that short- term reversal strategies cannot be used to obtain abnormal returns. In line with Brown and Harlow (1988) they also find that over a longer period (days 21 through 120 after the decline) the stocks continue performing poorly, indicating more of a momentum effect.

Continuing with the bid-ask argument, Jegadeesh and Titman (1995) show that most of the short-term return reversals can be explained by the way dealers set bid and ask prices, taking into account their inventory imbalances. They furthermore find that these reversals are more likely in times of high-volume trading as this lead to larger inventory imbalances. Jegadeesh *et al*. (1995) ascribe the price-reversal strategy profits to compensation for bearing inventory risk and therefore, in practice, these profits cannot be obtained by traders transacting at bid and ask prices.

Another possible (partial) explanation for short- term price-reversal profits is found to be that of time-varying market risk. Hameed (1997) uses a time-varying factor model and finds that the predictability of short-horizon returns of small and large firms is a function of their sensitivity to a number of time-varying risk factors. In line with

Jegadeesh *et al*. (1995) Hameed also finds that trading volume has an effect on return autocorrelation, supported later by the findings of Chordia and Swaminathan (2000).

Avramov, Chordia and Goyal (2006) confirm price reversal effects over the short-term, especially for loser stocks. Interestingly, it is found that high turnover stocks experience higher negative serial correlation compared to lower turnover stocks using a weekly investment period, but this phenomenon is reversed when using a monthly investment horizon. For both horizons however, it is found that lower turnover stocks experience larger price reversals. They argue that, based on their findings, it would require high frequency trading of low liquidity stocks to profit from a short- term price reversal strategy. Such a strategy will however result in high transaction costs and price impact, eliminating the theoretical profits.

As part of an investigation as to whether providing liquidity to the market could result in abnormal returns, Rinne and Suominen (2010) examine the returns offered by a short- term price-reversal strategy, as such a strategy could be seen as providing liquidity. Their trading strategies result in statistically and economically significant excess returns. After controlling for factors such as size, value and bid-ask bounce, the strategy still proves profitable. However, these results are based on pre-transaction cost performance, and caution should therefore be taken before their results can be interpreted as a practical profitable trading strategy.

During the last decade, a number of studies have emerged that investigated the profitability of short- term price-reversal strategies in countries outside the US. As within the US, the results of these studies lead to the formation of two schools, those who are advocates of the strategy and those who believe the profitability of the strategy is not practically exploitable.

Lee, Chan, Faff and Kalev (2003) use weekly data of the constituents of the All Ordinaries Index for the period 1994 to 2001 to test the profitability of short- term price-reversal strategies in the Australian market. In addition to an equally weighted portfolio construction approach, Lee *et al*. also test the strategy using value-weighted portfolios. Furthermore they control for all of the possible explanations, suggested by prior researchers, that may (partially) explain the profitability of a short-term contrarian strategy (discussed above), to establish the robustness of their findings. Significant abnormal returns are obtained for both the equally weighted as well as the value- weighted strategies. The magnitude of these profits are found to be strongly related to firm size, while no compelling evidence is found for the profits to be related to the bid-ask bounce, seasonality or trading volume. However, when a practical short -selling strategy is employed that include transaction costs, the profits obtained are not statistically significant any longer. Their results lead them to conclude that, although the short -term price- reversal strategy has only limited value as a stand-alone strategy, it may be advantageous to use as an overlay strategy for existing strategies.

In a similar study, Antoniou, Galariotis and Spyrou (2006) control for all previously identified possible sources of short- term price-reversal profits and test whether such a strategy could be used to earn abnormal returns on the London Stock Exchange (LSE). As the profits remain statistically and economically significant even after controlling for all previously identified sources, they conclude that such a strategy could be profitable for traders on the LSE as it is mainly due to overreaction.

McInish, Ding, Pyun and Wongchoti (2008) investigate the profitability of short- term reversal and momentum strategies for seven Pacific-Basin capital markets over the period 1990 to 2000. Long/short portfolios are formed based on positive/negative excess return stocks based on a one-, two- and four-week ranking period. The portfolio is followed weekly for a period up to eight weeks. Previously identified factors such as trading activity, asymmetry in reaction to initial price changes, decomposition of profits as well as size and value effects are taken into account in their tests. Mixed results are obtained for the different markets. For five of the seven markets, it is found that winners experience price reversal, while losers experience price momentum. Of all countries however it is found that a contrarian strategy (based on winners) is only significant and persistent in Japan, while momentum strategies (based on losers) are significant and persistent only in Japan and Hong Kong. Noting the constraints on trading activity such as short selling in some of these markets, combined with their findings, McInish *et al*. (2008) conclude that short- term contrarian and momentum strategies are not effectively profitable in these markets.

3.2.1.4 Momentum and price reversal over very short periods: South African studies.

Most of the published South African studies related to momentum and price-reversal strategies are based on medium to long- term investment horizons which is discussed in the previous section. However, Van Rensburg (2001) found that winner stocks over the past one-month, under-performed loser stocks. Although the underperformance is not statistically significant, his finding suggests a possible short-term reversal effect on the JSE.

3.3 Tests concerning the semi-strong form EMH

As discussed earlier, tests concerning the semi-strong form EMH focus mainly on firm- specific characteristics and events studies. Firm- specific characteristics refer to a firm's financial statement entries and financial ratios calculated from these entries. Some of these characteristics can be classified as style indicators, and are subcategorised into value, growth and size style-factors. Those shares that are regarded as trading at a discount relative to their intrinsic or fundamental values are normally referred to as value shares, while those shares associated with companies experiencing significant increases in earnings relative to the economy, are regarded as growth shares. Size refers to the market capitalisation of a firm. Price multiples such as price-to-earnings (P/E), price-to-book (P/B), price-to-cash flow (P/CF) and price-to-sales (P/S) as well as dividend yield (D/Y) are normally regarded as value indicators. Variables such as earnings growth, profit margin and return on equity (ROE) are generally classified as growth indicators. The majority of studies concerning the semi-strong EMH reviewed in this section, focus on style-factors.

Based on the review provided in this section, it is clear that some researchers regard the identified characteristics and/or events as indicators that could be used in exploiting potential market anomalies to obtain abnormal returns, thereby rejecting the semi-strong form EMH, while others regard it as common risk factors that should be included in an asset pricing model, failing to reject the semi-strong form EMH.

3.3.1 International studies

Ball and Brown (1968) investigate the usefulness of accounting income numbers (earnings) by examining the content and timeliness of the information captured in earnings numbers. They find that at least half of all information regarding a company that comes available during a year is reflected in the earnings number, and that this number is a good indicator of the future movement in the stock's price. With regards to timeliness however, they find that investors act on expectations of earnings even 12 months before it is reported in the annual income statement, and that these expectations are usually in line with actual numbers. They conclude that other, more prompt media sources (possibly including interim reports) are used to formulate expectations and therefore annual reports are not regarded as timely information.

Basu (1977) investigates the relation between common stock prices and the firm's P/E ratio. Sample shares were ranked according to their P/E ratios and five portfolios were created. The performance of the low P/E portfolios was compared to that of the high P/E portfolios over a period of 14 years. Portfolios were rebalanced once a year according to the P/E rankings. Basu found that the low P/E portfolios, on average, outperformed the high P/E portfolios, on both an absolute and risk-adjusted basis. Although the semi-strong form of the EMH could not be rejected when transaction costs, search costs and tax effects were taken into account, Basu (1977) concludes that publicly available P/E ratios seem to possess information content that may be worth investigating when constructing portfolios.

Reinganum (1981) finds that returns obtained from portfolios constructed based on firm size or earnings-to-price (E/P) ratios, differ substantially from that suggested by the CAPM. Due to the persistency of these abnormal returns, he argues that the cause is more likely to be an incorrectly specified equilibrium model rather than market inefficiency. Furthermore Reinganum (1981) finds that when returns are controlled for the size effect, the E/P anomaly disappears. This leads him to conclude that the size effect subsumes the E/P effect.

Banz (1981) investigates the relation between a firm's market capitalisation and its stock return over a forty- year period from 1936 to 1975. He finds that, on average, smaller firms outperformed larger firms on a risk-adjusted basis over this period, and argues that these results could be an indication of an incorrectly specified CAPM model. Banz notes however, that the size effect is not stable over time, as tests using different ten-year sub periods delivered significant differences in the size factor coefficient. He concludes that further research is necessary to ensure that size is an explanatory factor of stock returns and that it is not only a proxy of another true but unknown factor correlated with size.

Roll (1981) attempts to explain the size effect by comparing risk adjusted returns of an equally weighted index (of New York and American listed stocks) to that of a value-weighted index (S&P 500). By construction, an equally weighted index has higher exposure to smaller firms compared to a value -weighted index. Due to the infrequent trading of smaller stocks and the higher exposure to these, Roll finds that the equally weighted index shows higher autocorrelation compared to the value-weighted index. This leads to downward biased risk figures, resulting in the equally weighted index showing higher risk adjusted returns compared to the value- weighted index. To better estimate risk under conditions of infrequent trading, Roll calculates betas using Dimson's (1979) aggregated coefficients method. He finds that the equally weighted index is substantially riskier than the value-weighted index, which justifies its higher return. Roll therefore concludes that the anomaly observed with regards to firm size is in fact caused by an underestimation of risk due to infrequent trading of smaller stocks.

Stoll and Whaley (1983) creates 10 portfolios using constituents from the New York Stock Exchange (NYSE) based on market capitalisation, to investigate the small firm effect. As opposed to Roll (1981), Stoll *et al*. find that the use of relative risk factors obtained by using the Dimson (1979) aggregated coefficients method rather than the simple linear regression method is not sufficient to explain the small firm anomaly. Stoll *et al*. (1983) go on to test the effect transaction costs may have on the findings of Banz (1981) and Reinganum (1981). It is found that over short investment periods (one month), the abnormal return of the small firm portfolio was significantly negative, while it was not significantly different from zero for investment periods between 3 months and one year. In contrast with Banz (1981) and Reinganum (1981), Stoll *et al*. conclude that the CAPM, based on net of cost returns, cannot be rejected.

Blume and Stambaugh (1983) show that using recorded closing prices to compute single-period returns on individual stocks, are biased upward due to a "bid-ask" effect. They ascribe the findings of Reinganum (1982) and Keim (1983) that small firms significantly outperform larger firms, to this computational bias. Furthermore they argue that using a rebalanced equally weighted portfolio approach will not eliminate this bias, as such a portfolio return is simply an arithmetic average of returns on individual stocks. Blume *et al*. (1983) follow a buy-and-hold approach to test the size effect, as it is argued that such an approach will avoid the "bid-ask" bias due to a "diversification" effect. They find that the size effect is significantly less than what was reported earlier and furthermore that all of the size effect is due to the January effect.

Basu (1983) confirms Reinganum's (1981) findings that portfolios with higher E/P ratios and of smaller size outperform those with lower E/P and larger size on a risk-adjusted basis. However, controlling the returns for differences in risk and E/P ratios, the size effect virtually disappears. In contrast to Reinganum (1981), Basu (1983) concludes that the E/P effect subsumes the size effect rather than the other way around, and argues that the relation between E/P and stock returns is therefore more complicated than originally suggested.

Cook and Rozeff (1984) try to solve the puzzle of the relation between E/P, size and returns documented by Reinganum (1981) and Basu (1983). They find that, in addition to the presence of the January effect, both E/P and size effects are present, and that neither subsumes the other. They ascribe the reason for the contradicting results documented by Reinganum (1981) and Basu (1983) to a fortuitous choice of methods and sample-selection respectively.

Banz and Breen (1986) argue that sample biases may lead to spurious conclusions. They show that when look-ahead and ex-post-selection (or survivorship) biases are removed from the sample, the conclusions of Basu (1977, 1983), Reinganum (1981) and Cook *et al*. (1984) cannot be reached. Specifically, the unbiased sample used by Banz *et al*. (1986) shows that a relation between size, E/P or combination of the two and return, is nonexistent.

In an attempt to find a final, conclusive answer to the contradicting results proposed by the above researchers regarding the relation (if any) between E/P, size and stock returns, Jaffe, Keim and Westerfield (1989) collect data over a period of 35 years and control the data for survivorship bias. Their findings support those of Cook and Rozeff (1984) in that both E/P and size are related to returns, and that neither subsumes the other.

Building on the research of Ball *et al*. (1968), Ou and Penman (1989) gather information on 68 financial statement variables for the period 1970 to 1984 to determine if the direction of change in one-year ahead earnings can be determined by means of financial statement analysis. They conducted their research in three stages. Firstly, each descriptor was tested for significance by means of a LOGIT earnings prediction model. In the second stage, descriptors found to be significant on a 10% level in the first stage were used in a multivariate model. After dropping those descriptors that were not significant in the multivariate model, a stepwise procedure was followed and ultimately 28 descriptors (see Appendix A) were identified to be significant in determining the direction of change in earnings. From the 28 descriptors, Ou *et al*. (1989) derive a summary descriptor to use as an indicator of future earnings. They conclude that, according to their analysis results, this measure is not solely a risk attribute, and that it captures equity value not reflected in share prices.

Fama and French (1992) show that the book-to-market (B/M) ratio combined with size absorbs the roles of leverage and E/P ratios to capture cross -sectional variance in stock returns. Introducing the excess return on the market as a third factor in addition to the B/M and size factors, Fama and French (1993) propose their three-factor equilibrium model which, according to them, captures all previously documented apparent anomalies. They conclude therefore that these so-called anomalies are in fact an indication of an incorrectly specified equilibrium model rather than market inefficiencies.

Instead of following a statistical procedure to identify financial variables as possible indicators of future earnings as was done by Ou *et al*. (1989), Lev and Thiagarajan (1993) identify candidate descriptors from written pronouncements of financial analysts. Additionally Lev *et al*. (1993) extend the search for financial descriptors by conditioning the returns-fundamentals relation on macroeconomic variables in an attempt to investigate the economic relevance of descriptors. Twelve candidate descriptors are identified (see Appendix A) and tested of which most are found to be relevant to stock-return while also used by investors to assess persistency of earnings as well as future earnings growth.

Davis (1994) uses a sample that is clean of look-ahead and survivorship bias to address the arguments documented by Banz *et al*. (1986) and finds that E/P, CF/P and B/M all have explanatory power in returns. He argues that due to the high level of correlation between these variables, it is difficult to assess the marginal explanatory power of each and can therefore not propose a clear winner of the three. Furthermore he finds no evidence of explanatory power of firm size, but notes that this may be due to his sample selection procedure, in which only firms in the top half of the size spectrum are selected to avoid problems associated with infrequent trading and bid-ask spreads. He states that the size variable could well have proved significant if smaller firms were included.

Abarbanell and Bushee (1997) examine the economical justification of the candidate indicators identified by Lev *et al*. (1993). They confirm that there is justification for analysts to rely on most (but not all) of these indicators in assessing future performance, but that analysts do not entirely compound this information in their forecasts. A possible explanation for this phenomenon offered by Abarbanell *et al*. (1997) is that analysts are more concerned with near-term earnings and therefore information regarding longer term earnings captured by some of these indicators may be ignored. Another reason offered is that analysts fail to impound the information attained within these indicators in their forecast revisions.

In a follow-up study, Abarbanell and Bushee (1998) investigate the possibility of creating strategies based on earlier findings (Lev *et al*., 1993 and Abarbanell *et al*., 1997) to earn abnormal returns. They find that such strategies can indeed be formulated and that one-year-ahead earnings- news contributes to a large proportion of the abnormal returns. Furthermore they find that abnormal returns are concentrated around subsequent earnings announcements and that these abnormal returns obtained are unaffected by controls for Fama and French's (1992) size and book-to-market risk factors.

Fama (1998) argues that anomalies could largely be limited to small stocks or that small stocks are "just a source of bad-model problems" (Fama, 1998: 304). He suggests that a reasonable change in the method of estimating abnormal returns could cause anomalies to disappear and that long-term return anomalies are therefore fragile.

In addition to their findings regarding momentum and contrarian anomalies (see Section 3.2.1.1), Boynton *et al*. (2006) find that the premia associated with size and B/M anomalies are also substantially reduced after controlling for the statistical biases. However, as with the momentum anomaly, they conclude that neither the size nor B/M anomalies can be invalidated. Lewellen *et al*. (2006) find no indication of a size anomaly but argue that the B/M (and momentum, as discussed in Section 3.2.1.1) anomaly exist.

Liu, Nissim and Thomas (2002) investigate the valuation properties of a number of variables, including cash flow from operations, earnings before interest, tax, depreciation and amortisation (EBITDA), sales, earnings, book value of equity and forecast of earnings-per-share (EPS). They find that forward earnings perform best and improve as the forecast period increases, earnings perform better than book-value, while cash flow measures perform poorly. Interestingly, their findings suggest that, of all multiples considered, the sales multiple performs worst, contradicting the findings of Barbee *et al*. (1996). Building on these findings, Liu, Nissim and Thomas

(2007) extend their research to include countries outside the US, e.g. Australia, France, Hong Kong, Taiwan, Germany, Japan, South Africa and the United Kingdom. Confirming their findings of 2002, they find that earnings forecasts provide better measures of equity value compared to cash flow measures and dividends, in most countries.

Due to the lack of earnings forecast data for especially smaller and younger firms, Yoo (2006) tests whether using a composite approach in which a weighted average of four historical multiples (E/P, B/P, EBITDA/P and S/P) is calculated could offer an indication of equity value which is more accurate than a) using individual multiples and b) using only the forecast earnings multiple as suggested by Liu *et al*. (2002). He finds that the composite approach is indeed a more accurate reflection of equity value. To investigate b) he combines the earnings forecast multiple with the other four price multiples and compare the value obtained to that obtained using the earnings forecast multiple only. Yoo's (2006) findings however show that using the composite approach including the earnings forecast multiple does not improve on the accuracy of using the earnings forecast multiple only, and therefore confirms the valuation strength of the earnings forecast multiple suggested by Liu *et al*. (2002).

Barbee, Jeong and Mukherji (2008) argue that price to sales (P/S) has the most consistently significant relationship with stock returns. They decompose the P/S ratio into the products of other multiples and profitability ratios to determine the source of the high explanatory power of P/S. They conclude that the net profit margin is the most important ratio in explaining stock returns.

3.3.2 South African studies

De Villiers, Lowlings, Pettit and Affleck-Graves (1986) used the constituents of the industrial sector of the JSE for the period 1976 to 1980 to test for the size effect. Instead of a size effect, their analysis supported a different effect, namely a high-price effect referring to the phenomenon that high priced shares significantly outperform low priced shares.

Classifying industrial firms on the JSE as "premium" or "discount" with regards to their market to book value, Plaistowe and Knight (1986) investigate whether the B/M ratio can be used as a significant piece of information regarding the future performance of the firm. They find that the discount portfolio (shares with B/M values less than 1) significantly outperforms the premium portfolio. Three possible reasons are presented for their finding: The South African market is inefficient, and a strategy such as the one tested could be used by investors to earn abnormal returns in a consistent fashion, the joint distribution of share and market return is not stationary through time which may lead to irregularities in their statistical approach, or the results are due to selection bias, meaning that the market model is missing a variable that captures this anomaly.

In line with the findings of international researchers such as Cook *et al*. (1984) and Jaffe *et al*. (1989), Page and Palmer (1991) find that the E/P has a positive relationship with stock returns. They also argue that this relationship is stronger than that of the size-return relationship, but that the latter is nevertheless present as well, confirmed by a follow-up study by Page in 1996.

Waelkens and Ward (1997) corrected their 10-year sample dataset (1983 – 1993) on the industrial sector of the JSE for survivorship bias as well as for thin trading. Furthermore prices were adjusted for the bid-ask spread. In line with the findings of De Villiers *et al*. (1986), a possible high-price effect was observed. Noting that although the relation between high prices and market capitalisation has not yet been established, it is quite possible (and appears as such through their analysis) that such a relationship does exist as market capitalisation is a function of share price. If this is the case, the findings of Waelkens *et al*. (1997) may therefore also imply that buying small capitalisation shares may not deliver abnormal returns as is suggested by some international studies (discussed earlier). In fact, such a relationship implies the opposite, in that buying larger capitalisation shares may offer positive abnormal returns. Waelkens *et al*. (1997) conclude that, although their analysis suggests mostly the opposite of the commonly known size or low price effect documented by proponents of these anomalies, their findings still suggest that the JSE is market inefficient.

Van Rensburg (2001) includes numerous financial statement entries in analysing risk on the JSE. Although his findings suggest that some of the accounting variables tested have predictive power, a cluster analysis lead him to conclude that mainly three factors should be considered, namely earnings to price, (E/P), size and momentum. In a further study Van Rensburg and Robertson (2003a) find evidence of the existence of an independent relationship between size, P/E and stock returns on the JSE. They conclude that at least two style-based factors should be incorporated in a cross-section of returns model for the JSE.

Recognizing the argument of Fama and French (1992) that size and B/M combine to capture the cross-section of variation in stock returns and that the B/M ratio captures the influence of leverage and P/E, Auret and Sinclaire (2006) state that the P/E and size model suggested by Van Rensburg and Robertson (2003a) needs to be tested for its robustness by also including B/M as a possible explanatory style factor. To perform the test for robustness, Auret *et al*. (2006) use data over the same period (1990-2000) used to construct the Van Rensburg *et al*. (2003a) model. After correcting it for look-ahead and survivorship bias as well as for thin-trading, a similar procedure as Van Rensburg *et al*. (2003a) was followed to firstly determine the significance of six candidate style factors in explaining the cross- section of returns on the JSE individually. At this stage it was found that the B/M ratio was not only significant, but even more so than that of either the size or P/E factors. When B/M is added to the Van Rensburg *et al*. two-factor model, it is found that B/M almost completely subsumes both size and P/E as explanatory variables. However, including B/M in the analysis did not lead to an improvement on the original two-factor model of Van Rensburg *et al*. (2003a), which is ascribed to the high level of correlation found between B/M and the other candidate factors. Auret *et al*. (2006) conclude that the Van Rensburg *et al*. (2003a) two factor model is robust, but recommend that further research be conducted over a longer period of time to investigate the nature of the risk for which B/M is a proxy.

Basiewicz and Auret (2009) attend to the recommendations of Auret and Sinclaire (2006) and investigate the cross- section of returns on the JSE over the period 1989 until 2005. To increase the robustness of their results, Basiewicz *et al*. (2009) introduce a stricter liquidity filter rule compared to earlier studies to adjust for transaction costs. The logic behind this is that smaller firms may produce higher returns, but due to their illiquidity it is possible that this size premium may disappear after transaction costs have been taken into account. Following a portfolio sorts and Fama-Macbeth (1973) regression approach, it is found that the size and value premia exist, even after the adjustments for illiquidity and transaction costs. The strong predictive power of the B/M ratio found in the study of Auret *et al*. (2006) is confirmed, and in addition the effect of the size and B/M factors in explaining cross section of returns is found to be independent. Furthermore they find that the B/M ratio subsumes all other value indicators and conclude that it is the best value indicator to use with size in a style two-factor model to explain cross- section of returns on the JSE.

Using P/E ratios to allocate stocks to winner (high P/E) and loser (low P/E) portfolios, Cubbin, Eidne, Firer and Gilbert (2006) examine mean reversion regarding the P/E value on the JSE. They find that stocks tend to revert back to the mean, causing loser portfolios to increase in value while winner portfolios decrease in value. They mention however that unlike some of the international studies' findings, the loser portfolio only starts to consistently outperform the winner portfolio after a period of approximately eight months. Even after correcting for survivorship bias, the presence of the P/E-return relationship on the JSE is confirmed by Gilbert and Strugnell (2010), leading them to conclude that the mean reversion regarding P/E's (and therefore returns) on the JSE is a robust phenomenon.

As two (B/M and size) of the three factors of the Fama and Fench (1993) three-factor model are found to be significant on the JSE (Basiewicz *et al*., 2009), a logical next step is to test the applicability of the Fama and French (1993) three- factor model in its entirety on the JSE. Basiewicz and Auret (2010) do exactly that, and find that the three-factor model compares favourably to the CAPM as well as the two-factor model proposed by Van Rensburg and Slaney (1997). Furthermore they find that, in contrast with the findings of Van Rensburg and Robertson (2003b), after risk adjustment with the Fama and French three-factor model, B/M loses its predictive power while that of size is weakened. This implies that the value and size factors are proxies for common risk factors rather than an indication of market inefficiencies on the JSE.

Interestingly, contradicting results are documented in two of the most recent studies. Auret and Cline (2011) find no evidence of a size or value effect on the JSE. A different approach compared to Auret *et al*. (2006); Basiewicz *et al*. (2009 and 2010) is followed in deriving their results. They do however mention that focusing only on the industrial sector (as the definition of B/M differs between the sectors on the JSE) while introducing a liquidity filter and adjusting for transaction costs as were done in earlier studies could lead to these differences in results.

In contrast, Strugnell, Gilbert and Kruger (2011) confirm the size and value (based on the P/E rather than on the B/M ratio) effect on the JSE. Although they note that there is some tentative evidence of a decreasing size premium over time, they do not find it to be conclusive. Strugnell *et al*. (2011) suggest that a similar study be performed in which transaction costs are taken into account as this could lead to different results. Furthermore they suggest that using value-weighted portfolios rather than equally weighted portfolios could offer further insights.

3.4 Tests of the EMH based on an extreme performer approach

In Section 3.2 and 3.3 the approaches and results of the more traditional tests concerning the weak- and semi-strong form EMH relevant to this thesis were discussed. From these studies, a number of technical indicators and firm- specific characteristics have been identified (summarised in Appendix A) that could potentially impact the cross -section of returns on the JSE. Specifically, these factors could either form part of a pricing model (according to proponents of market efficiency) as they represent common risk factors, or can be used to formulate investment strategies that could offer abnormal returns in a consistent fashion (according to opponents of the EMH or proponents of market anomalies). In this section a relatively new and rather unexplored approach to test the EMH, the extreme performer approach, is discussed. Similar to the more traditional approaches the extreme performer approach offers the opportunity to identify potential technical indicators and firm- specific characteristics that may affect the cross- section of equity returns; however the focus is on equities that showed extreme positive and negative return levels during a specific period of time.

3.4.1 International Studies

3.4.1.1 Reinganum (1988)

Using 222 stocks that at least doubled in price during one year from 1970 to 1983, Reinganum (1988) investigates the shared characteristics of these stocks. These “winner” companies’ financial conditions in the buy quarter are compared to the conditions in the sell quarter as well as the quarters immediately preceding the buy quarter. These conditions are divided into five categories, namely “smart money”, valuation measures, technical indicators, accounting earnings and profitability measures and lastly, miscellaneous.

Within the “smart money” category, two variables are identified, namely the number of institutions holding a specific issue and the aggregate holdings of institutions as a percentage of outstanding common stock. A major increase in both these indicators is found between the buy and sell quarters. However, he also finds that investment advisors increase their investment in these stocks only after the price appreciation starts, and their action could therefore not be seen as a good predictive indicator.

Using stock price level, P/E ratios, market capitalisation (small cap stocks), beta and price-to-book ratios as valuation measures (second category), Reinganum (1988) concludes that only price-to–book ratios of less than one could be used as a good predicting indicator of a winner stock.

Reinganum (1988) proposes two indicators with regards to the technical indicator category in order to identify winner stocks. Firstly, a relative strength ratio of at least 70, where relative strength is defined as the weighted average of quarterly price changes over the previous year, and secondly, firms with a positive change in their relative strength ranking from the previous quarter.

Within the accounting earnings and profitability category, Reinganum (1988) concludes that positive pre-tax profit margins, quarterly earnings- and sales-acceleration and positive 5-year quarterly earnings growth rates are good indicators of future winners.

Lastly, Reinganum (1988) finds that winner firms usually have less than 20 million shares outstanding and that most stock prices are within a fifteen percent range of the two-year high. These indicators are classified under the miscellaneous category.

Reinganum (1988) uses the nine indicators identified in his research to formulate filter rules to select stocks in creating a portfolio. Those stocks used to identify the indicators were deliberately excluded from the portfolio to avoid possible biased results. He finds that the portfolio significantly outperforms the S&P 500 index, and that the outperformance was not concentrated in only a few firms or during specific periods, but rather that most firms (approximately 80% of selected firms) outperformed the index and the overall portfolio outperformance was on an annual basis.

3.4.1.2 Beneish, Lee and Tarpley (2001)

Beneish, Lee and Tarpley (2001) combine the results of Basu (1977), Reinganum (1988), Ou and Penman (1989), Bernard and Thomas (1989, 1990), Chan, Hamao, and Lakonishok (1991), Fama and French (1992), Holthausen and Larcker (1992), , Lakonishok, Shleifer and Vishny (1994), Davis (1994), La Porta (1996), Sloan (1996), Beneish (1997), Abarbanell and Bushee (1997) and Piotroski (2000) to test the predictive power of twenty market-based and fundamental accounting variables on extreme performers.

Using all firms in the CRSP and merged Compustat universe and excluding firms with share prices below $5 to account for thin trading, Beneish *et al*. (2001) find that market-based indicators can be used to filter stocks that could potentially be extreme performers (i.e. within the top or bottom 2% with respect to performance) while fundamental signals can be used to separate extreme winners from extreme losers. Extreme winners are defined as those shares within the top 2% of size-adjusted performance during the "target quarter", the latter being the calendar quarter that starts three months after the current fiscal quarter end. The three-month lag ensures that the accounting information from the current fiscal quarter is publicly available before the accumulation period. Similarly, the extreme losers are those shares that falls in the bottom 2% of size-adjusted performance during the target quarter. Their study is based on the period 1977 to 1997, and their findings are based on common characteristics identified within the extreme performers relative to the control group (the remaining 96% of sample shares). Of the 20 literature-gathered variables used, the common characteristics (relative to the control group) found to be good indicators of extreme performance (either winners or losers) include age (younger firms), smaller market capitalisation, higher recent trading volume (prior 6-month average daily trading volume), higher sales growth, greater return volatility, higher research and development (R&D) intensity and lower sales-to-price ratios. Once the shares have been filtered as potential extreme performers, a second filter-rule approach is employed to separate the potential losers from the potential winners. It is found that those shares with lower sales-growth, deteriorating margins, lower R&D spending, more negative earnings surprises, worse recent (6-month) price performance, more aggressive accruals and higher capital expenditures are likely to be the losers.

Finally Beneish *et al*. (2001) perform an out-of-sample test of their filtering strategy and find that those shares identified as potential winners outperform those identified as potential losers by an 8.7% to 17.8% margin during the following year.

3.4.1.3 Glickman, DiRienzo and Ochman (2001)

In a similar fashion as Beneish *et al*. (2001), Glickman, DiRienzo and Ochman (2001) use the Russell 1000 and Russell 2000 indices to identify the characteristics of those shares that fall in the top and bottom 2.5% of total returns during the next quarter for the period 1992 to 2000.

Compared to the other shares within the indices, the top 2.5% are found to share the following characteristics: higher daily volatility over the previous quarter, higher past trading volume, smaller market capitalisation and larger long- term means of long-term growth rates (the exact period used for the long-term growth rates is however not specified).

The bottom 2.5% are found to have, on average, higher positive accruals, more negative cash flows from operations, more receivables, higher probability of declining asset turnover from previous year, lower returns over previous year and higher returns for the period from three years ago until one year ago.

A notable difference between the findings of Glickman, DiRienzo and Ochman. (2001) and that of Reinganum (1988) is the effect of a contrarian strategy. According to Reinganum (1988), a contrarian strategy does not contribute to identifying “winners”. Glickman *et al*. (2001) however find that such a strategy could indeed assist in identifying possible future top performers.

Using the technical and fundamental factors identified in their research as stock filters, Glickman *et al*. (2001) formulate a strategy to construct long and short portfolios. The filter rules are applied to the Russell 1000 and Russell 2000 indices over the period October 1992 until February 2000. Shares that are filtered as possible extreme outperformers are used to construct a long portfolio, while those that are filtered as possible extreme underperformers are used to construct a short portfolio. Portfolios are formed on a monthly basis and are held for three months. It is found that the portfolios offer abnormal returns, in that the long-short portfolio created from the Russell 1000 (2000) returns 8.77% (7.34%) per quarter with a standard deviation of 19.35% (10.52%).

3.4.1.4 Dong, Duan and Jang (2003)

In an attempt to enhance the work of Beneish *et al*. (2001), Dong, Duan and Jang (2003) apply a neural network approach in identifying extreme performers. A neural network is a series of algorithms that attempt to identify underlying relationships in a set of data and has the ability to adapt to changing input so that the network produces the best possible result without the need to redesign the output criteria. Following this approach allows Dong *et al*. (2003) to move away from a parametric to a non-parametric model which should be a more accurate approach as the data used is non-linear.

Using the same data sources as Beneish *et al*. (2001), and also excluding shares with prices below $5 to account for thin trading, Dong *et al*. (2003) finds that their neural network approach offers a model with similar predictive power but with less than a third of the filter variables needed compared to the linear model of Beneish at al. (2001). The lesser amount of data needed is beneficial as less data collection is needed while the variables identified should also be easily obtainable. They find that the common characteristics amongst top performing shares include smaller market capitalisation, higher share price, younger firms and reported revenue and sale losses.

3.4.1.5 O'Neil (2002, 2004)

Using a self- compiled database of thousands of stocks, O'Neil (2002) identifies and analyses the 500 best performing stocks over a 40 year period (1953 to 1993) to identify common characteristics amongst these shares. The study conducted by Reinganum (1988) is closely related to the work of O'Neil, as Reinganum (1988) made use of data supplied by O'Neil and Co. and also garnered winner stocks from O'Neil's publication "The Greatest Stock Market Winners: 1970 – 1983". Based on the seven identified common factors, O'Neil (2004) uses the acronym CAN SLIM to describe a stock filtering strategy. The acronym refers to **C**urrent quarterly earnings per share, **A**nnual earnings per share, **N**ew -products, -services, -management or -improvements in industry conditions, **S**upply and demand, **L**eaders or laggards, **I**nstitutional sponsorship and **M**arket direction.

The filter rules applied to each of the identified indicators can briefly be summarised as follows:
Current quarterly earnings per share must be 18 to 20 percent higher, while showing accelerated growth.

With respect to annual earnings per share, the rule requires an annual growth rate of at least 25 percent over the previous three years, increasing annual pre-tax profit margin or ROE, an ROE of at least 17% and a reasonable increase in next year's consensus earnings estimates.

The rule applied to the "New" indicator is mainly based on technical analysis, and is formulated as buying shares of which the price is within 10 to 15 percent of the year's price highs while the daily trading volume should increase by at least 50 percent above average daily volume. The rule further stipulates that additional securities be bought if the price increases by another 2 to 3 percent above purchase price, no more purchasing after an increase of at least 5 percent and sell all shares at a decrease of 7 percent or more relative to purchase price to limit losses.

With regards to supply and demand, O'Neil recommends to focus on shares of companies with less than 25 million shares outstanding, companies that are undertaking share buy-backs or have management ownership. He recommends that small capitalisation stocks be avoided and that daily trading volume be monitored as an indication of an increase or decrease in demand.

According to the leaders or laggards rule, O'Neil recommends that companies be ranked within their industry according to annual earnings- and sales- growth, pre- and after- tax profit margins, ROE and product quality. Then, focusing on the top two or three companies within each industry, a company with a relative strength ratio of at least 70 should be bought.

The institutional sponsor rule requires that the number of institutional owners of a share must have increased during the last few quarters and there must be at least 25 institutional owners before it must be considered. According to O'Neil institutional ownership is a reflection of the perspective of those parties that have the greatest influence on a stock's price.

Lastly, O'Neil recommends the use of technical analysis to determine the market direction, and suggests that securities be avoided when the technical indicators are predicting a weak market.

Unfortunately only the results and findings as discussed above are published in O'Neil's book, with no indication of empirical results based on this methodology.

3.4.2 South African studies

3.4.2.1 Tunstall, Stein and Carris (2004)

Based on the period 1994 to 2004, Tunstall, Stein and Carris (2004) analyse extreme performing stocks on the JSE securities exchange to determine which common characteristics are present amongst these stocks. Extreme winners are defined as stocks that have returned more than 100 percent over a year, while extreme losers are defined as stocks that have decreased by at least 50 percent over a year. To account for thin trading, stocks with prices less than 50 cents are excluded.

Two sub-samples are formed based on an alphabetical approach. Those shares with names starting with the letters A to M form the first sub-sample while the others form the second. The analysis is based on the first sub-sample while the second is used to construct portfolios based on filter rules derived from their findings using the first subsample. Finally the performance of the formed portfolios is compared to that of the overall market.

Tunstall *et al*. (2006) find that small market capitalisation, low market to book values, low earnings growth, low ROE and low forecast earnings growth are common trades among shares defined as winners. Losers generally show high previous 12-month momentum, high market-to-book values, low dividend yields, relative high standard deviations of monthly returns, low payout ratios and high capital gearing.

By formulating filter rules based on the above characteristics and applying it on the second sub-sample for holding periods of 12 months, Tunstall *et al*. (2004) find that it may be possible to create portfolios that outperform the market, more so if short-selling is allowed. It should be noted however that no explicit risk-adjustment technique was applied in their research process.

3.4.2.2 Kornik (2006)

Kornik (2006) identifies 92 variables from the literature that could possibly be used to identify extreme performing shares and to separate winners (shares that have at least doubled during the previous year) from losers (shares that have at least halved during the previous year). The variables are categorised as information variables, technical indicators, valuation measures, fundamental variables and industry position variables.

Monthly data for the period January 1995 until December 2004 is gathered on the identified variables of shares listed on the JSE Securities exchange. Kornik develops and applies a stepwise median comparison test to create possible filter rules. The rules are analysed using risk-adjusted return measures such as the Sharpe ratio to determine the final winner and loser filter rules. It is found that shares classified as winners tend to have high past earnings yield, high past momentum (three-month momentum lagged 9-months), low profit margins, high return on assets, low change in total assets and a low change in accounts receivable relative to sales. Losers on the other hand tend to have high market-to-book ratios, low prices relative to past highs (current share price as a percentage of the past 12 month high), low earnings yield, low sales relative to cash held, low dividend yields and listed for a shorter period.

An independent sample of shares is adjusted for risk using the CAPM and the two-factor APT model (with Resources and Financial-Industrial indices as factors as suggested by Van Rensburg, 2002). Kornik applies the filter-rules derived and finds that the portfolios constructed still offers significant abnormal risk-adjusted returns, indicating that neither of the equilibrium models (CAPM or APT) can fully capture the anomalies identified.

3.5 Summary and conclusion

This chapter provides a review of over half a century's literature concerning tests and results of mainly the weak and semi-strong form EMH. From the review it is clear that the debate surrounding capital market efficiency is far from over, although some convergence of results is evident especially since the late 1990's. The different approaches followed in conducting the tests have resulted in the ramification of the overarching debate surrounding capital market efficiency into a number of different topics. Hence, a review such as the one provided in this chapter makes it possible to not only formulate a comprehensive view of the EMH debate, but also identify areas in which additional research can make a valuable contribution to the debate, possibly even precipitate the apparent convergence process.

Tests regarding the weakform EMH (discussed in Section 3.2) include autocorrelation tests of independence of returns, tests of the overreaction theorem and tests involving technical trading rules. Various contradicting results are reported, however it does seem from the latest research that most researchers find evidence of a price-reversal effect over very short as well as longer investment periods, while a momentum effect is apparent over medium terms. No final conclusion regarding the period to use when applying momentum and/or contrarian strategies are obtained however, as the periods reported by the different researchers vary considerably.

Tests regarding the semi-strong form EMH (discussed in Section 3.3) are dominated by those concerned with the identification of firm specific characteristics that explains future stock returns or the cross- section of returns. During the past decade, the results of these studies converged to suggesting mainly two style factors, namely size and value, as the most prominent explanatory variables of expected returns. With regards to value, the two indicators mostly researched are P/E and B/M, with the latter receiving most attention in current international literature, especially after Fama and French (1992) suggested that size and B/M collectively subsumes the effect of P/E. Not surprisingly the focus of the more recent studies has therefore shifted towards determining whether the size and value (specifically B/M) indicators together with a technical indicator (specifically momentum) are capital market anomalies that could be exploited to provide abnormal returns or simply common risk factors that should be included in equilibrium asset pricing models.

Alternatively to the more 'traditional' EMH tests discussed in Section 3.2 and Section 3.3, a relatively new and unexplored approach named the extreme performer approach is discussed in Section 3.4. Through the latter approach researchers attempt to identify technical and fundamental factors that are common amongst equities that experienced an extreme increase or decrease in price during a specific period. Once these factors have been isolated, filter-rule strategies are developed and applied to construct portfolios. It was generally found that these portfolios offer abnormal returns. In contrast to the contradicting conclusions regarding the EMH obtained using the more traditional tests, research to date based on the extreme performer approach suggests that capital markets are inefficient and that portfolios offering abnormal returns can indeed be constructed.

4

DATA AND METHODOLOGY

4.1 Introduction

The data analysed in chapters five through nine are introduced in this chapter. The data consist of substantial amounts of technical and fundamental factors with regard to each company under review. The methodology followed in the remainder of the thesis is also briefly outlined in this chapter.

The chapter is structured as follows: In Section 4.2 the problem statement and research objectives of the thesis are discussed. An overview of the data set is provided in Section 4.3, followed by a discussion of potential statistical biases and how the data set has been adjusted to control for these biases in Section 4.4. In Section 4.5 the firm- specific variables to be used for the analyses in this thesis are discussed, followed by summary descriptive statistics of these variables in Section 4.6. An overview of the methodology is provided in Section 4.7. More detail of the methodology is provided in the relevant chapters where the analysis is conducted. The chapter is concluded in Section 4.8.

4.2 Problem statement and research objectives

This thesis aims to examine the impact of firm-specific factors on the cross-sectional variation in Johannesburg Securities Exchange (JSE) listed equity returns using data for the period 1994 to 2011.

From the extensive literature review (Chapter 3) three possible approaches are identified that can be used to ascertain the identity of technical and fundamental factors that may explain the cross-section of equity returns. These approaches include a cross-sectional regression approach, a factor-portfolio construction approach and an extreme performer approach. In addition to examining the effect on the identity and explanatory power of the factors according to each respective approach, it allows for the formulation of a number of sub-questions which will assist with framing an in-depth, comprehensive understanding of the impact the different factors may have on the variation in the cross-sectional equity returns on the JSE. These sub-questions include:

1. Does the identity and explanatory power of these factors change over time?
2. Will varying holding periods have a significant effect on the identity and explanatory power of these factors?
3. What is the effect on the identity and explanatory power of these factors when the liquidity level of the sample is changed?
4. Could the identified factors be used to construct portfolios that offer abnormal returns?
5. Could well-known market models explain the excess returns offered by portfolios constructed, based on the identified factors?

The methodology to be followed to address the problem statement and to answer the aforementioned sub-questions is described in more detail in Section 4.7.

4.3 Overview of data set

Monthly data over a seventeen and a half year period from January 1994 through May 2011 on the Johannesburg Securities Exchange are used for the thesis. JSE All Share members that were listed during this period are included irrespective of whether a specific share has been delisted during the period under review. For a full list of shares that have either been delisted or restructured with a change in share code during this period see Appendix B.1. In total 219 companies (including those that have been delisted and/or undergone a restructuring process) were used, resulting in approximately 45 000 firm- months of data.

South Africa entered into democracy in 1994, and the period under review was specifically chosen to start only from this date as to avoid any possible distortions in the results obtained due to economical and political events prior to the transition as suggested by Brooks, Davidson and Faff (1997). They argue a transformation of South African financial markets from a state of segmentation to a degree of integration in world markets in the post 1990s period.

A period of approximately 17.5 years is one of the longest periods the author is aware of to be used for this type of research on the JSE, and should be more than enough to draw convincing conclusions. It further allows for creating two independent subsamples over a period of nine years and eight and a half years respectively for analysis and subsequent robustness test purposes. Each of these subsample periods covers a full investment cycle characterised by bear markets and bull markets, as well as extreme financial market conditions. The first subsample period starts in 1994 and covers the bull markets during 1996, 1999 and 2001, the 1998 Asian crisis and the 2000/2001 internet-bubble and 9/11 events. The second subsample starts in January 2003 and covers the strong bull-run experienced until 2007 and again in 2009, the financial crisis in 2008 and finally the current debt-crisis in Europe.

4.4 Potential statistical biases

4.4.1 Data-snooping

Using the same or a related historical database from previously conducted empirical studies for purposes of inference or model selection, as is the case in a number of US studies (as most of these studies use data from the same database, namely Compustat, over the same or similar periods), generally gives rise to data-snooping (White, 2000). Data snooping may result in obtaining satisfactory results due to chance rather than merit inherent in the method producing the results. Although prior empirical studies have been consulted in identifying candidate characteristics to be used in this thesis, specific steps have been taken to mitigate the possible effect(s) of data-snooping. First, the data set is unique in the sense that, to the author's knowledge, this is the longest period to be used to date for the analyses that follows on the JSE and covers every possible market cycle, including extreme events such as the financial crisis (2008) and European debt situation (current). Secondly, the data set does not coincide with any studies in which related analyses are performed as it includes data until as recent as May 2011. The only possible studies available based on a data set that coincides with this one are therefore those that are being conducted at the time of writing which, of course, are not available to the public yet. Thirdly, two independent data sets are used to perform the analysis (using the first subset) and test for robustness of the findings (using the second subset). Lastly, the primary findings documented in the literature chapter are primarily based on US data, while a "fresh" dataset of the JSE is used for this thesis.

4.4.2 Infrequent trading

Infrequent (or thin) trading refers to shares not being traded on every consecutive interval.

Increasing the periodic intervals (or differencing intervals, e.g. from weekly to monthly) used for the analysis may reduce the effect of infrequent trading, as more of the constituents will be traded during each consecutive interval. Schwartz and Whitcomb (1977) find that the coefficient of determination (or R^2) of the market model and the mean value of beta increases when the differencing interval is increased. This implies that infrequent trading, if not controlled for, could result in underestimating systematic risk.

Scholes and Williams (1977) show that, due to infrequent trading, ordinary least square estimators for securities trading either very frequently or very infrequently are biased upwards for alpha and downwards for beta. On the other hand, alpha and beta estimators are found to be biased in the opposite direction for those securities experiencing more average trading frequencies. To correct for these biases and inconsistencies within the coefficient estimators, Scholes *et al*. (1977) use the direction and magnitude of the biases to construct consistent estimators of alpha and beta.

Dimson (1979) argues that due to the underestimation of systematic risk for infrequently traded securities, the systematic risk of those securities that trade frequently will most probably be overestimated as the average beta of all shares should by definition be unity. To correct for this bias in systematic risk, Dimson (1979) derives the Aggregate Coefficients method to be used in estimating betas when share price data suffer from thin trading. The method is applied to UK Stock Exchange shares and it is found that most of the systematic risk bias is eliminated.

An alternative approach found in the literature to avoid the possible bias introduced by thin trading is to simply introduce liquidity filters when sampling stocks (e.g. Davis, 1994). Due to the high correlation between market value and trading activity (James and Edmister, 1983), the presence of smaller capitalisation stocks in a sample are most probably the cause of biased results due to infrequent trading. Yet another approach could therefore be to use market-value weighted portfolios instead of equally-weighted portfolios, as less emphasis will be placed on small capitalisation stocks, possibly reducing the effect of biases introduced by thin trading.

The potential problems associated with thin trading are mitigated in two ways based on the approach followed in this thesis. First, monthly data instead of higher frequency data is used. Secondly, the effect of adjusting the sample liquidity level will be examined. The liquidity level referred to is based on the market capitalisation value of the firms included in the sample. A sample of larger firms reflects higher levels of liquidity while the addition of smaller firms to the sample will lower liquidity levels.

4.4.3 Survivorship bias

Survivorship bias is the result of including only those companies that are currently listed in the data set, and in the process ignoring the weaker, non-surviving firms. The literature provides cases for and against the argument that survivorship bias may have a significant effect on a study's results.

Brown, Goetzmann, Ibbotson and Ross (1992) suggest that survivorship bias will lead to biases in first and second moments and cross moments in return, including beta. This will induce a spurious relationship between volatility and return, which could have serious implications for studies of capital market anomalies.

Davis (1996) investigates the effect of the Compustat survivorship bias on previously documented anomalies like the book-to-market ratio, earnings yield and cash flow yield over the 15 year period from July 1963 to June 1978. The data set is adjusted to include delisted shares, and he finds that controlling for survivorship bias leads to attenuated coefficients for these variables previously found to be significant in explaining realised stock returns, but that the coefficients are still significant. Davis (1996) recommends that care should be taken using data covering surviving firms only as this could lead to coefficients being significantly overstated.

Gilbert and Strugnell (2010) find that, irrespective of using a data set that has been controlled for survivorship bias or not, mean-reversion is detected on the JSE. However, they also find that returns on portfolios constructed using the dataset that is subject to survivorship bias offers returns that are significantly higher than those constructed from a data set that is free from survivorship bias. They conclude that although survivorship bias does not necessarily affect the presence of mean-reversion on the JSE, the effect is present and material, and should be avoided in empirical financial studies.

In order to avoid any possible negative effect in the results of the thesis due to survivorship bias, the data set includes all companies that have been listed during the period under review. In addition, a liquidity screening approach (as mentioned above) is applied that will further help to mitigate the potential effects of survivorship bias.

4.4.4 Look-ahead bias

Look-ahead bias is due to a dating problem, in that data may be reported for a specific point in time but are actually only available to the investor at a later point in time (Banz & Breen, 1986). The effect of look-ahead bias can be significant on the results of empirical financial studies. Banz *et al*. (1986) compare the effect of look-ahead bias on previously documented capital market anomalies. They find that significant return differences exist between portfolios formed using the biased and bias-free data sources, while look-ahead bias can also cause different conclusions regarding the apparent anomalies.

In an attempt to avoid the potential effect of look-ahead bias on the results, the data used for the thesis have been sourced from databases that are only updated once the data is available.

4.4.5 Outliers

To deal with outliers in this thesis, a winzorising approach was followed (Foster, 1978). First, a natural logarithmic transformation was applied to those variables that are significantly positively skewed and for which it is statistically (and practically) suitable. Those variables that have undergone this transformation process are listed in Appendix B.2. Due to an asymmetrical distribution’s mean being much closer to the outliers than its median, the second step was to remove all outliers further than five standard deviations from its median from the sample. Thirdly, the mean and standard deviation are recalculated and all remaining outliers are winzorised to an outer boundary equal to three times the standard deviation from the mean. Lastly, histograms were created for each variable as a final check for remaining outliers (Appendix B.4).

4.5 Choice and categorisation of variables

Of the variables identified in prior empirical research (reviewed in Chapter 3 and summarised in Appendix A1) as many as possible have been included in this thesis. Data limitations however, does not allow for all of these variables to be investigated in this thesis. For this reason, and where possible, alternative proxies for these variables have been identified to be investigated for the South African market. In addition to these previously identified variables, those variables that make economic sense from a South African point of view have also been included. The purpose of including as many variables is twofold. First, this thesis addresses, inter alia, the hypothesis of efficient markets. In order to make a reliable recommendation as to the rejection of (or failure to reject) the null hypothesis (where the null hypothesis states that markets are efficient), a data set consisting of as many previously tested characteristics as possible as well as potential new candidate characteristics is needed to create a thorough database. Secondly, using such an original and comprehensive data set will ensure that data-snooping bias is avoided (refer to Section 4.4.1).

Data on the selected variables were collected from I-Net Bridge, Bloomberg and Datastream. The choice and categorisation of selected variables is motivated by the following rearrangement of the Gordon-Shapiro (1956) constant growth model:

$$E(R_i) = \frac{E(D_{i1})}{P_{i0}} + E(g_i) \qquad \text{...(4.1)}$$

where

$E(R_i)$ = the expected return for asset *i*

$E(\mathrm{D}_{i1})$ = expected dividend at time 1 = $D_{i0}(1+g_i)$

P_{i0} = share price of asset *i* at t = 0

$E(g_i)$ = the expected (constant) growth rate of dividends of asset *i*.

From equation (4.1) it is seen that the Gordon-Shapiro (1956) constant growth model implies a positive relationship between the expected return of an asset and a) ‘value’ measures (indicated by the first term on the right hand side of equation (4.1)) as well as b) expected future 'growth' measures (indicated by the second term on the right hand side of equation (4.1)).

By investigating the construction of the dividend yield measure, it is clear that this characteristic will share a close relationship with other measures of this characteristic. For example, the relationship between the measures of the 'value' characteristic, namely the dividend yield (D/P), earnings yield (E/P) and book-to-market ratio (B/P) can be presented as follows (Van Rensburg, 2001):

$$\frac{E}{P}=\frac{D}{P}\left(\frac{1}{b}\right)=\frac{B}{P}\left(\frac{E}{B}\right)=\frac{B}{P}(ROE)$$

where

E = earnings per share

P = price per share

D = dividend per share

b = payout ratio (i.e. $\frac{D}{E}$)

B = book (or net asset value) per share

ROE = Return on equity = $\frac{E}{B}$

The three ratios (D/P, E/P and B/P) display analytic interrelationships, and are therefore likely to put across (by construction) similar information, at least to a certain degree. Selecting the E/P ratio as the benchmark, the above relationship indicates that the dividend yield (D/P) puts across additional information regarding the payout ratio (b) while the book to market ratio (B/P) puts across additional information regarding the return on equity (ROE). One of the empirical questions this thesis will address is which (if any) of these *a priori* equally motivated formulations are most appropriately specified in an asset pricing model.

It may also be possible that some variables that are *prima facie* associated with the rejection of the efficient market hypothesis may also have explanatory power with regard to the cross-section of equity returns. These variables include those associated with price momentum and overreaction (see for example Jegadeesh & Titman, 1993; De Bondt & Thaler, 1985 reviewed in Chapter 3).

In accordance with the above, the variables used in this thesis are categorised into a) value measures, b) growth measures and c) technical measures.

4.5.1 Value measures

In addition to the dividend yield (D/P) measure implied by the Gordon-Shapiro (1956) constant growth model and those shown above to have a close relationship with the dividend yield (i.e. E/P and B/P), price-to-sales (P/S) and price to cash flow (P/CF) ratios have also been classified as value measures for this thesis.

Due to the possible incorrect interpretation of the previously documented (reviewed in Chapter 3) price-to-earnings anomaly during times of negative earnings, the inverse of the P/E ratio (i.e. earnings yield) is used instead. According to the P/E anomaly, shares with relatively lower P/E ratios tend to outperform those with higher P/E ratios. However, when shares are sorted based on a P/E ratio, negative earnings may result in such a share being regarded as a low P/E share (due to the negative value), while in fact such a share should be treated as a potentially high P/E or expensive share. Sorting the shares based on the earnings- yield instead would correctly identify shares with low (negative) earnings-yield as those with high P/E ratios.

For purposes of consistency, the price is used as the denominator in all value measures.

4.5.2 Growth measures

Growth measures are used by analysts to form an opinion about future growth prospects of the company under review (and therefore share performance) relative to other companies within the industry and relative to the general economy. Variables such as dividend growth, as implied by the Gordon-Shapiro (1956) constant growth model, earnings growth and return on equity (ROE) are generally regarded by these analysts as growth measures. As can be seen from the final list of variables included (Table 4.2), additional variables have been identified that are categorised as growth measures in this thesis.

For the purposes of this thesis, earnings growth has been calculated slightly different than the norm. Generally, earnings growth is calculated as follows:

$$g_e = \frac{e_t - e_{t-1}}{e_{t-1}} \qquad ...(4.2)$$

where

g_e = growth in earnings

e_t = earnings at time t

However, in cases where a period of negative earnings is followed by positive earnings, using formula (4.2) may introduce errors in calculating earnings growth. For example, if company A reported a negative earnings of 100 at time *t-1*, followed by positive earnings of 100 at time *t*, the growth in earnings from period *t-1* to *t* will be -200% using formula (4.2). This value does not reflect the significant improvement in earnings however. Therefore, to avoid such a “miscalculation”, the earnings growth is calculated as:

$$g_e = \frac{e_t - e_{t-1}}{p_t} \qquad ...(4.3)$$

where

p_t = share price at time t

everything else as before.

4.5.3 Technical measures

Technical indicators mainly refer to those variables needed to identify and analyse historic price patterns and trading volume to assist in investment decision- making. For this thesis, the variables regarded as potential technical indicators are classified into one of three subcategories.

i. <u>Momentum</u>

According to the literature reviewed in Chapter 3, momentum and/or price-reversal strategies could possibly result in profitable portfolios. However, contradicting evidence of whether a momentum or price-reversal strategy (or a combination of the two) should be followed, as well as the period over which momentum should be measured and applied in constructing such portfolios, is reported. Therefore momentum variables over different periods are included in this thesis to test for momentum and price-reversal strategies on the JSE.

An indicator which is often used by technical analysts to confirm momentum is the average value of a security's price over a specific trailing period, generally referred to as the moving average. None of the literature consulted has investigated the relationship between the moving average and the variation in cross-section of share returns. Eleven moving average variables (ranging from 2 to 12 month moving averages) have been constructed together with dummy variables (where the dummy variable is assigned a value of one if the price of the share is greater than the specific moving average and zero otherwise) and are included in this thesis to test for such a relationship on the JSE, for the first time.

ii. Size

Market capitalisation has been reported in a number of articles (refer to Chapter 3) as either an indication of market inefficiency or a common risk factor. Nevertheless, from the literature review it appears that market capitalisation is one of the most important factors to take into consideration when constructing portfolios. Due to the South African market being dominated by only a few shares, the distribution of market capitalisation is significantly positively skewed. Therefore a logarithmic transformation process was followed to obtain a new variable which is distributed more normally. In addition to market capitalisation, a number of other variables that may be used as a proxy for the previously documented size effect have been included in the size subcategory to compare to the explanatory power of market capitalisation.

iii. Volatility

A number of studies have found that there is a significant relationship between return volatility and share performance. In this thesis the variance of monthly returns over the past year is used to investigate such a relationship on the JSE. Additionally, the CAPM beta is also classified as a volatility characteristic.

From the initial list of all variables considered (Appendix B.3), it seemed that a degree of similarity may be present between some of the selected variables as they are closely related. The original list is compiled of variables found to be significant in different studies during different periods of time over different investment horizons. In addition, variables that make economic sense from a South African point of view have also been included. This process of variable selection can therefore result in some variables being highly correlated with others, as similar effects are captured. A correlation matrix was created to investigate the degree of similarity between variables and is reported in Table 4.1 below.

Of those variables that capture similar effects as indicated by a high correlation coefficient between them, the ones that are regarded as the primary variables within a specific category were retained while most of the others were removed from the final list. This process is followed to ensure that similar effects are not captured by more than one variable that could potentially result in inaccurate conclusions. Variables that show a high correlation with others and that have previously been identified as significant in explaining variation in the cross-section of share returns have been retained in the final list of variables. The reason for retaining these variables is to investigate the robustness of their explanatory power and to determine whether related variables (indicated by a high correlation coefficient) may provide stronger explanatory power while capturing the same effect(s). The process of removing the majority of variables showing a correlation of at least 0.7 with others is in line with the process applied by Van Rensburg and Janari (2008). Due to the nature of its construction it can be expected that a number of momentum variables (see Table 4.2) will show a high correlation. All of these variables are retained however as the momentum period associated with the different variables, which could be the main reason for the high correlation, is also of interest in the analyses of this thesis. The final list of variables to be used in this thesis is reported in Table 4.2, while the correlation matrix for the final list of variables is presented in Table 4.3.

Table 4.1. Correlation matrix of initial variables considered

The correlation matrix of the list of initial variables considered is reported here. Those variables showing a correlation of 0.7 or higher are highlighted. The primary variables within each category defined (see Appendix B.3) were retained while most of the others capturing similar effects within the same category were removed from the final list. This process (which is similar to that followed by Van Rensburg and Janari, 2008) was followed to ensure that similar effects are not captured by more than one variable that could potentially result in inaccurate conclusions. Due to the nature of its construction a number of the momentum variables show a high correlation. The moving average dummy variables are omitted from the correlation matrix without loss of information.

	BETA	BVTMLOG	C24MBVTM	C24MDPSP	C24MEPSP	CFTP	DE	DPSLOG	DY	EARNREV3M	EG1	EPS	EPS1	EPS2	EQUITY	EY	G	ICBTIN	LNP
BETA	1.00	-0.16	0.02	-0.11	0.03	-0.17	0.07	0.36	-0.14	-0.08	0.18	0.45	0.46	0.51	0.47	-0.20	-0.02	0.07	0.50
BVTMLOG		1.00	0.40	-0.09	-0.04	0.62	0.10	-0.22	0.19	-0.04	0.01	-0.14	-0.16	-0.09	0.16	0.53	-0.51	0.14	-0.34
C24MBVTM			1.00	-0.19	-0.23	0.30	0.16	-0.05	0.07	-0.10	0.03	-0.04	-0.06	0.01	0.08	0.24	-0.07	0.16	-0.12
C24MDPSP				1.00	0.61	0.02	-0.10	0.15	0.25	0.02	-0.23	0.14	0.10	-0.02	-0.10	0.31	0.19	-0.20	-0.04
C24MEPSP					1.00	0.08	-0.11	-0.02	0.12	0.12	-0.30	0.11	0.08	0.02	-0.12	0.46	0.00	-0.18	-0.07
CFTP						1.00	0.16	-0.16	0.11	0.06	-0.07	-0.04	-0.06	-0.03	0.06	0.57	-0.36	0.06	-0.29
DE							1.00	-0.01	-0.07	-0.09	0.04	0.00	0.02	0.00	0.12	0.02	-0.04	0.52	0.02
DPSLOG								1.00	0.34	-0.12	-0.02	0.71	0.87	0.66	0.75	-0.10	0.37	-0.10	0.87
DY									1.00	-0.06	-0.15	0.21	0.23	0.10	0.22	0.30	0.44	-0.09	0.05
EARNREV3M										1.00	0.01	-0.03	-0.02	-0.02	-0.11	-0.03	-0.03	-0.05	-0.07
EG1											1.00	-0.13	-0.05	0.01	0.13	-0.38	-0.11	0.11	0.09
EPS												1.00	0.77	0.80	0.65	0.01	0.18	-0.07	0.71
EPS1													1.00	0.67	0.81	-0.02	0.22	-0.08	0.85
EPS2														1.00	0.64	-0.07	0.05	0.00	0.73
EQUITY															1.00	-0.07	-0.02	0.07	0.79
EY																1.00	-0.18	-0.05	-0.35
G																	1.00	-0.12	0.20
ICBTIN																		1.00	-0.03
LNP																			1.00

	LOGASSETS	MOM1	MOM3	MOM6	MOM12	MOM36	MOM60	MVLOG	OBOS2MMA	OBOS3MMA	OBOS4MMA	OBOS5MMA	OBOS6MMA	OBOS7MMA	OBOS8MMA	OBOS9MMA	OBOS10MMA	OBOS11MMA	OBOS12MMA	POUTRAT	PRICEREL12	PTSINV	RETVAR12	ROE	SPSLOG
BETA	0.57	0.01	0.00	0.00	0.03	0.07	0.06	0.64	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	-0.18	-0.15	0.41	0.03	0.21
BVTMLOG	0.06	-0.10	-0.17	-0.23	-0.27	-0.41	-0.43	-0.35	-0.10	-0.13	-0.16	-0.18	-0.20	-0.21	-0.22	-0.22	-0.23	-0.24	-0.25	-0.15	-0.18	0.11	0.12	-0.59	-0.07
C24MBVTM	0.09	-0.16	-0.27	-0.36	-0.52	-0.51	-0.36	-0.08	-0.16	-0.22	-0.26	-0.29	-0.32	-0.34	-0.36	-0.38	-0.41	-0.43	-0.45	-0.01	-0.43	0.15	0.25	-0.11	0.01
C24MDPSP	-0.17	-0.05	-0.07	-0.07	0.03	0.27	0.11	-0.08	-0.06	-0.07	-0.08	-0.09	-0.09	-0.09	-0.08	-0.06	-0.05	-0.04	-0.04	-0.02	0.03	0.02	-0.07	0.25	0.02
C24MEPSP	-0.09	0.00	0.00	0.02	0.16	0.36	0.08	-0.03	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.02	0.04	0.06	0.07	0.08	-0.29	0.09	0.07	-0.06	0.24	0.03
CFTP	0.02	-0.08	-0.12	-0.17	-0.20	-0.34	-0.38	-0.33	-0.08	-0.10	-0.12	-0.13	-0.15	-0.16	-0.16	-0.17	-0.17	-0.18	-0.19	-0.24	-0.11	0.29	0.03	-0.32	0.14
DE	0.31	-0.04	-0.04	-0.06	-0.09	-0.18	-0.20	0.13	-0.03	-0.04	-0.04	-0.04	-0.05	-0.05	-0.06	-0.06	-0.06	-0.06	-0.07	-0.04	-0.07	0.00	0.06	-0.04	0.04
DPSLOG	0.41	-0.05	-0.10	-0.12	-0.09	0.09	0.08	0.54	-0.06	-0.09	-0.10	-0.11	-0.12	-0.13	-0.14	-0.15	-0.15	-0.15	-0.15	0.45	-0.16	-0.46	0.07	0.17	0.44
DY	0.00	-0.09	-0.16	-0.21	-0.20	-0.11	-0.09	-0.04	-0.10	-0.15	-0.17	-0.19	-0.21	-0.22	-0.24	-0.25	-0.25	-0.26	-0.26	0.65	-0.12	-0.03	-0.13	0.08	-0.10
EARNREV3M	-0.12	0.11	0.27	0.28	0.27	0.13	0.04	-0.08	0.09	0.15	0.21	0.24	0.27	0.28	0.29	0.28	0.29	0.29	0.29	-0.09	0.26	0.02	-0.09	0.03	0.00
EG1	0.15	0.04	0.06	0.10	0.07	-0.09	-0.02	0.15	0.04	0.04	0.05	0.06	0.08	0.09	0.09	0.09	0.10	0.10	0.10	0.25	0.01	-0.05	0.18	-0.24	-0.06
EPS	0.42	0.00	0.00	-0.01	0.03	0.09	0.07	0.52	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	0.13	-0.08	-0.34	0.11	0.16	0.41
EPS1	0.48	-0.02	-0.04	-0.03	0.01	0.13	0.09	0.59	-0.03	-0.04	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04	0.24	-0.11	-0.39	0.14	0.12	0.41
EPS2	0.43	0.03	0.04	0.03	0.04	0.07	0.05	0.51	0.04	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.10	-0.02	-0.37	0.07	0.08	0.44
EQUITY	0.63	-0.04	-0.08	-0.10	-0.09	-0.07	-0.10	0.59	-0.04	-0.06	-0.07	-0.08	-0.09	-0.10	-0.10	-0.11	-0.11	-0.11	-0.11	0.28	-0.17	-0.37	0.23	-0.20	0.39
EY	-0.13	-0.15	-0.24	-0.32	-0.32	-0.17	-0.20	-0.38	-0.16	-0.21	-0.24	-0.27	-0.30	-0.32	-0.33	-0.33	-0.34	-0.34	-0.35	-0.35	-0.24	0.18	-0.01	-0.01	0.02
G	-0.11	-0.02	-0.04	-0.05	-0.02	0.17	0.20	0.14	-0.02	-0.04	-0.05	-0.05	-0.06	-0.06	-0.07	-0.08	-0.09	-0.09	-0.09	0.60	-0.04	-0.09	-0.09	0.75	-0.10
ICBTIN	0.20	-0.01	-0.01	-0.01	-0.04	-0.17	-0.12	0.03	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.04	-0.04	0.00	0.06	-0.13	-0.01
LNP	0.51	0.01	0.01	0.03	0.07	0.19	0.17	0.69	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.28	-0.07	-0.54	0.13	0.11	0.49
LOGASSETS	1.00	-0.04	-0.09	-0.11	-0.13	-0.16	-0.24	0.84	-0.04	-0.07	-0.08	-0.09	-0.09	-0.10	-0.11	-0.11	-0.12	-0.12	-0.12	0.09	-0.16	0.09	0.17	-0.17	0.41
MOM1		1.00	0.58	0.37	0.28	0.15	0.12	0.01	0.99	0.89	0.80	0.73	0.67	0.62	0.59	0.55	0.52	0.50	0.48	-0.01	0.45	-0.04	-0.01	-0.01	-0.04
MOM3			1.00	0.69	0.50	0.27	0.19	0.00	0.58	0.78	0.92	0.94	0.93	0.90	0.87	0.84	0.81	0.79	0.77	-0.05	0.62	-0.07	-0.03	-0.01	-0.06
MOM6				1.00	0.68	0.39	0.29	0.00	0.37	0.51	0.62	0.71	0.80	0.87	0.91	0.92	0.92	0.91	0.90	-0.07	0.65	-0.12	-0.08	0.00	-0.05
MOM12					1.00	0.53	0.31	0.02	0.28	0.39	0.46	0.52	0.57	0.62	0.66	0.70	0.73	0.77	0.81	-0.11	0.59	-0.19	-0.14	0.06	-0.04
MOM36						1.00	0.64	0.07	0.15	0.20	0.24	0.28	0.31	0.34	0.36	0.38	0.40	0.42	0.44	-0.10	0.27	-0.31	-0.10	0.36	-0.01
MOM60							1.00	-0.01	0.12	0.15	0.18	0.20	0.23	0.25	0.26	0.27	0.28	0.29	0.30	0.00	0.18	-0.29	-0.08	0.30	-0.01
MVLOG								1.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.20	-0.06	-0.12	0.13	0.11	0.27
OBOS2MMA									1.00	0.90	0.81	0.74	0.68	0.63	0.59	0.56	0.53	0.51	0.49	-0.02	0.47	-0.04	-0.02	-0.01	-0.03
OBOS3MMA										1.00	0.96	0.90	0.85	0.80	0.76	0.72	0.69	0.67	0.65	-0.04	0.59	-0.05	-0.04	-0.01	-0.04
OBOS4MMA											1.00	0.98	0.94	0.90	0.86	0.82	0.79	0.77	0.74	-0.05	0.66	-0.06	-0.05	-0.01	-0.04
OBOS5MMA												1.00	0.99	0.96	0.92	0.89	0.86	0.84	0.81	-0.06	0.70	-0.07	-0.06	-0.01	-0.05
OBOS6MMA													1.00	0.99	0.97	0.94	0.91	0.89	0.87	-0.07	0.72	-0.08	-0.07	-0.01	-0.05
OBOS7MMA														1.00	0.99	0.97	0.95	0.93	0.91	-0.08	0.74	-0.09	-0.08	-0.01	-0.05
OBOS8MMA															1.00	0.99	0.98	0.96	0.94	-0.09	0.76	-0.10	-0.09	-0.01	-0.04
OBOS9MMA																1.00	1.00	0.99	0.97	-0.10	0.78	-0.11	-0.10	-0.01	-0.04
OBOS10MMA																	1.00	1.00	0.99	-0.11	0.79	-0.11	-0.11	-0.01	-0.04
OBOS11MMA																		1.00	1.00	-0.12	0.79	-0.12	-0.12	0.00	-0.04
OBOS12MMA																			1.00	-0.12	0.79	-0.13	-0.13	0.00	-0.03
POUTRAT																				1.00	-0.04	-0.13	-0.03	0.06	-0.12
PRICEREL12																					1.00	-0.02	-0.39	0.03	-0.03
PTSINV																						1.00	-0.10	-0.06	0.02
RETVAR12																							1.00	-0.13	-0.03
ROE																								1	-0.01
SPSLOG																									1

Table 4.2 Variables used in this thesis

The table lists those variables that have been selected for the analyses performed in this thesis. Variables are listed per category (column 1). The codes associated with each indicator as used throughout the thesis are provided in column 2. Column 3 provides a description of the variable while the formula used for derived variables and ratios are given in the last column (where applicable).

Category		Code	Description	Formula
Value		bvtmlog	Natural log of book value to market	ln[book value to market]
		cftp	Cash flow to price	Cash flow / price
		dy	Dividend yield	dividend / price
		ey	Earnings yield	earnings / price
		stp	Sales to price	sales / price
Growth		eg1	% 1-year earnings forecast revision	$[w_1(eps1 – eps) + w_2(eps2 – eps1)]/eps$ where w_1 = (#days from month t to financial year end)/365 $w_2 = 1 – w_1$ eps = earnings per share eps1 = 1-year forward-looking eps eps 2 = 2-year forward-looking eps
		dpslog	Natural log of dividend per share (dps)	ln[dividend per share]
		icbtin	Inverse of Interest coverage before tax	1/[interest coverage before tax]
		de	Debt to equity	total debt / total equity
		roe	Return on equity	earnings / equity
		poutrat	Payout ratio	dividend / earnings
		earnrev3m	3-month % change in 1-year forward looking eps (eps1)	$([eps1_t – eps1_{t-3}])/[eps1_{t-3}]$
		c24mdpsp	Change in 24-month dps to price	$([DPS_t – DPS_{t-24}])/[price_t]$
		c24mepsp	Change in 24-month eps to price	$([eps_t – eps_{t-24}])/[price_t]$
		c24mbvtm	Change in 24-month book value to market	$[bvtm_t – bvtm_{t-24}]/bvtm_{t-24}$
Technical	Momentum	mom1	Previous 1-month return	$([\text{Total return}_t – \text{Total return}_{t-1}])/[\text{Total return}_{t-1}]$ Where Total return refers to the capital appreciation and dividend yield of a share.
		mom3	Previous 3-month's return	$([\text{Total return}_t – \text{Total return}_{t-3}])/[\text{Total return}_{t-3}]$
		mom12	Previous 12-month's return	$([\text{Total return}_t – \text{Total return}_{t-12}])/[\text{Total return}_{t-12}]$
		mom36	Previous 36-month's return	$([\text{Total return}_t – \text{Total return}_{t-36}])/[\text{Total return}_{t-36}]$
		mom60	Previous 60-month's return	$([\text{Total return}_t – \text{Total return}_{t-60}])/[\text{Total return}_{t-60}]$
		ma_p	price relative to p-month moving average in price	equal to 1 if $price_t$ > p-month moving average in price; 0 otherwise. p = 2 to 12.
		$OBOS_p mMA$ where p = 2 to 12	Overbought – oversold with p-month moving average of price	$[price_t – ma_k]/ma_k$ for k = 2 to 12.
		pricerel12	Comparison of price to 12-month high	$price_t/max[price_{t-12 \text{ to } t}]$
	Size	mvlog	Log of market value	ln[market value]
		eps	Earnings per share	earnings / # shares in issue
		spslog	Natural log of sales per share	ln[sales per share]
		lnp	Natural log of price	ln[price]
	Volatility	retvar12	Variance of monthly returns over previous12 months	Var[prior 12 monthly returns]
		beta	Beta	CAPM Beta, where beta is based on 3 year monthly returns.

Table 4.3. Correlation matrix of final variables

The correlation matrix of the final list of variables is reported here. Once again, the moving average dummy variables are omitted from the correlation matrix. The highlighted values indicate a high correlation coefficient (>0.7). Some of the variables showing a high correlation with others within the same category have been retained however as they have previously been identified as significant in explaining the cross-section of share returns, and will be tested again in this thesis. The moving average dummy variables are omitted from the correlation matrix without loss of information.

	BETA	BVTMLOG	C24MBVTM	C24MDPSP	C24MEPSP	CFTP	DE	DPSLOG	DY	EARNREV3M	EG1	EPS	EY	ICBTIN	LNP	MOM1	MOM3	MOM6	MOM12	MOM36	MOM60	MVLOG	OBOS2MMA	OBOS3MMA	OBOS4MMA	OBOS5MMA	OBOS6MMA	OBOS7MMA	OBOS8MMA	OBOS9MMA	OBOS10MMA	OBOS11MMA	OBOS12MMA	POUTRAT	PRICEREL12	PTSINV	RETVAR12	ROE	SPSLOG
BETA	1.00	-0.20	0.05	-0.16	-0.02	-0.19	0.00	0.46	-0.14	-0.03	0.16	0.52	-0.25	0.01	0.55	0.01	0.01	0.02	0.07	0.07	0.07	0.68	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.07	-0.16	-0.19	0.40	0.07	0.24
BVTMLOG		1.00	0.40	-0.07	-0.01	0.62	0.07	-0.25	0.19	-0.06	-0.01	-0.19	0.54	0.15	-0.36	-0.09	-0.14	-0.21	-0.29	-0.42	-0.43	-0.37	-0.08	-0.09	-0.11	-0.12	-0.14	-0.15	-0.16	-0.17	-0.18	-0.19	-0.21	-0.16	-0.13	0.14	0.10	-0.59	-0.10
C24MBVTM			1.00	-0.25	-0.26	0.29	0.12	-0.02	0.07	-0.10	0.02	-0.04	0.22	0.14	-0.10	-0.16	-0.27	-0.36	-0.52	-0.52	-0.35	-0.06	-0.15	-0.20	-0.24	-0.27	-0.29	-0.32	-0.34	-0.36	-0.38	-0.41	-0.43	0.00	-0.40	0.14	0.24	-0.12	0.00
C24MDPSP				1.00	0.68	0.04	-0.04	0.07	0.21	0.04	-0.16	0.08	0.29	-0.16	-0.05	-0.03	-0.03	-0.01	0.07	0.28	0.09	-0.09	0.01	0.02	0.03	0.03	0.04	0.05	0.06	0.07	0.07	0.08	0.08	-0.05	0.17	0.04	-0.10	0.21	0.03
C24MEPSP					1.00	0.10	-0.05	-0.05	0.09	0.12	-0.26	0.08	0.43	-0.15	-0.06	0.01	0.02	0.05	0.17	0.35	0.08	-0.05	0.05	0.07	0.09	0.10	0.11	0.13	0.14	0.16	0.16	0.17	0.18	-0.30	0.22	0.08	-0.07	0.19	0.06
CFTP						1.00	0.16	-0.18	0.12	0.03	-0.08	-0.07	0.58	0.06	-0.30	-0.07	-0.10	-0.15	-0.21	-0.34	-0.37	-0.33	-0.05	-0.07	-0.08	-0.09	-0.10	-0.11	-0.11	-0.12	-0.13	-0.14	-0.15	-0.24	-0.08	0.30	0.03	-0.31	0.11
DE							1.00	-0.08	-0.07	-0.09	0.02	-0.07	0.04	0.50	-0.04	-0.04	-0.05	-0.07	-0.10	-0.17	-0.17	0.09	-0.03	-0.04	-0.04	-0.04	-0.05	-0.05	-0.05	-0.06	-0.06	-0.06	-0.07	-0.05	-0.07	0.06	0.03	-0.03	0.01
DPSLOG								1.00	0.30	-0.07	-0.02	0.73	-0.15	-0.16	0.87	-0.04	-0.08	-0.08	-0.04	0.06	0.06	0.59	-0.05	-0.07	-0.09	-0.09	-0.10	-0.11	-0.11	-0.12	-0.12	-0.12	-0.11	0.44	-0.14	-0.47	0.10	0.19	0.45
DY									1.00	-0.07	-0.15	0.17	0.31	-0.10	0.02	-0.09	-0.15	-0.20	-0.20	-0.12	-0.11	-0.05	-0.10	-0.14	-0.17	-0.19	-0.20	-0.22	-0.23	-0.24	-0.25	-0.25	-0.26	0.66	-0.13	-0.02	-0.11	0.08	-0.11
EARNREV3M										1.00	0.03	0.01	-0.06	-0.06	-0.02	0.10	0.25	0.27	0.27	0.14	0.06	-0.04	0.10	0.16	0.21	0.24	0.26	0.28	0.28	0.28	0.28	0.29	0.29	-0.08	0.25	0.01	-0.06	0.03	0.03
EG1											1.00	-0.09	-0.36	0.09	0.09	0.04	0.07	0.10	0.08	-0.05	-0.01	0.14	0.04	0.05	0.06	0.07	0.09	0.09	0.10	0.10	0.10	0.11	0.11	0.22	0.03	-0.04	0.16	-0.22	-0.05
EPS												1.00	-0.05	-0.12	0.73	0.01	0.03	0.04	0.09	0.11	0.08	0.56	0.01	0.01	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.04	0.04	0.14	-0.04	-0.35	0.16	0.17	0.43
EY													1.00	-0.03	-0.37	-0.14	-0.23	-0.29	-0.31	-0.18	-0.19	-0.40	-0.13	-0.17	-0.20	-0.23	-0.25	-0.26	-0.27	-0.28	-0.29	-0.30	-0.30	-0.34	-0.19	0.20	-0.01	-0.02	-0.01
ICBTIN														1.00	-0.09	-0.02	-0.03	-0.03	-0.05	-0.14	-0.12	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.06	-0.05	0.04	0.05	-0.16	-0.04
LNP															1.00	0.02	0.02	0.05	0.12	0.20	0.16	0.72	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.03	0.04	0.04	0.05	0.27	-0.06	-0.55	0.14	0.12	0.52
MOM1																1.00	0.59	0.39	0.30	0.15	0.10	0.02	0.92	0.83	0.75	0.69	0.64	0.59	0.56	0.54	0.51	0.50	0.48	-0.01	0.44	-0.04	-0.02	-0.01	-0.03
MOM3																	1.00	0.70	0.50	0.26	0.17	0.01	0.55	0.74	0.87	0.89	0.88	0.86	0.83	0.81	0.78	0.76	0.75	-0.04	0.60	-0.07	-0.03	-0.01	-0.05
MOM6																		1.00	0.68	0.39	0.25	0.02	0.37	0.50	0.60	0.69	0.76	0.83	0.87	0.88	0.88	0.88	0.87	-0.07	0.62	-0.11	-0.05	0.01	-0.03
MOM12																			1.00	0.56	0.32	0.06	0.27	0.37	0.44	0.49	0.54	0.58	0.62	0.66	0.70	0.74	0.77	-0.09	0.54	-0.19	-0.11	0.08	0.00
MOM36																				1.00	0.63	0.08	0.13	0.18	0.22	0.25	0.28	0.31	0.34	0.36	0.38	0.40	0.42	-0.11	0.26	-0.29	-0.08	0.35	0.03
MOM60																					1.00	0.00	0.09	0.11	0.13	0.14	0.16	0.18	0.20	0.21	0.22	0.24	0.25	-0.04	0.13	-0.29	-0.08	0.31	0.02
MVLOG																						1.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.21	-0.07	-0.15	0.14	0.13	0.29
OBOS2MMA																							1.00	0.88	0.78	0.71	0.66	0.61	0.58	0.55	0.53	0.51	0.49	-0.04	0.48	-0.03	-0.03	-0.02	-0.02
OBOS3MMA																								1.00	0.95	0.89	0.83	0.79	0.75	0.72	0.69	0.67	0.65	-0.06	0.61	-0.04	-0.05	-0.03	-0.03
OBOS4MMA																									1.00	0.97	0.93	0.89	0.85	0.82	0.79	0.77	0.75	-0.07	0.68	-0.05	-0.05	-0.03	-0.03
OBOS5MMA																										1.00	0.98	0.95	0.92	0.89	0.87	0.84	0.82	-0.08	0.73	-0.05	-0.05	-0.03	-0.03
OBOS6MMA																											1.00	0.99	0.97	0.94	0.92	0.90	0.88	-0.09	0.76	-0.06	-0.05	-0.03	-0.03
OBOS7MMA																												1.00	0.99	0.97	0.96	0.94	0.92	-0.10	0.78	-0.07	-0.06	-0.03	-0.02
OBOS8MMA																													1.00	0.99	0.98	0.97	0.95	-0.11	0.80	-0.07	-0.06	-0.03	-0.02
OBOS9MMA																														1.00	1.00	0.99	0.98	-0.12	0.81	-0.08	-0.07	-0.03	-0.02
OBOS10MMA																															1.00	1.00	0.99	-0.13	0.82	-0.09	-0.08	-0.02	-0.01
OBOS11MMA																																1.00	1.00	-0.13	0.82	-0.10	-0.09	-0.02	-0.01
OBOS12MMA																																	1.00	-0.14	0.82	-0.11	-0.10	-0.01	-0.01
POUTRAT																																		1.00	-0.08	-0.13	-0.02	0.09	-0.11
PRICEREL12																																			1.00	0.00	-0.33	0.00	-0.01
PTSINV																																				1.00	-0.10	-0.07	-0.01
RETVAR12																																					1.00	-0.11	-0.01
ROE																																						1.00	0.00
SPSLOG																																							1.00

4.6 Descriptive statistics

For each variable to be used, traditional descriptive statistics such as the mean, median, standard deviation, kurtosis and skewness are reported in appendix B.4. Additionally, histograms are presented for each variable for visual inspection of the effect that the log transformation (where applicable) and winzorising processes had on the distribution of the variable. These statistics and histograms are provided for both subsamples.

4.7 Overview of methodology

A brief overview of the methodology followed in Chapter 5 through Chapter 9 is provided in this section. The methodology is described in detail within each specific chapter.

In Chapter 5 a univariate cross-sectional regression approach is followed to isolate those technical and fundamental factors from Table 4.2 that explain the cross-section of returns on the JSE on a monthly basis. A time-series of cross-sectional slopes resulting from the regression is created for each of the variables analysed which represent the ‘reward’ to the specific characteristic in each month. Those variables for which the time series mean value cross-sectional slope coefficient is significantly different from zero (based on a Student’s t-test) are regarded as potential factors to be used in subsequent multifactor analyses. The regressions are performed over three sample periods, namely January 1994 through December 2002, January 2003 through May 2011 and January 1994 through May 2011. Using these different periods allows for the examination of whether the identity and explanatory power of the factors change over time. Next, the effect of sample liquidity on the identity and explanatory power of the factors is examined by using different market cap levels as liquidity filters. The market cap is divided into deciles and the univariate cross-sectional regressions are repeated using a liquidity filter set equal to the 3rd through 7th market cap deciles. To obtain a comprehensive view of the effect of liquidity on the results, a two-factor cross-sectional regression is conducted using a dummy-variable to indicate whether a share forms part of the ‘Large-cap’ sample (where the latter refers to shares included in the sample when the liquidity filter is set equal to the 5th market cap decile) or the ‘All-share’ sample. Next, the effect of payoff period on the identity and explanatory power of the factors is examined by repeating the univariate cross-sectional regressions over a three, six, twelve, twenty-four and thirty-six month payoff period. Finally, the combined effect of time, liquidity and payoff period is examined by performing these univariate cross-sectional regressions over different payoff periods for the All-share and Large-cap samples respectively, over the three sample periods.

Single-factor portfolios are created in Chapter 6 by ranking each factor and subsequently forming two equally weighted portfolios. This is done by including the top and bottom 30% of shares (based on the factor ranking) into each respective portfolio, correspondingly referred to as Portfolio_1 and Portfolio_3. Portfolios are rebalanced every month (according to the factor ranking) to create monthly portfolio returns for each of the three sample periods. The returns of Portfolio_3 are subtracted from that of Portfolio_1 to create a monthly "long/short" hedge fund return series. A t-test is applied to determine whether this "long/short" return series differs significantly from zero to examine whether the concerned factor could be used in the portfolio construction process to offer abnormal returns. The procedure is repeated for a payoff period of 3-months to examine the effect that payoff period may have on the results. The analysis is performed for the All-share and Large-cap samples respectively. Lastly, the raw returns are adjusted for risk using the CAPM and Van Rensburg (2002) two-factor APT model to determine whether either of the market models can explain the factor portfolio excess returns.

Those technical and fundamental factors found to be significant in explaining the cross-section of returns in Chapter 5, or that can be used in creating factor portfolios that offer significant abnormal returns in Chapter 6, are used in multifactor analyses in Chapter 7. A multiple regression approach similar to Van Rensburg and Robertson (2003) is followed to determine the combination of factors that explain the cross - section of returns on the JSE. The process starts off by applying a cross-sectional regression based on all permutations of pairs of candidate factors identified in Chapters 5 and 6. Next, a three-factor regression is performed for each month for all permutations of significant pairs of candidate factors together with an additional candidate factor. This process is repeated until no more candidate factors can be added to the multiple regression equation without some or all of the factors losing their joint significance. The potential effect of time and liquidity is examined by performing the multifactor cross-sectional regressions for the All-share and Large-cap samples over each of the three respective sample periods.

A third approach to examine the impact of factors on the cross-section of returns, referred to as the 'extreme performer' approach in this thesis, is applied in Chapter 8 and Chapter 9. Two subsamples are formed by applying a cross -sectional split of the data over all-time series for the entire period (January 1994 through May 2011). An approximate equal number of shares representing each of the economic groups on the JSE are included in the two subsamples. The first subsample, Sample_A, is subsequently used to do the analysis while the second, Sample_B is used for 'out of sample' testing. Shares are classified as winners or losers (collectively referred to as extreme performers) by defining a winner as a share that increased at least 6% (100%) and a loser as a share that decreased at least 5% (50%) during a 1-month (12-month) period. Using binary dummy variables to distinguish between winners (losers) and the remainder of shares, regressions are performed to determine which factors differ significantly between winners (losers) and the rest. This process is repeated to determine which factors differ significantly between winner and loser shares specifically by including only extreme performers in the sample while ignoring the rest. The latter process is done to identify which factors could be used in subsequent analysis to filter potential winner and loser shares. Once the factors that differ significantly between winners and losers have been identified, logistic regression is performed to create logit models which can be used to predict potential winner and loser shares. These filtered shares are used to construct equally weighted winner, loser and benchmark portfolios to examine whether such a filter rule approach could offer portfolios that significantly outperform (in the case of the winner portfolio) or underperform (in the case of the loser portfolio) the benchmark portfolio. Raw returns obtained from the winner portfolio are adjusted for risk using the CAPM and Van Rensburg (2002) two-factor APT model to determine whether either of the market models can explain the winner portfolio excess returns. The entire procedure is applied for a 1-month (Chapter 8) and 12-month (Chapter 9) pay-off period to examine the effect that payoff period may have on the results.

4.8 Conclusion

In this chapter the data to be employed and methodology to be followed to identify those firm-specific factors that explain the cross-sectional variation in Johannesburg Securities Exchange (JSE) listed equity returns, are discussed. In order to obtain a comprehensive view of the cross-sectional variation in returns, a number of sub-questions based on the literature review are formulated and examined in this thesis. These questions are discussed in Section 4.2.

A general description of the data to be employed is provided in Section 4.3. The data selected cover the period from January 1994 through May 2011. This specific period was selected to avoid any possible distortions in the results obtained due to economical and political events that occurred in South Africa prior to the transition period of 1994. Furthermore, this period allows for the formation of two independent subsamples of approximately equal length, both covering full investment cycles. The independent subsamples will allow for the empirical research to be conducted on the first subsample, while the second can be used for out-of-sample testing. Finally the research can be conducted over the full 17.5 year period, providing three sets of results to be compared.

Statistical biases that have been identified through prior related research, namely data snooping, infrequent trading, survivorship bias, look-ahead bias and outliers are discussed in Section 4.4. An overview is provided of the process followed in this thesis to control for these biases to avoid potential inaccuracies in the results caused by these biases.

The identification, selection, data gathering on and categorisation of the variables employed in this thesis is discussed in Section 4.5. A rearrangement of the Gordon-Shapiro (1956) constant growth model was applied in selecting and categorising variables into value and growth categories respectively, while price momentum and overreaction variables have been categorised under the technical category. Descriptive statistics are provided in Section 4.6 to gain a better understanding of the final set of variables to be employed in this thesis.

A summary of the methodology to be followed in the remaining chapters of this thesis is provided in Section 4.7. In Chapter 5 a one-factor cross-sectional regression model is applied using the standardised values of the selected variables to ascertain the identity of technical and fundamental factors that explain the cross-sectional variation in returns on the JSE. The process is done over three sample periods and using different market cap decile samples over a number of payoff periods to examine the effect that time, liquidity and payoff period may have on the results. Single-factor portfolios are created in Chapter 6 to examine whether a different approach could offer different results compared to the one-factor cross-sectional regression approach. Factors are ranked and used to create “long/short” hedge fund portfolios. The results are used to test whether such an approach could present portfolios that offer abnormal returns, and whether the returns could be explained by market models. The results of Chapter 5 and Chapter 6 are used in Chapter 7 to perform multifactor analyses on the factors identified to have a significant impact on the cross-section of returns. Multifactor models are developed to determine whether such models could increase the explanatory power of the cross-section of returns. A third approach, the ‘extreme performer’ approach is applied in Chapter 8 (for a 1-month payoff period) and Chapter 9 (for a 12-month payoff period). A combination of cross-sectional regression and logistic regression is used to determine which factors differ significantly between winner and loser shares and ultimately develop logit models to filter potential winner and loser shares. The logit models are applied to create winner and loser portfolios and the performance is evaluated relative to a benchmark portfolio. Risk-adjusted analysis is further performed on the returns obtained from the winner portfolio.

5

A UNIVARIATE REGRESSION APPROACH TO IDENTIFY FIRM- SPECIFIC FACTORS THAT EXPLAIN THE CROSS - SECTION OF RETURNS ON THE JSE

5.1 Introduction

The objective of this chapter is to identify those firm- specific factors that contribute to explaining the cross-section of returns on the JSE and to examine the effect that time, liquidity and payoff period may have on the results.

In Section 5.3 univariate cross-sectional regression analysis is performed on each of the factors listed in Table 4.2 (Chapter 4), over three sample periods. A time-series of cross-sectional slopes resulting from the regression is created for each of the variables analysed which represent the ‘reward’ to the specific characteristic in each month. Those variables for which the time series mean value cross-sectional slope coefficient is significantly different from zero are regarded as the potential explanatory factors to be used in subsequent analysis. Results are compared over the three sample periods to determine the effect that time may have on the identity and explanatory power of the factors.

The effect of sample liquidity on the identity and explanatory power of the factors is examined by using different market cap levels as liquidity filters (Section 5.3.2). Shares are selected based on the market cap criteria to form subsamples of shares representing different liquidity levels. This is done for each of the three sample periods to further examine the combined effect of time and liquidity on the results.

In Section 5.4 the effect of payoff period on the identity and explanatory power of the factors is examined by repeating the univariate cross-sectional regressions over a three, six, twelve, twenty-four and thirty-six month payoff period. Performing the regressions for the All-share (Section 5.4.1) and Large-cap (Section 5.4.2) samples over the three sample periods respectively, allows for an integrated examination of the effect that time, payoff period and liquidity may have on the results.

5.2 Methodology

Apart from the dummy variables (applied to test for the significance of a moving average technical factor), each variable in Table 4.2 (Chapter 4) is standardised by subtracting the mean and dividing it by its standard deviation. The process of standardisation facilitates the comparison of the magnitude of slope values across factors. In Section 5.3 the following univariate cross-sectional regression model (similar to Fama and Macbeth, 1973) is applied over three time periods (January 1994 through December 2002, January 2003 through May 2011 and January 1994 through May 2011):

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} A_{it} + \varepsilon_{i,t+1} \qquad \text{...(5.1)}$$

where

$r_{i,t+1}$ = realised return on share i for month t+1

$\gamma_{0,t+1}$ = intercept term

A_{it} = standardised value of the specific factor of the share at the end of month t

$\gamma_{1,t+1}$ = cross-sectional slope coefficient, estimated using ordinary least squares

$\varepsilon_{\mathrm{i},t+1}$ = error term

The use of three time periods allows not only for comparison of results to that reported by other researchers (see Chapter 3) but also to examine the effect that time may have on the results (i.e. a robustness test).

A time-series of cross-sectional slopes resulting from the regression (5.1) is created for each of the variables analysed. The null hypothesis of whether the time series mean value cross-sectional slope coefficient is equal to zero is performed using a Student's t-test at a 5% level of significance. Those factors for which the hypothesis is rejected are regarded as potential factors to be used in subsequent analyses.

To examine the effect that liquidity may have on the results, the above univariate regression process is repeated six times, each time using a different market capitalisation quantile as a filter to select the shares included in the regression (Section 5.3.2). First, all possible shares are included without introducing any liquidity filter (referred to as the 'All-share' sample). Next, the 3rd market capitalisation decile is introduced as a liquidity filter, allowing only those shares that collectively make up the top 30% of the total market capitalisation to be included in the analysis. The process is subsequently repeated by defining the 4th through 7th market capitalisation deciles as the next liquidity filter. Each subsequent regression process therefore allows for less liquid shares to be included. The process is repeated for each of the three periods under review, offering a set of fifteen univariate regression results based on five different liquidity filters for the different periods. The results are reported (Section 5.3.2) for the case where the liquidity filter is set equal to the 5th market cap decile, (referred to as the 'Large-cap' sample). The remainder of the results are reported in Appendix C.

The relation between the significance of each factor and the liquidity of the shares included in the sample are further examined (Section 5.3.3) by performing the following two-factor cross-sectional regression:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} A_{it} + \gamma_{2,t+1} D_{it} A_{it} + \varepsilon_{i,t+1} \qquad \text{...(5.2)}$$

where

$r_{i,t+1}$ = realised return on share i for month t+1

$\gamma_{0,t+1}$ = intercept term

A_{it} = standardised value of the specific factor of the share at the end of month t

$\gamma_{1,t+1}$ = cross-sectional slope coefficient 1, estimated using ordinary least squares

$\gamma_{2,t+1}$ = cross-sectional slope coefficient 2, estimated using ordinary least squares

D_{it} = Dummy variable set equal to 1 if share *i* is classified as a Large-cap (i.e. forms part of the sample for which the liquidity filter is set equal to the 5th market cap decile) and 0 otherwise.

$\varepsilon_{i,t+1}$ = error term

The coefficient associated with the Large-cap dummy variable ($\gamma_{2,t+1}$) indicates the increase (if positive) or decrease (if negative) in the slope coefficient associated with the specific factor due to the share being classified as a Large-cap. Therefore regression (5.2) can be used to determine the extent to which the Large-cap shares contribute to the factor significance within the All-share sample.

In Section 5.4 the effect of varying payoff periods are examined by applying the following univariate cross-sectional regression model:

$$r_{i,t+k} = \gamma_{0,t+k} + \gamma_{1,t+k} A_{it} + \varepsilon_{i,t+k} \qquad \text{...(5.3)}$$

where

$r_{i,t+k}$ = realised return on share i for period t+k where k = 3, 6, 12, 24 and 36 months.

$\gamma_{0,t+1}$ = intercept term

A_{it} = standardised value of the specific factor of the share at the end of month t

$\gamma_{1,t+k}$ = cross-sectional slope coefficient for period t+k.

$\varepsilon_{i,t+k}$ = error term

Similar to Section 5.3 a time-series of cross-sectional slopes resulting from the regression (5.3) is created for each of the variables analysed. The null hypothesis of whether the time series mean value cross-sectional slope coefficient is equal to zero is performed using a Student's t-test. Those factors for which the hypothesis is rejected are regarded as potential factors to be used in subsequent analysis. Regression (5.3) is applied for the All-share (Section 5.4.1) and Large-cap (Section 5.4.2) samples over the three sample periods to integrate the effect that time, payoff period and liquidity may have on the results.

5.3 Univariate cross-sectional regression results

5.3.1. All-share sample

The results of regression (5.1) when all possible shares are included in the sample are reported in Table 5.1 below. Each panel in Table 5.1 reports the average coefficient values and their associated t-statistics for all factors in descending order of significance for each of the three sample periods.

Table 5.1: Monthly cross-sectional regression results. No adjustment for thin trading (liquidity). Average number of shares included in samples = 146.

A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns. No liquidity filter has been applied for the first analysis, allowing for the inclusion of as many stocks as possible. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional slope coefficients is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 – 2002)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.012	**5.437**	MOM6	0.003	1.080
LNP	-0.009	**-5.376**	MA10	0.006	1.033
MVLOG	-0.009	**-4.393**	BETA	0.003	0.993
MOM12	0.008	**3.312**	MA6	0.005	0.982
OBOS12MMA	0.021	**3.058**	MA7	0.005	0.922
OBOS11MMA	0.019	**2.845**	MA9	0.005	0.922
OBOS10MMA	0.017	**2.662**	OBOS3MMA	-0.004	-0.915
OBOS9MMA	0.016	**2.592**	MOM3	0.002	0.904
OBOS8MMA	0.014	**2.316**	MA8	0.005	0.897
BVTMLOG	0.005	**2.229**	C24MBVTM	0.002	0.791
EG1	0.003	**2.193**	MA5	0.004	0.733
OBOS7MMA	0.010	1.834	C24MDPSP	-0.002	-0.727
RETVAR12	0.004	1.697	OBOS5MMA	0.003	0.719
DPSLOG	-0.003	-1.687	MA2	-0.002	-0.650
MOM60	-0.006	-1.652	PRICEREL12	0.002	0.540
POUTRAT	-0.003	-1.610	ROE	-0.001	-0.450
EARNREV3M	-0.038	-1.599	MOM1	-0.001	-0.417
EY	0.003	1.567	SPSLOG	-0.001	-0.354
OBOS2MMA	-0.006	-1.534	MA3	-0.001	-0.243
STP	0.003	1.509	MA4	0.001	0.232
MA11	0.007	1.300	EPS	0.000	-0.208
OBOS6MMA	0.007	1.255	DY	0.000	-0.188
MA12	0.006	1.205	C24MEPSP	0.000	0.044
DE	-0.003	-1.153	OBOS4MMA	0.000	-0.008
MOM36	0.003	1.092			

Panel B: Subsample_2 (2003 – 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.006	**3.810**	OBOS10MMA	0.008	1.295
C24MDPSP	0.003	**3.231**	OBOS3MMA	-0.005	-1.206
C24MEPSP	0.003	**2.866**	MVLOG	-0.002	-1.144
MOM6	0.006	**2.849**	OBOS4MMA	-0.005	-1.119
BVTMLOG	0.003	**2.605**	MA4	0.004	1.111
MA11	0.010	**2.420**	OBOS9MMA	0.006	1.099
OBOS2MMA	-0.008	**-2.402**	ICBTIN	0.001	1.062
EARNREV3M	0.004	**2.365**	OBOS8MMA	0.005	0.891
MA10	0.009	**2.361**	LNP	-0.001	-0.742
MA12	0.010	**2.340**	STP	0.001	0.729
MOM1	-0.004	**-2.049**	MA3	0.002	0.716
DY	0.003	1.999	DPSLOG	-0.001	-0.583
MA8	0.007	1.941	OBOS7MMA	0.003	0.562
MOM12	0.005	1.936	MOM3	-0.001	-0.427
MA7	0.007	1.897	OBOS5MMA	-0.002	-0.357
MA9	0.007	1.897	MOM36	0.001	0.344
Pricerel12	0.005	1.836	DE	0.000	-0.269
MA6	0.006	1.728	POUTRAT	0.000	0.246
EY	0.002	1.690	MOM60	0.000	0.176
MA5	0.006	1.652	BETA	0.000	-0.129
C24MBVTM	-0.004	-1.615	ROE	0.000	0.094
OBOS12MMA	0.011	1.609	MA2	0.000	-0.085
EPS	0.001	1.571	RETVAR12	0.000	-0.050
OBOS11MMA	0.009	1.436	OBOS6MMA	0.000	0.036
SPSLOG	-0.001	-1.372	EG1	0.000	0.023

Panel C: Total_sample (1994 – 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.009	**6.587**	EG1	0.002	1.597
LNP	-0.005	**-4.602**	Pricerel12	0.004	1.570
MVLOG	-0.005	**-4.133**	OBOS3MMA	-0.004	-1.489
MOM12	0.007	**3.638**	MA5	0.005	1.486
OBOS12MMA	0.016	**3.315**	C24MEPSP	0.002	1.395
BVTMLOG	0.004	**3.203**	SPSLOG	-0.001	-1.268
OBOS11MMA	0.014	**3.056**	POUTRAT	-0.002	-1.211
OBOS10MMA	0.013	**2.836**	DY	0.001	1.165
OBOS2MMA	-0.007	**-2.689**	ICBTIN	0.001	1.062
OBOS9MMA	0.011	**2.655**	MOM60	-0.002	-1.054
MA11	0.009	**2.527**	MOM36	0.002	0.933
MOM6	0.004	**2.451**	OBOS6MMA	0.003	0.929
MA12	0.008	**2.436**	DE	-0.001	-0.882
OBOS8MMA	0.009	**2.308**	C24MBVTM	-0.002	-0.831
MA10	0.007	**2.229**	RETVAR12	0.002	0.827
EY	0.003	**2.214**	OBOS4MMA	-0.003	-0.798
MA8	0.006	1.832	MA4	0.002	0.760
MA7	0.006	1.790	BETA	0.001	0.733
MA9	0.006	1.790	MA2	-0.001	-0.568
MA6	0.006	1.745	C24MDPSP	0.001	0.545
OBOS7MMA	0.007	1.720	ROE	-0.001	-0.397
DPSLOG	-0.002	-1.709	MOM3	0.001	0.334
MOM1	-0.002	-1.661	OBOS5MMA	0.001	0.257
STP	0.002	1.654	EPS	0.000	0.242
EARNREV3M	-0.038	-1.599	MA3	0.001	0.178

Considering the results reported in each panel in Table 5.1 separately, it is seen that eleven candidate factors are identified using data from 1994 through 2002 as well as using the data from 2003 through May 2011 while sixteen candidate factors are identified based on the entire sample period. Comparing the results however, shows that only two common candidate factors are significant on a 95% level during each of the three periods, namely cash-flow to price (CFTP) and book-value-to-market (BVTMLOG). Considering a 90% level of significance allows for the inclusion of a third factor that is common amongst all sample periods, namely the prior 12-month return (MOM12) momentum factor.

CFTP shows the highest level of significance of all factors for all periods. Both the CFTP and BVTMLOG factors are classified as 'value' factors and the above results therefore suggest that there is evidence of a significant value effect on the JSE. The presence of a value effect is in line with the majority of international as well as South African studies (see Chapter 3). Specifically, the presence of a value effect captured by the BVTMLOG factor is reported in most literature. However, almost none of the studies reviewed in Chapter 3 found such a strong level of significance associated with the CFTP value factor as reported here. Van Rensburg and Robertson (2003) found CFTP to be significant, though not as significant as reported here. Another interesting observation is the relatively low level of significance associated with the earnings-yield (EY) factor. A number of South African studies have found the E/Y (or its inverse, the P/E) to have a highly significant relation with stock returns (see for example Page & Palmer, 1991, Van Rensburg, 2001, Cubbin, Eidne, Firer & Gilbert, 2006 and Strugnell, Gilbert & Kruger, 2011). The results reported here contradict that finding and instead suggest that, regarding a value effect, CFTP has the most significant relation with stock returns, followed by BVTMLOG.

The positive, significant slope coefficient associated with MOM12 suggests that a 12-month momentum effect exists on the JSE. This is in line with the findings of Van Rensburg (2001) and Hsieh and Hodnett (2011). In contrast with the findings of Hsieh et. al. (2011) however, there is no evidence of a significant prior 60-month return (MOM60) price-reversal effect.

The size (or small firm) effect, which is *inter alia* represented by the natural log of price (LNP) and market-capitalisation (MVLOG) factors, is evident when analysing both Subsample_1 and Total_sample. This is in line with the results reported by most researchers (see Chapter 3). However, no significant evidence of a size effect is found when using Subsample_2. The “disappearance” of the size effect since 2002 is however in line with the observation by Strugnell, Gilbert and Kruger (2011) that there is some tentative evidence of a decreasing size premium over time on the JSE.

The results of Panel A and Panel C show that most of the factors that are significant on a 95% confidence level for the first subsample are also significant over the entire sample period. When compared to Panel B, it seems that except for the three common factors mentioned above, very different factors were significant in explaining the cross-section of returns on the JSE during 2003 through 2011.

Another interesting result is the rather large number of technical factors that contribute to explaining the cross-section of returns during each of the periods under review. Specifically, in addition to the MOM12 momentum factor discussed above, longer-term moving average (MA) and longer-term over-bought-over-sold (OBOS) factors seem to have significant explanatory power. To understand how the MA and OBOS factors are interpreted in this thesis it is best to use an example based on the results presented in Table 5.1.

From Subsample_1 (Panel A) it is seen that OBOS12mMA is most significant of all OBOS factors as per the Student's t-test. A positive slope is associated with OBOS12mMA. This means that the higher the current price of the specific share is relative to its 12-month moving-average, the higher the expected one-month forward return is. A positive slope is associated with all OBOS factors based on a 6-month or longer moving average period (although not all significant). The closer the moving-average period gets to 12-months, the more significant the factor becomes. This is further support of a 12-month momentum effect as indicated by MOM12, confirmed by the high level of correlation between the MOM12 and the OBOS factors based on 11- and 12-month moving averages (see Table 4.3, Chapter4). OBOS factors associated with shorter term moving averages (less than 5-months) show mostly negative coefficients, indicating a possible shorter-term price-reversal effect. However, the latter is not significant as per the Student's t-test.

Although none of the MA factors are significant in Subsample_1 (Panel A), those associated with a moving-average period of at least 10-months are significant for both Subsample_2 (Panel B) and Total_sample (Panel C). The dummy variables used to capture the MA effect is set equal to one if the current price of the share is greater than the associated moving average, and zero otherwise. In keeping with this, the positive coefficient associated with the majority of the MA factors indicates that if the current price of the share is greater than its moving average (over the specific period), a higher forward one-month return is expected. The higher level of significance associated with the longer-term moving averages (up to and including 12-month moving averages) is therefore once again an indication of a longer-term momentum effect on the JSE.

Time series graphs of the payoff to the most significant factors within each category identified in Table 5.1 is presented in Appendix C.1.

5.3.2. The effect of liquidity

To examine the effect of thin trading (liquidity) on the results, regression (5.1) was repeated using five market-value related liquidity filters. Shares were ranked according to their market value during each of the three sample periods. The top 30%, 40%, 50%, 60% and 70% of shares based on market capitalisation was included in the analysis respectively. The results for the first and last two filter levels are reported in Appendix C.2 through Appendix C.5 while the results associated with a liquidity filter set equal to the 5^{th} market cap decile is reported in Table 5.2 below.

Table 5.2: Monthly cross-sectional regression results when liquidity filter is set to the 5^{th} decile based on market capitalisation value. Average number of shares included is 68 per month.
A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns and a liquidity filter set equal to the 5^{th} decile based on market cap. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional slope coefficients is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.023	**5.605**	MOM3	0.003	1.038
MOM12	0.010	**3.291**	MOM60	-0.005	-1.018
LNP	-0.005	**-2.441**	MA10	0.005	0.989
C24MEPSP	0.009	**2.285**	MA6	0.006	0.981
BETA	0.007	**2.269**	EARNREV3M	-0.003	-0.967
OBOS12MMA	0.021	**2.154**	EG1	0.001	0.909
BVTMLOG	0.005	**2.056**	MVLOG	-0.003	-0.888
MOM6	0.007	1.955	SPSLOG	-0.003	-0.716
OBOS11MMA	0.019	1.945	OBOS4MMA	0.004	0.673
OBOS8MMA	0.016	1.919	MA8	0.004	0.667
OBOS9MMA	0.017	1.913	DY	0.002	0.656
OBOS10MMA	0.018	1.898	MA4	0.003	0.532
OBOS7MMA	0.015	1.861	MA7	0.003	0.506
EPS	0.003	1.788	MA9	0.003	0.506
MA12	0.009	1.754	DPSLOG	-0.001	-0.488
MOM36	0.006	1.687	DE	-0.002	-0.388
MA11	0.009	1.675	C24MBVTM	-0.002	-0.349
OBOS6MMA	0.013	1.665	OBOS2MMA	-0.002	-0.335
MA2	-0.006	-1.538	MOM1	-0.001	-0.333
ICBTIN	-0.016	-1.438	OBOS3MMA	0.002	0.303
PRICEREL12	0.006	1.408	MA3	-0.001	-0.193
OBOS5MMA	0.009	1.254	POUTRAT	0.000	0.185
ROE	0.004	1.164	C24MDPSP	0.000	-0.136
RETVAR12	-0.004	-1.097	EY	0.000	-0.032
MA5	0.006	1.041	STP	0.00	0.00

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.006	**3.559**	MA8	0.003	0.585
MOM1	-0.008	**-3.140**	MOM12	0.002	0.543
BVTMLOG	0.004	**3.073**	BETA	0.001	0.537
EPS	0.002	**2.215**	MA6	0.002	0.526
OBOS3MMA	-0.013	**-2.126**	OBOS12MMA	0.004	0.461
EY	0.005	1.923	OBOS10MMA	0.004	0.450
C24MDPSP	0.002	1.643	OBOS11MMA	0.004	0.437
C24MEPSP	0.002	1.498	MA7	0.002	0.433
DPSLOG	-0.003	-1.497	MA9	0.002	0.433
OBOS2MMA	-0.037	-1.480	ICBTIN	0.001	0.406
DY	0.003	1.434	SPSLOG	-0.001	-0.400
OBOS4MMA	-0.009	-1.263	MA4	-0.002	-0.392
MOM6	0.003	1.262	OBOS6MMA	-0.003	-0.382
MA3	-0.004	-1.151	OBOS9MMA	0.003	0.374
EARNREV3M	0.002	1.132	MOM60	-0.001	-0.372
MA12	0.005	1.095	EG1	0.001	0.355
MA11	0.005	1.091	OBOS8MMA	0.003	0.350
LNP	-0.002	-1.043	MA5	0.001	0.338
C24MBVTM	0.004	1.032	MOM3	0.001	0.173
MA2	-0.003	-0.855	OBOS7MMA	0.001	0.151
MA10	0.004	0.774	RETVAR12	0.001	0.138
OBOS5MMA	-0.006	-0.739	MVLOG	0.000	-0.103
STP	0.001	0.735	POUTRAT	0.000	0.080
MOM36	-0.002	-0.625	PRICEREL12	0.000	0.067
ROE	-0.001	-0.624	DE	0.000	0.000

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.015	**6.353**	MA5	0.004	1.040
BVTMLOG	0.004	**3.234**	MOM60	-0.002	-0.978
C24MEPSP	0.005	**2.632**	ROE	0.002	0.968
EPS	0.003	**2.626**	EG1	0.001	0.918
LNP	-0.004	**-2.523**	OBOS6MMA	0.005	0.901
MOM12	0.006	**2.423**	MA8	0.003	0.887
MOM6	0.005	**2.326**	MOM3	0.002	0.858
MOM1	-0.004	**-2.273**	EY	0.002	0.838
BETA	0.004	**2.130**	MA3	-0.003	-0.821
MA12	0.007	**2.037**	MVLOG	-0.002	-0.784
MA11	0.007	1.984	ICBTIN	-0.002	-0.777
OBOS12MMA	0.013	1.854	SPSLOG	-0.001	-0.729
MA2	-0.005	-1.739	MA7	0.002	0.666
OBOS11MMA	0.011	1.705	MA9	0.002	0.666
OBOS10MMA	0.011	1.690	C24MDPSP	0.001	0.592
OBOS9MMA	0.010	1.644	RETVAR12	-0.002	-0.580
OBOS8MMA	0.010	1.615	MOM36	0.001	0.503
OBOS2MMA	-0.019	-1.514	C24MBVTM	0.002	0.493
OBOS7MMA	0.008	1.422	OBOS4MMA	-0.002	-0.458
DPSLOG	-0.002	-1.325	OBOS5MMA	0.002	0.330
OBOS3MMA	-0.005	-1.274	EARNREV3M	0.000	0.294
MA10	0.004	1.257	DE	0.000	-0.278
DY	0.003	1.239	STP	0.000	0.272
MA6	0.004	1.107	POUTRAT	0.000	0.201
PRICEREL12	0.003	1.085	MA4	0.001	0.191

Using the 5th market cap decile allows for the largest 68 shares (in terms of market cap) per month (on average) to be included. A value effect captured mainly by CFTP and BVTMLOG remains significant across all periods. A momentum effect is evident for the periods 1994 through 2002 as well as 1994 through 2011, indicated by the significant positive coefficients associated with MOM6, MOM12 as well as the longer term MA and OBOS factors. These results, combined with those reported in Appendix C, suggest that the momentum effect is dependent on the time period as well as the level of liquidity of the sample as the momentum effect becomes less significant as the level of liquidity is increased, especially since 2003. A short term price reversal effect is observed for the period 2003 through 2011, indicated by the significant negative slopes associated with the prior 1-month return (MOM1) and the OBOS factor based on a 3-month moving average. The size-effect observed in the All-share sample for Subsample_1 and Total_sample disappears when including only the most liquid shares as represented by the 3rd and 4th market cap deciles respectively (see Appendix C). This is to be expected however, as the majority of small firms are excluded from these samples. Noting that the coefficient associated with LNP becomes significant again for the first time when the liquidity filter is set equal to the 5th market cap decile, it seems that the top 68 odd shares in terms of market cap may well be the minimum point for the size effect to be observed on the JSE. Note however that the MVLOG factor, also representing the size effect, is not yet significant at this point, but its level of significance increases as the level of liquidity is decreased. Interesting to note is that earnings per share (EPS), also categorised as a size factor, was insignificant when using the All-share sample but became significant for the Large-cap sample. Furthermore, a positive coefficient is associated with EPS. These observations seem to be at odds with the results obtained for all other size factors. This may either suggest that EPS should in fact not be regarded as a proxy for size, or that it is highly affected by liquidity and possibly by payoff period (examined in Section 5.4).

An interesting result is the significance associated with the CAPM beta found for Subsmaple_1 (on a 95% level of significance) and Total_sample (on a 90% level of significance) as reported in Table 5.2. Van Renburg and Robertson (2003) find that beta is "if anything, inversely related to returns on the JSE", which contradicts the CAPM theory. Based on the analysis in this thesis the results do not necessarily confirm the results of Van Rensburg et.al. (2003) as the beta coefficients reported across all market value deciles as well as for the All-share sample are positive for all sample periods (or zero in some cases for Subsample_2), indicating a possible direct (or no) relationship between returns and beta. According to Van Rensburg *et al*. (2003) and Ward *et al*. (2012) the use of the single factor CAPM model to explain returns on the JSE is inappropriate. Although the results reported in Table 5.2 show that the CAPM beta may be significantly related to share returns on the JSE, it in fact contributes to the findings of Van Rensburg *et al*. (2003) and Ward *et al*. (2012) in three ways. First, the significant positive relationship between beta and share returns are only found once the largest, most liquid shares are included in the sample. Secondly, the significance is evident only during specific periods under review. Thirdly, of all factors found to be significant in explaining the cross-section of returns, beta ranks amongst the lowest. Therefore the results suggest that the CAPM beta is highly dependent on the time period under review as well as the level of liquidity of the shares included in the sample, while there are a number of other factors that are much more significant in explaining returns on the JSE, confirming that the use of the single factor CAPM model to explain returns on the JSE is inappropriate.

5.3.3. Comparison of All-share and Large-cap factor significance

The approach followed in Section 5.3.2 allows for the examination of the effect of liquidity on the results. Applying regression (5.2) further allows for the examination of factor significance with regards to the extent and relation of the contribution the Large-cap shares make to the significance of the specific factor. A positive (negative) coefficient associated with the Large-cap dummy variable ($\gamma_{2,t+1}$) is an indication of whether the inclusion of the Large-cap shares helps to explain additional (less) of the cross-sectional variation in returns. The results of regression (5.2) are reported in Table 5.3 below.

Table 5.3: The relation between the significance of factors and the liquidity (in terms of market cap size) of shares

Slope coefficients are estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using a two-factor cross-sectional regression with a dummy variable set equal to 1 if a share is classified as a Large-cap share and 0 otherwise. This allows for examining the relation between the significance associated with a factor and the liquidity of the sample. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional dummy slope coefficients is significantly different from zero at the ninety-five per cent level of confidence. The factors are sorted based on the level of significance associated with the Large-cap dummy variable

Panel A: Subsample_1 (1994 - 2002)

	All-share coefficient		Large-cap dummy coefficient			All-share coefficient		Large-cap dummy coefficient	
Factor	**Average coefficient**	**t-statistic**	**Average coefficient**	**t-statistic**	**Factor**	**Average coefficient**	**t-statistic**	**Average coefficient**	**t-statistic**
MA2	0.003	0.833	-0.014	**-3.199**	OBOS4MMA	0.002	0.410	-0.007	-0.990
DY	-0.002	-1.198	0.015	**2.902**	C24MBVTM	0.010	2.283	-0.007	-0.987
MA9	0.011	1.836	-0.013	**-2.863**	MOM12	0.007	2.982	0.003	0.887
MA7	0.011	1.836	-0.013	**-2.823**	MOM1	0.001	0.306	-0.003	-0.881
MA6	0.011	1.829	-0.012	**-2.670**	BVTMLOG	0.004	1.284	0.003	0.861
MA3	0.004	0.809	-0.013	**-2.636**	STP	0.003	1.226	-0.003	-0.801
MA5	0.009	1.599	-0.013	**-2.609**	MOM36	0.003	0.757	0.003	0.739
MVLOG	-0.014	-4.785	0.014	**2.598**	OBOS5MMA	0.005	0.938	-0.005	-0.727
MA8	0.010	1.720	-0.012	**-2.511**	EARNREV3M	0.001	0.422	-0.002	-0.649
MA4	0.007	1.134	-0.012	**-2.382**	SPSLOG	-0.001	-0.193	-0.003	-0.611
MA10	0.011	1.808	-0.012	**-2.326**	BETA	0.003	1.061	-0.001	-0.521
CFTP	0.010	4.057	0.008	**2.085**	OBOS6MMA	0.007	1.351	-0.003	-0.453
MA11	0.012	1.959	-0.009	-1.905	OBOS12MMA	0.020	2.710	0.004	0.428
C24MEPSP	-0.002	-0.758	0.012	1.897	C24MDPSP	-0.002	-0.690	0.002	0.425
MA12	0.011	1.889	-0.009	-1.878	OBOS3MMA	-0.003	-0.585	-0.003	-0.411
ICBTIN	0.007	1.046	-0.017	-1.848	OBOS7MMA	0.011	1.824	-0.002	-0.297
EPS	-0.004	-1.364	0.008	1.766	OBOS11MMA	0.019	2.558	0.002	0.256
EY	0.002	0.905	0.008	1.700	OBOS8MMA	0.014	2.202	-0.002	-0.255
POUTRAT	-0.005	-2.181	0.005	1.612	MOM60	-0.007	-1.673	0.001	0.224
LNP	-0.011	-4.944	0.005	1.481	OBOS9MMA	0.016	2.440	-0.001	-0.116
ROE	-0.004	-1.051	0.007	1.418	OBOS10MMA	0.017	2.430	0.001	0.114
MOM3	0.003	1.323	-0.004	-1.418	PRICEREL12	0.002	0.564	0.000	-0.100
DPSLOG	-0.004	-2.060	0.003	1.332	OBOS2MMA	-0.006	-1.252	0.001	0.088
MOM6	0.003	0.905	0.005	1.192	RETVAR12	0.003	1.493	0.000	-0.037
EG1	-0.005	-0.848	0.007	1.101	DE	-0.004	-0.620	0.000	-0.036

Panel B: Subsample_2 (2003 - 2011)

	All-share coefficient		Large-cap dummy coefficient			All-share coefficient		Large-cap dummy coefficient	
Factor	Average coefficient	t-statistic	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic	Average coefficient	t-statistic
C24MEPSP	0.004	3.428	-0.003	-1.891	MA12	0.007	1.557	0.003	0.692
MOM1	-0.001	-0.530	-0.005	-1.755	OBOS6MMA	0.003	0.419	-0.005	-0.689
PRICEREL12	0.008	2.289	-0.005	-1.638	LNP	0.000	0.106	-0.002	-0.602
MOM36	0.005	1.360	-0.006	-1.598	MOM3	-0.002	-0.662	0.002	0.598
MOM6	0.009	3.449	-0.005	-1.538	MA8	0.002	0.440	0.002	0.555
MOM12	0.008	2.431	-0.005	-1.396	MA7	0.003	0.775	0.002	0.543
MA2	0.002	0.498	-0.004	-1.259	MA9	0.003	0.775	0.002	0.543
EARNREV3M	0.008	1.848	-0.004	-1.195	C24MBVTM	-0.005	-1.456	0.002	0.537
DPSLOG	0.001	0.875	-0.003	-1.194	MOM60	0.001	0.280	-0.001	-0.488
OBOS12MMA	0.017	2.324	-0.011	-1.171	MA5	0.002	0.586	0.002	0.480
C24MDPSP	0.005	3.100	-0.002	-1.154	BETA	0.001	0.364	-0.001	-0.476
OBOS11MMA	0.016	2.167	-0.010	-1.084	OBOS5MMA	-0.001	-0.170	-0.003	-0.474
RETVAR12	0.003	0.625	-0.004	-1.036	SPSLOG	-0.002	-1.013	0.001	0.425
OBOS2MMA	-0.005	-0.960	-0.005	-1.036	DE	0.001	0.368	-0.001	-0.390
OBOS8MMA	0.011	1.674	-0.008	-1.006	EG1	-0.003	-0.292	0.003	0.307
OBOS10MMA	0.014	2.006	-0.009	-0.999	DY	0.003	1.166	0.001	0.275
OBOS9MMA	0.012	1.838	-0.008	-0.989	POUTRAT	0.000	0.108	0.000	0.269
OBOS7MMA	0.008	1.301	-0.008	-0.988	BVTMLOG	0.003	1.270	0.000	0.207
MA6	0.001	0.299	0.004	0.920	MVLOG	-0.001	-0.105	0.001	0.158
ICBTIN	0.003	1.285	-0.003	-0.919	MA11	0.010	2.240	0.000	-0.122
EY	0.003	1.647	0.003	0.870	MA10	0.008	1.916	0.000	0.120
CFTP	0.005	1.852	0.002	0.814	OBOS4MMA	-0.006	-1.040	-0.001	-0.106
EPS	0.004	1.235	-0.002	-0.778	ROE	0.000	0.097	0.000	0.055
OBOS3MMA	-0.004	-0.652	-0.005	-0.763	MA3	0.001	0.246	0.000	-0.041
MA4	0.000	0.000	0.003	0.735	STP	0.001	0.303	0.000	0.007

Panel C: Total_sample (1994 - 2011)

	All-share coefficient		Large-cap dummy coefficient			All-share coefficient		Large-cap dummy coefficient	
Factor	**Average coefficient**	**t-statistic**	**Average coefficient**	**t-statistic**	**Factor**	**Average coefficient**	**t-statistic**	**Average coefficient**	**t-statistic**
MA2	0.003	0.964	-0.009	**-3.352**	MA12	0.009	2.453	-0.003	-0.895
DY	0.000	0.147	0.008	**2.751**	MOM36	0.004	1.546	-0.002	-0.872
CFTP	0.008	4.162	0.005	**2.183**	OBOS5MMA	0.002	0.486	-0.004	-0.858
MA3	0.003	0.808	-0.007	**-2.121**	BVTM	0.003	1.775	0.002	0.836
EY	0.002	1.701	0.005	1.907	OBOS4MMA	-0.002	-0.532	-0.004	-0.817
MA5	0.006	1.678	-0.006	-1.871	LNP	-0.005	-3.445	0.002	0.813
MA9	0.007	1.963	-0.006	-1.826	OBOS6MMA	0.005	1.216	-0.004	-0.808
MA7	0.007	1.963	-0.006	-1.798	OBOS3MMA	-0.003	-0.878	-0.004	-0.806
MA10	0.010	2.586	-0.006	-1.771	OBOS9MMA	0.014	3.034	-0.005	-0.784
MOM1	0.000	-0.188	-0.004	-1.761	RETVAR12	0.003	1.183	-0.002	-0.715
ICBTIN	0.004	1.646	-0.006	-1.744	BETA	0.002	1.083	-0.001	-0.700
MVLOG	-0.008	-2.205	0.008	1.744	MOM3	0.001	0.369	-0.001	-0.641
MA8	0.006	1.664	-0.005	-1.560	OBOS10MMA	0.015	3.145	-0.004	-0.629
POUTRAT	-0.002	-1.659	0.003	1.555	C24MBVTM	0.002	0.760	-0.002	-0.611
MA11	0.011	2.928	-0.005	-1.510	STP	0.003	1.115	-0.002	-0.603
MA4	0.003	0.978	-0.005	-1.499	OBOS11MMA	0.017	3.348	-0.004	-0.578
MA6	0.006	1.710	-0.005	-1.496	OBOS2MMA	-0.005	-1.562	-0.002	-0.553
EARNREV3M	0.006	1.875	-0.004	-1.361	OBOS12MMA	0.019	3.566	-0.003	-0.490
ROE	-0.002	-0.857	0.004	1.321	MOM12	0.008	3.735	-0.001	-0.387
C24MEPSP	0.002	1.215	0.004	1.254	DE	0.000	-0.060	-0.001	-0.300
PRICEREL12	0.005	1.950	-0.003	-1.088	DPSLOG	-0.001	-1.088	0.000	0.256
EPS	-0.001	-0.293	0.003	1.072	MOM60	-0.002	-0.886	-0.001	-0.239
EG1	-0.004	-0.739	0.005	0.919	MOM6	0.006	2.880	0.000	0.170
OBOS7MMA	0.009	2.211	-0.005	-0.901	C24MDPSP	0.002	1.049	0.000	-0.151
OBOS8MMA	0.012	2.746	-0.005	-0.898	SPSLOG	-0.002	-0.987	0.000	0.125

From Table 5.3 it seems that the significance of the moving average dummy variables, across all terms, is negatively affected by the inclusion of Large-cap shares, specifically for Subsample_1 and Total_sample. As can be expected, the significance of factors such as the dividend yield is associated more with Large-cap shares, as these are mainly the companies that pay dividends to shareholders. Furthermore it is noted that factors capturing the size effect (specifically, LNP and MVLOG) become less significant when bigger companies are included, which is in line with the univariate regression results reported in Section 5.3. Although the strong value effect captured by CFTP across all periods (refer to Section 5.3) is significant irrespective of the level of liquidity of the samples, it does seem from Table 5.3 that the inclusion of smaller companies magnifies this effect. Similarly, the longer term momentum effect observed (captured by factors such as MOM12 and OBOS12mMA) across all periods is magnified when smaller firms are included in the sample, while the significance of the shorter term price reversal effect (captured by MOM1) is associated more with Large-cap shares.

5.4 The effect of varying payoff periods

5.4.1. All-share sample

Univariate cross-sectional regressions (5.3) were performed on all variables on a monthly basis for each of the three sample periods using the different realised return periods discussed in Section 5.2, as dependent variable. The results for the All-share sample are reported in Table 5.4. The first column in Table 5.4 reports the t-statistics for all factors in descending order of significance as applicable to the one-month forward return. The t-statistic and associated ranking of each factor are reported in subsequent columns for each of the realised return periods for comparison purposes.

Table 5.4: Monthly cross-sectional regression results for different payoff periods: All-share sample

A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns over a one, three, six, twelve, twenty-four and thirty-six month period. No liquidity filter has been applied for the first analysis, allowing for the inclusion of as many stocks as possible. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Factors are sorted and ranked based on its statistical significance associated with explaining the cross-section of one-month forward returns in the first column. The subsequent columns report the t-statistic and rank of the specific factor for each respective payoff period.

Panel A: Subsample_1 (1994 – 2002): All-share sample

	1-month forward return		3-month forward return		6-month forward return		12-month forward return		24-month forward return		36-month forward return	
Factor	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank
CFTP	5.437	1	5.596	2	7.899	1	9.710	3	7.884	7	7.896	7
LNP	-5.376	2	-5.896	1	-7.227	2	-13.097	1	-15.811	1	-17.149	2
MVLOG	-4.393	3	-5.286	3	-6.452	3	-11.336	2	-15.210	2	-13.172	3
MOM12	3.312	4	2.791	8	2.408	17	3.543	28	1.990	27	4.144	17
OBOS12MMA	3.058	5	2.334	11	2.258	18	4.122	22	1.373	34	2.012	33
OBOS11MMA	2.845	6	2.169	13	2.192	19	4.389	18	1.521	33	2.055	31
OBOS10MMA	2.662	7	1.951	16	2.052	20	4.510	15	1.647	31	2.144	30
OBOS9MMA	2.592	8	1.845	19	1.895	23	4.680	13	1.847	29	2.317	29
OBOS8MMA	2.316	9	1.871	17	1.760	24	4.862	9	2.044	26	2.547	24
BVTMLOG	2.229	10	3.669	7	3.839	8	2.813	35	2.638	19	4.432	16
EG1	2.193	11	2.148	14	3.234	10	1.414	42	1.060	44	3.043	21
OBOS7MMA	1.834	12	1.782	20	1.627	25	4.913	8	2.095	24	2.455	25
RETVAR12	1.697	13	2.629	9	3.179	11	4.788	10	7.857	8	6.851	10
DPSLOG	-1.687	14	-4.567	4	-5.046	5	-6.450	6	-8.688	4	-12.628	4
MOM60	-1.652	15	-3.887	5	-5.928	4	-8.449	4	-8.192	5	-24.882	1
POUTRAT	-1.61	16	-2.382	10	-1.931	21	0.039	50	-3.061	15	-4.082	18
EARNREV3M	-1.599	17	-2.040	15	-2.678	14	-2.806	36	-2.804	18	-3.026	22
EY	1.567	18	0.452	42	0.959	34	3.030	31	5.376	10	6.026	11
OBOS2MMA	-1.534	19	0.395	44	0.381	44	0.919	46	0.331	49	0.794	41
STP	1.509	20	-0.056	49	0.267	47	0.931	45	4.529	13	0.111	49
MA11	1.3	21	0.890	32	1.259	31	2.697	37	-1.112	42	-1.808	35
OBOS6MMA	1.255	22	1.526	23	1.422	28	4.718	12	2.125	22	2.323	28
MA12	1.205	23	0.539	38	0.799	37	1.847	41	-1.831	30	-2.408	27
DE	-1.153	24	-1.846	18	-2.828	13	-4.506	16	2.064	25	5.962	12
MOM36	1.092	25	-0.773	35	-2.593	15	-4.662	14	-7.670	9	-7.419	9
MOM6	1.08	26	1.712	22	1.924	22	5.552	7	2.993	17	3.405	19
MA10	1.033	27	0.427	43	0.807	36	2.870	33	-0.721	47	-0.677	42
BETA	0.993	28	0.940	30	1.018	32	3.207	30	2.440	20	1.926	34
MA6	0.982	29	0.869	33	0.748	38	4.425	17	1.185	39	0.124	47
MA7	0.922	30	0.609	37	0.516	41	3.950	24	1.089	43	0.397	44
MA9	0.922	31	0.639	36	0.516	42	3.950	25	1.269	36	0.397	45
OBOS3MMA	-0.915	32	0.305	45	0.920	35	2.273	40	1.172	41	1.377	39
MOM3	0.904	33	1.044	28	1.525	27	4.772	11	2.117	23	2.413	26
MA8	0.897	34	0.799	34	0.509	43	3.840	26	0.119	50	0.353	46
C24MBVTM	0.791	35	1.130	26	2.458	16	2.481	39	1.231	38	4.542	15
MA5	0.733	36	0.504	40	0.373	45	3.989	23	1.269	37	0.110	50
C24MDPSP	-0.727	37	-2.249	12	-3.925	7	-7.530	5	-4.472	14	-5.450	14
OBOS5MMA	0.719	38	1.304	25	1.310	30	4.124	21	1.919	28	2.036	32
MA2	-0.65	39	-0.066	48	0.161	48	1.227	44	-0.387	48	-1.482	37
PRICEREL12	0.54	40	-0.268	46	0.006	50	2.523	38	-0.957	46	-1.410	38
ROE	-0.45	41	-1.772	21	-3.055	12	-4.206	20	-5.149	11	-5.887	13
MOM1	-0.417	42	0.896	31	1.611	26	-0.736	48	-0.978	45	-0.988	40
SPSLOG	-0.354	43	0.022	50	0.272	46	-0.581	49	-8.097	6	-10.854	5
MA3	-0.243	44	0.533	39	0.692	39	2.949	32	1.271	35	0.622	43
MA4	0.232	45	0.117	47	0.111	49	3.725	27	1.178	40	-0.113	48
EPS	-0.208	46	-1.104	27	-0.967	33	-0.916	47	-4.661	12	-7.686	8
DY	-0.188	47	-3.852	6	-4.014	6	-2.852	34	-3.012	16	-2.788	23
C24MEPSP	0.044	48	-0.490	41	-0.684	40	-1.278	43	-2.435	21	-3.203	20
OBOS4MMA	-0.008	49	1.023	29	1.329	29	3.523	29	1.629	32	1.754	36
ICBTIN	NA	NA	1.350	24	3.544	9	4.309	19	9.599	3	8.059	6

Panel B: Subsample_2 (2003 – 2011): All-share sample

	1-month forward return		3-month forward return		6-month forward return		12-month forward return		24-month forward return		36-month forward return	
Factor	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank
CFTP	**3.81**	1	6.543	1	6.793	4	6.524	7	8.567	7	7.725	7
C24MDPSP	**3.231**	2	4.699	7	3.977	10	1.773	41	-2.733	29	-3.713	23
C24MEPSP	**2.866**	3	5.538	2	6.040	5	3.363	30	-1.566	40	-3.810	22
MOM6	**2.849**	4	4.323	8	5.083	8	6.639	6	5.209	10	4.579	12
BVTMLOG	**2.605**	5	5.240	3	5.903	6	7.949	5	9.980	5	8.270	6
MA11	**2.42**	6	1.740	27	2.383	31	3.389	29	0.794	45	2.951	31
OBOS2MMA	**-2.402**	7	-1.052	35	1.556	37	2.837	34	2.659	30	1.955	41
EARNREV3M	**2.365**	8	3.021	11	1.723	36	2.747	37	1.865	35	1.559	44
MA10	**2.361**	9	1.846	25	2.418	28	3.353	31	1.386	42	2.208	38
MA12	**2.34**	10	1.622	31	2.310	33	3.436	28	0.734	47	3.482	25
MOM1	**-2.049**	11	-0.922	38	1.533	38	2.787	35	2.844	28	2.618	36
DY	1.999	12	3.659	10	4.363	9	4.545	20	4.031	21	4.699	11
MA8	1.941	13	1.576	32	2.423	27	3.595	27	2.256	31	2.933	32
MOM12	1.936	14	2.410	19	2.553	25	3.885	22	3.442	23	4.115	14
MA7	1.897	15	1.624	29	2.390	29	3.828	24	1.812	37	3.002	29
MA9	1.897	16	1.624	30	2.390	30	3.828	25	1.812	38	3.002	30
Pricerel12	1.836	17	2.226	22	3.528	21	6.388	8	1.254	43	0.342	50
MA6	1.728	18	1.828	26	2.491	26	3.844	23	1.843	36	2.708	35
EY	1.69	19	5.070	4	5.165	7	5.339	16	5.818	8	6.836	8
MA5	1.652	20	1.563	33	2.106	34	3.292	32	1.776	39	2.719	34
C24MBVTM	-1.615	21	-2.951	12	-3.259	23	-2.205	38	3.009	27	1.012	46
OBOS12MMA	1.609	22	2.841	13	3.772	13	6.103	9	4.801	15	3.875	20
EPS	1.571	23	1.396	34	1.464	39	-0.906	45	-9.048	6	-22.510	1
OBOS11MMA	1.436	24	2.738	14	3.708	14	5.992	10	4.798	16	3.912	19
SPSLOG	-1.372	25	-4.787	6	-7.366	1	-12.562	1	-20.695	1	-19.147	2
OBOS10MMA	1.295	26	2.661	15	3.688	19	5.910	12	4.818	14	3.940	18
OBOS3MMA	-1.206	27	0.165	47	2.349	32	3.638	26	3.363	24	2.843	33
MVLOG	-1.144	28	-4.256	9	-6.834	3	-10.798	3	-11.982	4	-10.073	5
OBOS4MMA	-1.119	29	0.884	39	3.213	24	4.514	21	4.013	22	3.377	26
MA4	1.111	30	0.781	41	1.383	41	2.112	39	1.878	34	1.792	42
OBOS9MMA	1.099	31	2.649	16	3.691	18	5.906	13	4.884	13	3.988	16
ICBTIN	1.062	32	2.461	18	3.773	12	4.714	19	4.132	20	1.639	43
OBOS8MMA	0.891	33	2.610	17	3.699	16	5.912	11	4.932	11	3.997	15
LNP	-0.742	34	-4.806	5	-7.114	2	-12.459	2	-14.732	2	-12.368	3
STP	0.729	35	1.044	36	1.106	43	1.008	43	1.482	41	1.443	45
MA3	0.716	36	0.384	44	1.132	42	1.845	40	2.182	32	1.959	40
DPSLOG	-0.583	37	-2.343	21	-3.788	11	-9.729	4	-12.246	3	-10.752	4
OBOS7MMA	0.562	38	2.408	20	3.707	15	5.858	14	4.920	12	3.963	17
MOM3	-0.427	39	1.986	24	3.367	22	4.786	18	4.468	18	4.237	13
OBOS5MMA	-0.357	40	1.631	28	3.623	20	5.141	17	4.445	19	3.678	24
MOM36	0.344	41	-0.289	46	0.148	46	0.418	46	-0.760	46	2.506	37
DE	-0.269	42	1.030	37	2.060	35	3.183	33	3.361	25	3.219	28
POUTRAT	0.246	43	0.547	43	0.132	49	-0.235	48	0.269	50	0.668	47
MOM60	0.176	44	-0.049	49	0.103	50	-0.225	49	-2.146	33	-0.622	49
BETA	-0.129	45	-0.311	45	0.135	48	-0.045	50	0.633	48	2.095	39
ROE	0.094	46	-0.026	50	0.297	45	-2.772	36	-5.471	9	-5.114	10
MA2	-0.085	47	-0.727	42	0.140	47	0.987	44	1.019	44	0.663	48
RETVAR12	-0.05	48	-0.146	48	0.874	44	-0.351	47	-0.547	49	3.266	27
OBOS6MMA	0.036	49	2.057	23	3.697	17	5.605	15	4.727	17	3.827	21
EG1	0.023	50	-0.882	40	-1.391	40	-1.756	42	-3.219	26	-5.304	9

Panel C: Total_sample (1994 – 2011): All-share sample

	1-month forward return		3-month forward return		6-month forward return		12-month forward return		24-month forward return		36-month forward return	
Factor	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank	t-statistic	rank
CFTP	**6.587**	1	7.983	1	10.352	1	11.416	3	11.371	4	10.833	5
LNP	**-4.602**	2	-6.800	2	-8.594	2	-15.770	1	-18.526	2	-19.695	2
MVLOG	**-4.133**	3	-6.196	3	-7.896	3	-14.224	2	-18.180	3	-16.003	4
MOM12	**3.638**	4	3.691	7	3.479	13	5.261	23	3.703	27	5.748	13
OBOS12MMA	**3.315**	5	3.471	9	3.967	8	7.145	13	3.874	26	3.824	26
BVTMLOG	**3.203**	6	5.068	4	5.563	5	5.213	25	5.910	11	7.725	7
OBOS11MMA	**3.056**	7	3.251	10	3.831	10	7.275	11	3.965	23	3.865	25
OBOS10MMA	**2.836**	8	2.994	11	3.648	11	7.303	10	4.058	22	3.920	23
OBOS2MMA	**-2.689**	9	0.000	50	0.923	44	1.961	39	1.227	43	1.488	39
OBOS9MMA	**2.655**	10	2.867	12	3.459	14	7.414	9	4.244	20	4.040	21
MA11	**2.527**	11	1.686	24	2.314	25	4.239	32	-0.317	47	0.278	48
MOM6	**2.451**	12	3.514	8	3.957	9	8.445	4	5.360	12	5.321	15
MA12	**2.436**	13	1.320	29	1.904	31	3.611	34	-0.873	45	0.071	50
OBOS8MMA	**2.308**	14	2.843	13	3.293	15	7.545	7	4.419	18	4.212	18
MA10	**2.229**	15	1.281	32	1.941	30	4.348	29	0.230	48	0.709	46
EY	**2.214**	16	1.510	26	2.040	29	4.447	28	6.424	8	6.991	10
MA8	1.832	17	1.438	28	1.564	35	5.230	24	1.282	42	1.697	35
MA7	1.79	18	1.234	35	1.480	36	5.411	21	1.830	39	1.580	36
MA9	1.79	19	1.261	33	1.480	37	5.411	22	1.995	35	1.580	37
MA6	1.745	20	1.552	25	1.744	34	5.808	17	1.912	36	1.015	43
OBOS7MMA	1.72	21	2.659	16	3.121	16	7.535	8	4.427	17	4.069	20
DPSLOG	-1.709	22	-4.975	5	-5.699	4	-8.282	6	-11.159	5	-16.011	3
MOM1	-1.661	23	0.368	44	2.171	26	-0.494	48	-0.942	44	-0.977	44
STP	1.654	24	0.256	46	0.618	48	1.253	44	4.667	15	0.275	49
EARNREV3M	-1.599	25	-1.284	31	-2.118	28	-1.674	41	-2.115	34	-2.469	32
EG1	1.597	26	1.447	27	2.168	27	0.447	49	-0.326	46	2.243	33
Pricerel12	1.57	27	0.455	41	0.955	43	5.566	18	-0.011	50	-1.061	42
OBOS3MMA	-1.489	28	0.347	45	1.801	33	3.698	33	2.288	33	2.219	34
MA5	1.486	29	1.109	36	1.243	38	5.141	26	1.902	37	0.901	45
C24MEPSP	1.395	30	-0.026	48	-0.108	50	-1.000	46	-2.523	31	-3.541	28
SPSLOG	-1.268	31	-4.009	6	-5.193	6	-8.309	5	-21.534	1	-20.985	1
POUTRAT	-1.211	32	-2.091	19	-1.829	32	-0.027	50	-2.812	30	-3.763	27
DY	1.165	33	-2.429	17	-2.683	23	-1.511	42	-1.639	41	-1.493	38
ICBTIN	1.062	34	2.759	14	5.004	7	5.972	16	6.799	6	4.676	17
MOM60	-1.054	35	-2.680	15	-3.605	12	-5.041	27	-6.606	7	-8.064	6
MOM36	0.933	36	-0.711	38	-1.243	39	-2.479	38	-6.347	9	-5.187	16
OBOS6MMA	0.929	37	2.262	18	2.867	21	7.196	12	4.347	19	3.866	24
DE	-0.882	38	-0.005	49	0.971	41	1.762	40	3.910	24	5.550	14
C24MBVTM	-0.831	39	-0.166	47	0.862	45	1.193	45	3.033	29	4.111	19
RETVAR12	0.827	40	2.039	20	3.113	17	3.357	36	4.549	16	6.508	11
OBOS4MMA	-0.798	41	1.314	30	2.550	24	5.421	20	3.219	28	2.938	30
MA4	0.76	42	0.414	42	0.686	47	4.259	31	1.751	40	0.393	47
BETA	0.733	43	0.620	40	0.955	42	2.762	37	2.496	32	2.547	31
MA2	-0.568	44	-0.369	43	0.204	49	1.509	43	-0.098	49	-1.232	40
C24MDPSP	0.545	45	-1.239	34	-2.906	20	-5.441	19	-4.830	14	-5.794	12
ROE	-0.397	46	-1.759	23	-2.978	19	-4.293	30	-5.967	10	-7.350	9
MOM3	0.334	47	1.879	22	2.987	18	6.720	14	4.108	21	4.036	22
OBOS5MMA	0.257	48	1.893	21	2.721	22	6.370	15	3.909	25	3.463	29
EPS	0.242	49	-0.964	37	-0.837	46	-0.993	47	-4.951	13	-7.645	8
MA3	0.178	50	0.647	39	1.104	40	3.457	35	1.868	38	1.123	41

To further facilitate comparison, the Spearman rank correlation was calculated across the payoff periods. This statistic serves as an indication of the consistency of relative significance associated with each factor across the respective payoff periods. Specifically, a higher correlation indicates a higher level of ranking consistency between the specific periods. The results are reported in Table 5.5.

Table 5.5: Spearman rank correlation: All-share sample

The Spearman rank correlation is calculated and reported here. A higher correlation statistic indicates higher consistency in the ranking order associated with the level of relative significance of each factor across the respective payoff periods. Results in bold indicate a strong correlation (>0.8) of the ranking order between the specific payoff periods. The results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C).

Panel A: Subsample_1 (1994 – 2002): All-share sample

Return period	1-month	3-month	6-month	12-month	24-month	36-month
1-month	1	0.59	0.47	0.42	0.21	0.28
3-month		1	**0.91**	0.57	0.51	0.61
6-month			1	0.55	0.60	0.75
12-month				1	0.42	0.35
24-month					1	**0.81**
36-month						1

Panel B: Subsample_2 (2003 – 2011): All-share sample

Return period	1-month	3-month	6-month	12-month	24-month	36-month
1-month	1	0.56	0.41	0.26	0.01	0.07
3-month		1	**0.91**	0.72	0.55	0.51
6-month			1	**0.87**	0.68	0.63
12-month				1	0.71	0.60
24-month					1	**0.80**
36-month						1

Panel C: Total_sample (1994 – 2011): All-share sample

Return period	1-month	3-month	6-month	12-month	24-month	36-month
1-month	1	0.49	0.46	0.43	0.07	0.07
3-month		1	**0.93**	0.73	0.58	0.59
6-month			1	0.73	0.62	0.63
12-month				1	0.50	0.43
24-month					1	**0.88**
36-month						1

From Table 5.4 Panel A it is seen that the value factors represented by CFTP and BVTMLOG remain significant for each of the respective payoff periods. Although BVTMLOG remains significant, its significance ranking decreases substantially over longer return-periods, while CFTP remains under the top seven most significant factors. Interesting to note is that two additional value factors, namely DY and EY both become significant over longer term return-periods as well. Specifically, it is found that DY overtakes BVTM as the second most significant value factor over the three- and six-month return periods, while both of these value factors drop in ranking order over longer periods. EY however, becomes the more significant value factor (second to CFTP) over the longer return periods, specifically over the twenty-four and thirty-six month periods. Therefore it seems that at least one value factor, namely CFTP, remains a robust factor in explaining the cross-section of returns on the JSE, irrespective of the return period used.

The size effect captured by LNP and MVLOG remains significant, and becomes more significant than the value effect as the return-period is increased. The size effect is further supported by the increase in significance and ranking order associated with two additional size factors, namely SPSLOG and EPS, especially over the twenty-four and thirty-six month periods. In keeping with the results obtained for the Large-cap sample over a 1-month payoff period (Section 5.3.2), it appears that EPS may be correctly categorised as a size factor after all, but that its effect is highly sensitive to the payoff period.

Similar to the results in Section 5.3, the momentum effect captured by MOM12 seems to be more significant than the same effect captured by longer term over-bought-over-sold and moving-average factors, irrespective of return-period used. However, the momentum effect captured by MOM12 becomes less significant (relative to other factors) over longer return-periods. Note that although MOM36 represents a momentum effect over a one-month return period (although not statistically significant), this factor captures a price-reversal effect over longer payoff periods. In fact, together with the significance associated with MOM60, it seems that price-reversal becomes one of the most significant effects in explaining the cross-section of returns over longer payoff periods.

A growth effect is observed for the first time in the analysis when longer payoff periods are used, represented specifically by DPSLOG and to a lesser extent ICBTIN. However, the relationship between forward returns and DPSLOG seems to be the opposite than what is expected, as a significant negative slope coefficient is obtained across all longer-term (at least three-month) return

periods. Nevertheless, over the twenty-four and thirty-six month return periods, the growth effect presented by these two factors is more significant than the value effect.
Starting from a three-month return period, the positive slope associated with RetVar12 becomes significant and remains robust across the different return periods, indicating a significant direct relationship between the previous 12-month volatility and longer term forward returns, supporting the risk-return trade-off concept.
Furthermore, from Table 5.5 Panel A it appears that the ranking order of the significance associated with the respective factors in explaining the cross-section of returns over a three- and six-month and a twenty-four and thirty-six month payoff period remain relatively consistent.

From Table 5.4 Panel B it is seen that, for Subsample_2, the significance of the value effect captured by CFTP and BVTMLOG remained robust across all payoff periods while the two additional value factors, DY and EY became significant over longer payoff periods as well. Interesting to note is that the ranking order associated with the two robust factors, CFTP and BVTMLOG, reverse over the longer payoff periods with EY becoming almost just as significant over especially the twenty-four and thirty-six month payoff periods.

Although the size effect was not found to be significant for the one-month payoff period for Subsample_2, it became highly significant over all other payoff periods, supported by the significance of all size factors namely LNP, MVLOG, SPSLOG and EPS (where the latter became the most significant factor over the 36-month payoff period). Furthermore, the size effect became more significant than the value effect over payoff periods of six-months and longer, similar to the findings for Subsample_1.

In contrast to Subsample_1 however, the momentum effect (captured by MOM6 for Subsample_2 instead of MOM12 as for Subsample_1) remained significant across all payoff periods for Subsample_2, while the price reversal effect found for Subsample_1 (captured by MOM36 and MOM60) over longer payoff periods is not observed for Subsample_2.

Once again, as with Subsample_1, a growth effect is observed over longer payoff periods. This is best captured by the DPSLOG and ROE (instead of ICBTIN as for Subsample_1) factors. Note that, as with Subsample_1, a significant but indirect relationship between growth and longer-term returns is observed.

From Table 5.5 (Panel B) it is seen that the ranking order of the factors explaining the cross-section of returns over the period 2003 through 2011 is more consistent across payoff periods compared to that of Subsample_1, indicating a higher level of robustness associated with the significant factors over the period 2003 through 2011, especially over longer payoff periods.

The results for Total_sample (Table 5.4 Panel C) are very similar to that of Subsample_1, namely a robust value (captured by CFTP and BVTMLOG) and size (captured by LNP and MVLOG) effect across all payoff periods, a momentum effect (captured by MOM12) over the one-month payoff period, replaced by a longer-term price reversal effect (captured by MOM60) associated with longer payoff periods and a growth effect (captured by DPSLOG) showing an indirect relationship with returns over payoff periods of at least threemonths. From Table 5.5 (Panel C) it is seen that the ranking order of factors is similar over a three- and six-month and a twenty-four and thirty-six month period.

5.4.2. Large-cap Sample

To examine the effect of liquidity on the results, the univariate regressions were repeated using a liquidity filter set equal to the 5th market cap decile. The results are reported in Table 5.6.

Table 5.6: Monthly cross-sectional regression results for different payoff periods: Large-cap sample
A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns over a one, three, six, twelve, twenty-four and thirty-six month period. A liquidity filter set equal to the 5th market cap decile has been applied. This allows for the inclusion of only the largest 68 shares (on average) in the sample. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. In the first column factors are sorted and ranked based on its statistical significance associated with explaining the cross-section of one-month forward returns. The subsequent columns report the t-statistic and rank of the specific factor for each respective payoff period.

Panel A: Subsample_1 (1994 – 2002): Large-cap sample

	1-month forward return		3-month forward return		6-month forward return		12-month forward return		24-month forward return		36-month forward return	
Factor	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank
CFTP	5.605	1	4.057	9	7.128	1	7.045	4	3.553	11	4.543	11
MOM12	3.291	2	4.113	7	3.696	24	0.955	46	-1.085	34	1.776	19
LNP	-2.441	3	-2.541	21	-4.757	14	-7.937	3	-6.807	3	-9.092	2
C24MEPSP	2.285	4	-1.440	37	-1.362	43	-4.173	20	-3.864	9	-4.716	10
BETA	2.269	5	3.112	17	4.342	18	6.261	5	3.830	10	2.914	13
OBOS12MMA	2.154	6	4.650	1	5.310	10	3.650	25	0.472	41	0.291	47
BVTMLOG	2.056	7	1.663	32	3.993	21	4.943	14	4.213	7	8.066	3
MOM6	1.955	8	4.209	6	5.429	8	5.145	12	2.299	18	1.820	18
OBOS11MMA	1.945	9	4.516	2	5.511	7	4.139	21	0.810	37	0.362	46
OBOS8MMA	1.919	10	4.106	8	5.679	5	5.802	9	2.117	21	1.233	26
OBOS9MMA	1.913	11	4.329	5	5.916	2	5.337	11	1.688	25	0.908	33
OBOS10MMA	1.898	12	4.336	4	5.777	3	4.678	15	1.254	33	0.573	42
OBOS7MMA	1.861	13	3.966	10	5.773	4	6.167	6	2.395	16	1.580	22
EPS	1.788	14	2.085	23	2.870	30	2.451	40	0.031	48	-2.059	17
MA12	1.754	15	1.705	29	3.413	26	2.888	32	-0.092	47	0.658	40
MOM36	1.687	16	-1.176	39	-2.580	32	-2.766	36	-3.109	13	-5.504	9
MA11	1.675	17	1.660	33	3.758	22	3.068	31	0.174	46	0.710	38
OBOS6MMA	1.665	18	3.691	11	5.649	6	5.881	8	2.380	17	1.580	23
MA2	-1.538	19	1.559	35	1.814	41	2.673	39	-0.012	50	-0.776	37
ICBTIN	-1.438	20	-0.824	41	1.303	44	4.243	19	5.754	6	2.897	14
PRICEREL12	1.408	21	3.186	15	4.969	13	3.699	24	0.027	49	0.555	43
OBOS5MMA	1.254	22	3.195	13	5.342	9	5.452	10	2.224	19	1.471	24
ROE	1.164	23	0.865	40	1.106	45	2.074	41	2.789	15	1.678	20
RETVAR12	-1.097	24	-0.125	49	0.450	48	0.463	49	1.938	23	-0.986	31
MA5	1.041	25	1.857	25	2.414	37	3.153	29	1.364	29	0.171	49
MOM3	1.038	26	2.732	19	4.519	17	4.359	17	0.411	42	1.207	27
MOM60	-1.018	27	-4.489	3	-4.996	12	-3.982	22	-4.049	8	-5.889	8
MA10	0.989	28	1.681	30	4.159	20	3.446	26	0.288	44	0.951	32
MA6	0.981	29	1.404	38	2.455	36	3.244	27	1.357	30	0.701	39
EARNREV3M	-0.967	30	-2.832	18	-3.638	25	-1.420	45	-0.796	38	-0.872	34
EG1	0.909	31	0.706	43	1.073	46	0.220	50	-2.146	20	1.084	30
MVLOG	-0.888	32	-3.194	14	-3.133	27	-2.674	38	-5.896	5	-3.511	12
SPSLOG	-0.716	33	-1.721	27	-2.382	38	-5.958	7	-17.497	1	-22.217	1
OBOS4MMA	0.673	34	3.171	16	5.136	11	4.958	13	1.325	32	1.253	25
MA8	0.667	35	1.557	36	3.736	23	3.956	23	0.679	40	0.822	35
DY	0.656	36	0.255	48	2.182	39	4.595	16	3.347	12	6.485	5
MA4	0.532	37	1.835	26	2.725	31	3.161	28	1.827	24	0.381	45
MA7	0.506	38	0.702	44	2.530	33	2.823	34	1.458	26	1.197	28
MA9	0.506	39	0.702	45	2.530	34	2.823	35	1.458	27	1.197	29
DPSLOG	-0.488	40	0.550	46	0.407	49	-0.474	48	-2.823	14	-6.108	7
DE	-0.388	41	-0.022	50	-0.184	50	-1.474	44	1.456	28	-0.095	50
C24MBVTM	-0.349	42	-0.808	42	-1.453	42	-0.516	47	-1.353	31	2.484	15
OBOS2MMA	-0.335	43	1.969	24	2.876	29	3.107	30	0.350	43	0.465	44
MOM1	-0.333	44	1.672	31	2.474	35	2.830	33	0.246	45	0.599	41
OBOS3MMA	0.303	45	3.270	12	4.754	15	4.335	18	0.892	35	0.812	36
MA3	-0.193	46	2.307	22	2.930	28	2.702	37	0.873	36	-0.184	48
POUTRAT	0.185	47	1.604	34	4.330	19	8.616	2	9.503	2	7.751	4
C24MDPSP	-0.136	48	-2.548	20	-4.657	16	-8.890	1	-6.482	4	-6.423	6
EY	-0.032	49	-0.314	47	0.889	47	1.745	42	0.684	39	2.193	16
STP	0	50	-1.719	28	-2.035	40	-1.481	43	-1.978	22	-1.623	21

Panel B: Subsample_2 (2003 – 2011): Large-cap sample

	1-month forward return		3-month forward return		6-month forward return		12-month forward return		24-month forward return		36-month forward return	
Factor	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank
CFTP	3.559	1	4.972	1	6.019	1	5.526	4	8.170	1	10.332	2
MOM1	-3.14	2	-1.082	29	0.122	48	1.076	41	0.869	37	1.095	35
BVTMLOG	3.073	3	4.888	2	5.451	2	5.969	3	6.768	4	7.449	5
EPS	2.215	4	4.343	3	4.783	3	3.799	16	0.877	36	-0.177	49
OBOS3MMA	-2.126	5	-0.216	48	0.735	37	1.463	39	0.861	38	1.112	34
EY	1.923	6	3.475	5	3.572	6	4.084	8	6.645	5	10.866	1
C24MDPSP	1.643	7	3.291	6	2.878	8	2.225	27	0.166	48	1.645	24
C24MEPSP	1.498	8	3.257	7	3.177	7	1.399	40	-1.875	24	-2.056	15
DPSLOG	-1.497	9	-2.354	10	-2.660	9	-6.341	2	-6.023	7	-3.065	9
OBOS2MMA	-1.48	10	-1.339	20	0.064	49	0.861	44	0.624	42	0.487	42
DY	1.434	11	3.122	8	3.912	5	4.375	6	3.528	11	7.231	6
OBOS4MMA	-1.263	12	0.139	49	1.332	26	2.359	24	1.566	29	1.547	26
MOM6	1.262	13	2.509	9	2.597	10	4.294	7	2.631	13	2.005	16
MA3	-1.151	14	-1.237	23	-0.534	44	0.182	48	0.441	43	-1.251	32
EARNREV3M	1.132	15	2.004	11	1.146	28	2.229	26	1.149	33	1.207	33
MA12	1.095	16	0.726	34	0.598	42	1.832	29	1.768	25	1.979	17
MA11	1.091	17	0.947	31	0.882	33	1.752	34	1.444	31	1.532	27
LNP	-1.043	18	-3.683	4	-4.739	4	-6.818	1	-7.844	2	-7.881	4
C24MBVTM	1.032	19	1.101	28	1.815	22	3.526	18	5.756	8	4.145	8
MA2	-0.855	20	-1.034	30	-0.780	36	0.053	50	0.354	46	-0.368	46
MA10	0.774	21	0.322	42	0.463	45	1.881	28	0.200	47	0.752	39
OBOS5MMA	-0.739	22	0.683	36	1.762	23	3.092	21	1.931	21	1.654	22
STP	0.735	23	1.194	24	1.415	25	1.639	35	1.994	19	2.315	14
MOM36	-0.625	24	-0.700	35	-0.662	38	-1.516	37	-5.487	9	-1.964	18
ROE	-0.624	25	-0.746	33	-1.106	29	-3.690	17	-3.590	10	-2.974	10
MA8	0.585	26	0.260	44	0.574	43	1.761	31	1.595	28	0.753	38
MOM12	0.543	27	1.178	27	1.329	27	2.289	25	1.171	32	0.836	37
BETA	0.537	28	-0.352	41	0.418	46	0.939	43	1.644	27	1.658	21
MA6	0.526	29	0.459	39	0.649	41	1.489	38	0.756	40	-0.069	50
OBOS12MMA	0.461	30	1.737	14	2.287	12	3.968	11	1.922	22	1.310	31
OBOS10MMA	0.45	31	1.684	17	2.218	14	3.967	12	2.039	18	1.398	29
OBOS11MMA	0.437	32	1.688	16	2.249	13	3.940	13	1.968	20	1.336	30
MA7	0.433	33	0.220	46	0.659	39	1.760	32	1.114	34	0.440	43
MA9	0.433	34	0.220	47	0.659	40	1.760	33	1.114	35	0.440	44
ICBTIN	0.406	35	0.911	32	1.657	24	0.136	49	0.154	49	-0.492	41
SPSLOG	-0.4	36	-1.306	21	-1.857	21	-3.905	14	-6.237	6	-5.508	7
MA4	-0.392	37	-0.546	38	-0.027	50	0.792	45	0.800	39	-0.410	45
OBOS6MMA	-0.382	38	1.184	25	1.973	20	3.516	19	2.057	17	1.672	20
OBOS9MMA	0.374	39	1.738	13	2.192	16	3.998	9	2.142	16	1.495	28
MOM60	-0.372	40	-1.500	19	-2.012	19	-2.437	23	-2.782	12	-0.514	40
EG1	0.355	41	-0.241	45	-1.076	30	-0.948	42	-1.729	26	-2.598	11
OBOS8MMA	0.35	42	1.736	15	2.202	15	3.980	10	2.184	14	1.586	25
MA5	0.338	43	0.002	50	0.362	47	1.625	36	0.439	44	-0.337	47
MOM3	0.173	44	1.248	22	2.145	17	3.201	20	1.878	23	2.340	13
OBOS7MMA	0.151	45	1.599	18	2.127	18	3.831	15	2.149	15	1.650	23
RETVAR12	0.138	46	0.386	40	0.927	32	0.379	47	0.047	50	1.711	19
MVLOG	-0.103	47	-1.896	12	-2.553	11	-4.605	5	-7.738	3	-9.317	3
POUTRAT	0.08	48	1.182	26	1.020	31	0.410	46	-0.742	41	-1.066	36
PRICEREL12	0.067	49	0.650	37	0.838	35	2.996	22	0.396	45	-0.333	48
DE	0	50	0.312	43	0.856	34	1.792	30	1.542	30	-2.471	12

Panel C: Total_sample (1994 – 2011): Large-cap sample

	1-month forward return		3-month forward return		6-month forward return		12-month forward return		24-month forward return		36-month forward return	
Factor	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank	t-statistic	Rank
CFTP	6.353	1	5.260	1	8.637	1	8.522	2	6.127	5	6.913	4
BVTMLOG	3.234	2	2.959	15	5.641	4	6.756	6	6.072	6	9.662	2
C24MEPSP	2.632	3	-1.125	37	-0.966	46	-3.795	26	-3.787	10	-4.627	12
EPS	2.626	4	2.774	18	3.634	21	2.911	38	0.091	50	-2.055	20
LNP	-2.523	5	-4.099	9	-6.594	2	-10.162	1	-8.103	3	-9.999	1
MOM12	2.423	6	3.620	13	3.448	22	2.227	42	-0.474	45	1.963	22
MOM6	2.326	7	4.849	2	5.671	3	6.628	9	3.262	14	2.453	16
MOM1	-2.273	8	0.890	39	2.110	40	2.925	37	0.570	44	0.948	38
BETA	2.13	9	2.341	22	3.870	18	5.743	14	4.088	8	3.245	15
MA12	2.037	10	1.823	26	2.852	28	3.411	30	0.848	42	1.523	26
MA11	1.984	11	1.909	24	3.314	26	3.510	29	0.899	41	1.354	30
OBOS12MMA	1.854	12	4.652	3	5.220	11	5.393	17	1.480	34	0.782	42
MA2	-1.739	13	0.935	38	1.405	43	2.395	41	0.128	49	-0.855	40
OBOS11MMA	1.705	14	4.555	4	5.363	9	5.730	15	1.788	32	0.840	41
OBOS10MMA	1.69	15	4.443	6	5.514	7	6.144	11	2.191	24	1.047	36
OBOS9MMA	1.644	16	4.484	5	5.617	5	6.648	8	2.601	20	1.393	28
OBOS8MMA	1.615	17	4.324	7	5.513	8	6.974	5	2.978	17	1.739	24
OBOS2MMA	-1.514	18	0.015	50	2.406	34	3.031	36	0.576	43	0.609	45
OBOS7MMA	1.422	19	4.142	8	5.515	6	7.144	4	3.181	15	2.094	18
DPSLOG	-1.325	20	-0.259	45	-0.601	48	-2.551	39	-3.627	12	-6.425	7
OBOS3MMA	-1.274	21	2.486	20	4.007	17	4.319	21	1.151	38	1.127	34
MA10	1.257	22	1.593	28	3.336	25	3.894	25	0.351	47	1.198	33
DY	1.239	23	1.199	36	3.375	24	5.367	18	3.732	11	6.789	6
MA6	1.107	24	1.457	31	2.399	35	3.526	27	1.550	33	0.648	43
PRICEREL12	1.085	25	2.786	17	3.815	20	4.747	20	0.216	48	0.352	47
MA5	1.04	26	1.621	27	2.187	39	3.524	28	1.419	36	0.065	50
MOM60	-0.978	27	-3.967	10	-4.880	13	-4.258	22	-3.984	9	-4.953	11
ROE	0.968	28	0.831	41	1.063	44	1.862	44	2.451	21	1.390	29
EG1	0.918	29	0.560	44	0.538	49	-0.179	50	-2.604	19	1.079	35
OBOS6MMA	0.901	30	3.686	11	5.327	10	6.746	7	3.104	16	2.082	19
MA8	0.887	31	1.478	30	3.206	27	4.243	23	1.361	37	1.047	37
MOM3	0.858	32	2.954	16	4.773	14	5.403	16	1.019	39	1.989	21
EY	0.838	33	0.846	40	2.239	37	3.182	33	2.248	22	4.273	13
MA3	-0.821	34	1.358	32	2.217	38	2.440	40	0.979	40	-0.533	46
MVLOG	-0.784	35	-3.652	12	-3.816	19	-4.175	24	-8.366	2	-5.740	8
ICBTIN	-0.777	36	0.054	49	2.105	41	1.721	45	2.230	23	0.881	39
SPSLOG	-0.729	37	-1.927	23	-2.643	30	-5.907	13	-9.372	1	-8.992	3
MA7	0.666	38	0.724	42	2.440	31	3.311	31	1.804	30	1.276	31
MA9	0.666	39	0.724	43	2.440	32	3.311	32	1.804	31	1.276	32
C24MDPSP	0.592	40	-1.515	29	-3.418	23	-6.127	12	-5.722	7	-5.483	9
RETVAR12	-0.58	41	0.175	47	0.971	45	0.600	48	1.833	28	0.120	49
MOM36	0.503	42	-1.334	34	-2.424	33	-3.081	35	-3.457	13	-5.373	10
C24MBVTM	0.493	43	-0.077	48	-0.242	50	2.071	43	1.988	26	3.630	14
OBOS4MMA	-0.458	44	2.619	19	4.593	15	5.339	19	1.828	29	1.696	25
OBOS5MMA	0.33	45	2.983	14	4.994	12	6.168	10	2.874	18	1.950	23
EARNREV3M	0.294	46	-2.362	21	-2.762	29	-0.417	49	-0.471	46	-0.632	44
DE	-0.278	47	0.257	46	0.642	47	1.139	46	1.838	27	-2.320	17
STP	0.272	48	-1.344	33	-1.699	42	-1.084	47	-1.462	35	-1.459	27
POUTRAT	0.201	49	1.899	25	4.303	16	7.422	3	7.830	4	6.826	5
MA4	0.191	50	1.325	35	2.254	36	3.102	34	1.992	25	0.255	48

As with the All-share sample, the Spearman rank correlation was calculated across the payoff periods for the Large-cap sample. The results are reported in Table 5.7.

Table 5.7: Spearman rank correlation: Large-cap sample

The Spearman rank correlation is calculated and reported here for the large-cap sample. A higher correlation statistic indicates higher consistency in the ranking order associated with the level of relative significance of each factor across the respective payoff periods. Results in bold indicate a strong correlation (>0.8) of the ranking order between the specific payoff periods. The results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C).

Panel A: Subsample_1 (1994 – 2002): Large-cap sample

Return period	1-month	3-month	6-month	12-month	24-month	36-month
1-month	1	0.47	0.47	0.33	0.09	0.10
3-month		1	**0.87**	0.50	-0.04	-0.12
6-month			1	0.71	0.00	-0.04
12-month				1	0.43	0.31
24-month					1	0.75
36-month						1

Panel B: Subsample_2 (2003 – 2011): Large-cap sample

Return period	1-month	3-month	6-month	12-month	24-month	36-month
1-month	1	0.38	0.22	0.13	0.12	0.17
3-month		1	**0.82**	0.63	0.53	0.43
6-month			1	0.77	0.63	0.57
12-month				1	0.78	0.53
24-month					1	0.77
36-month						1

Panel C: Total_sample (1994 – 2011): Large-cap sample

Return period	1-month	3-month	6-month	12-month	24-month	36-month
1-month	1	0.42	0.38	0.32	-0.05	0.12
3-month		1	**0.91**	0.75	0.19	0.21
6-month			1	**0.86**	0.28	0.30
12-month				1	0.51	0.44
24-month					1	0.74
36-month						1

For the period January 1994 through December 2002 (Table 5.6 Panel A) it is seen that, similar to the All-share sample, the value factor represented by CFTP remains significant for each of the respective payoff periods. BVTMLOG however loses its significance over the three-month payoff period, but becomes the most significant value factor over the twenty-four and thirty-six month payoff periods. Additionally, a third value factor, namely DY becomes significant over longer term return-periods and even more significant than CFTP over the thirty-six month payoff period. Together with CFTP and BVTMLOG, DY causes the relative significance ranking associated with the value effect to remain high. In contrast to the All-share sample, the fourth value factor namely EY becomes significant only over a thirty-six month payoff period, but even so the ranking associated with its significance remains quite low. Of the value factors, it is therefore clear that at least one factor, namely CFTP, remains a robust factor in explaining the cross-section of returns on the JSE irrespective of the return period used. This is directly in line with the findings when using the All-share sample, indicating that the value effect (represented by CFTP) is also robust irrespective of the level of liquidity in the sample. Note however that alternative value factors may better capture the value effect than CFTP, depending on the payoff period under review.

The size effect captured by LNP remains significant and, similar to the All-share sample, becomes more significant than the value effect as the return-period is increased. The size effect is further supported by the increase in significance and ranking order associated with an additional size factor, namely SPSLOG, especially over the twenty-four and thirty-six month payoff periods during which it is ranked as the most significant factor in explaining the cross-section of returns on the JSE. In contrast to the All-share sample, the significance and ranking of the MVLOG and EPS size factors is not that distinct for the Large-cap sample. With regards to the size effect, it is therefore found that LNP remains robust across payoff periods as well as levels of liquidity. SPSLOG is a function of payoff period but not liquidity while MVLOG and EPS are a function of both payoff period and liquidity. Furthermore, it is found that EPS portray the expected size-factor characteristics (i.e. a negative coefficient) only over the longest payoff period tested.

Although the momentum effect captured by MOM12 is found to be highly significant over a one-month payoff period, MOM6 overtakes its significance in ranking order over three, six and twelve month payoff periods. As was the case for the All-share sample, it is further found that the momentum effect is replaced by a price-reversal effect over longer payoff periods, especially the twenty-four and thirty-six month periods. This price reversal effect is captured by MOM36 and MOM60, which both show relatively highly significant, negative coefficients over these periods.

Similar to the findings using the All-share sample, a growth effect is observed when longer payoff periods are used. However, this effect is captured best by POUTRAT and C24MDPSP, rather than DPSLOG as was the case with the All-share sample. Note that a significant positive relationship is found between POUTRAT and returns while a significant indirect relationship is observed between C24MDPSP and returns as well as between DPSLOG and return. The latter was also observed for the All-share sample. In contrast to the findings regarding the All-share sample, the growth effect observed over longer payoff periods is not necessarily more significant than the value effect when using the Large-cap sample.

The significant positive slope associated with RetVar12 over longer payoff periods for the All-share sample is not observed for the Large-cap sample. Note however that CAPM beta, which was found to be significant for the Large-cap sample over a one-month return period, remains significant across all payoff periods although its relative ranking decreases.

From Table 5.7 Panel A it appears that the ranking order of the significance associated with the respective factors in explaining the cross-section of returns over a three- and six-month payoff period remains relatively consistent, while the order is more volatile across the other payoff periods under review.

For the period 2003 through 2011 (Table 5.6 Panel B), the significance of the value effect captured by CFTP and BVTMLOG once again remained robust across all pay-off periods while the two additional value factors, DY and EY became significant over payoff periods of at least three-months as well. Together the relative significance associated with these four value factors as the payoff period increases, causes the presence of the value effect to become extremely strong for the Large-cap sample during this period.

Similar to the All-share sample, the size effect became very significant over all longer payoff periods (of at least 3 months), supported by the significance of especially three size factors namely LNP, MVLOG and SPSLOG. Furthermore, the size effect became approximately just as significant as the value effect over longer payoff periods. In keeping with the results from Section 5.3, it therefore seems that although the size effect seemed to disappear since 2003 with regards to a 1-month payoff period, it is still very significant over longer payoff periods irrespective of liquidity level.

Similar to the All-share sample, the momentum effect (captured by MOM6) remained significant across longer payoff periods for Subsample_2, while the price reversal effect (captured by MOM36 and MOM60) over longer payoff periods is not evident for Subsample_2. The short-term price-reversal effect (captured by MOM1) is significant only over the one-month return period.

A growth effect is observed over longer payoff periods (at least three-months). This is best captured by the DPSLOG factor (which is found to be most consistent in terms of significance ranking order relative to other growth factors). Note that, as with the All-share sample, a significant but indirect relationship between growth (represented by DPSLOG) and longer-term returns is observed.

From Table 5.7 (Panel B) it is seen that, similar to Subsample_1, the ranking order of the factors explaining the cross-section of returns over a three and six-month period appears to remain relatively consistent.

The results for Total_sample (Table 5.6 Panel C) are very similar to that of Subsample_1. Firstly, a robust value effect is observed which is captured by especially CFTP. Although BVTMLOG becomes less significant over the three-month payoff period, it remains significant throughout. The significant size (captured best by LNP) effect remains evident across all payoff periods. The significance level of the momentum effect (best captured by MOM12 over the one-month and MOM6 over three to twelve month payoff periods) is overtaken by that of a longer-term price reversal effect (captured by MOM60) associated with payoff periods in excess of twelve months. A growth effect is observed (captured best by POUTRAT and C24MDPSP) over payoff periods of at least twenty-four months, while the CAPM beta remains significant across all payoff periods although its relative ranking is quite volatile (and mostly decreases) over longer periods. From Table 5.7 (Panel C) it is seen that the ranking order of factors is similar over a three-month and six-month and a six-month and twelve-month period.

5.5 Conclusion

Based on a one-month payoff period and including all shares in the sample, significant value and momentum effects are observed on the JSE across all sample periods, while the size effect disappeared since 2003. The latter was however strong enough during the earlier part of the sample (1994 - 2002) so that it still tested as a significant effect over the entire period. Longer-term technical (momentum) factors seem to contribute a great deal to explaining the cross-section of monthly returns on the JSE. Therefore, ignoring liquidity, a value and momentum effect is observed on the JSE which is insensitive to time.

Continuing with a one-month payoff period and increasing the level of sample liquidity (by selecting shares based on a filtering level set equal to the 5th market cap decile), the value effect appears to be significant across all sample periods while the momentum effect disappears during the period January 2003 through May 2011. The value effect (best captured by the CFTP and BVTMLOG factors) therefore seems to be robust while the momentum effect becomes sensitive to time as a result of the change in the level of sample liquidity. Additionally a price-reversal effect is observed for Subsample_2 that remains significant on a 90% level irrespective of the liquidity filter applied. The size effect is only observed, once at least the top 68 shares in terms of market cap are included in the sample. Furthermore the size effect disappears during 2003 through 2011. The size effect is therefore sensitive to liquidity and time. The CAPM beta is found to be significant for the Large-cap sample for two of the three sample periods. Its significance therefore depends on time as well as the level of sample liquidity, confirming that the use of the single factor CAPM model to explain returns on the JSE is inappropriate.

When the payoff period is increased to at least three-months, a significant value and size effect is observed across all sample periods for both the All-share and Large-cap samples. Value (best captured by CFTP) therefore appears to be a robust factor that contributes significantly to explaining the cross-section of returns on the JSE. It is not affected by time, liquidity or payoff period. Although the size effect (best captured by LNP) disappears when using a one-month payoff period during 2003 through 2011, it is not affected by time, liquidity or payoff period given a minimum payoff period of three months. Momentum, price-reversal and growth effects appear to be sensitive to time, liquidity and/or payoff period. For Subsample_1 and Total_sample the significance associated with the momentum effect decreases while a longer term price-reversal effect becomes highly significant as the payoff period is increased. The momentum effect remains significant across longer payoff periods for Subsample_2 with no evidence of a longer-term price-reversal effect. A growth effect appears across all longer term payoff periods (three-months and longer) for all sample periods but the nature of its effect (positive or negative) on returns is not consistent. The ranking order of factors appears to be relatively consistent over a three- and six-month payoff period across all sample periods, irrespective of liquidity level applied.

6

SINGLE-FACTOR PORTFOLIO CONSTRUCTION ON THE JSE

6.1 Introduction

From the literature review (Chapter 3) it was seen that an alternative approach, referred to in this thesis as a 'single-factor portfolio construction' approach, is sometimes used to research the validity of the EMH. In this chapter such a factor portfolio construction approach is applied to ascertain the identity and examine the impact of firm-specific factors on the cross- section of equity returns on the JSE.

Portfolios are constructed based on each individual factor listed in Table 4.2 (Chapter 4) and the performance of these portfolios is subsequently evaluated. The effect of time, sample liquidity and payoff period on the results are examined by performing the analysis over each of the three sample periods for the All-share and Large-cap samples using a one-month and three-month holding period. Finally the single-factor portfolio returns are adjusted for risk using the CAPM and Van Rensburg (2002) two-factor APT models to determine whether the portfolio performance can be captured by these market models.

The methodology followed in this chapter is outlined in Section 6.2. In Section 6.3 the results are discussed for the All-share sample (Section 6.3.1) and the Large-cap sample (Section 6.3.2) respectively. The risk-adjusted performance evaluation is discussed in Section 6.4 followed by the conclusion in Section 6.5.

6.2 Methodology

Shares are ranked by the factor concerned at the end of the last trading day of the previous month. Three equally weighted portfolios are formed, with the top and bottom 30% of the ranked shares forming Portfolio_1 and Portfolio_3 respectively. Returns are calculated for these portfolios during the subsequent month, and the portfolios are rebalanced once again at the end of the last trading day of the specific month. The procedure is repeated every month of the three sample periods (i.e. January 1994 through December 2002, January 2003 through May 2011 and January 1994 through May 2011). Next a monthly "long/short" returns time series is calculated for each factor by subtracting the returns of Portfolio_3 from that of Portfolio_1. This essentially provides a return series for a hedge fund going long Portfolio_1 while shorting Portfolio_3.

The portfolio construction for the moving average factors differs slightly from that described above. Each month two portfolios are created, where one portfolio goes long those shares that are trading at a price above its moving average while the second portfolio goes short those shares that are trading at a price below its moving average. Once again a monthly "long/short" returns time series is calculated for each moving average factor by subtracting the returns of the second portfolio from that of the first.

To determine whether the difference in these portfolios' mean returns is significantly different from zero, the following Student's t-statistic is employed:

$$t = \frac{\tilde{R}_F \sqrt{n}}{\sigma_F}$$

where:

$\tilde{R}_F$	=	the mean value of the "long/short" returns to factor portfolio *F*
n	=	the number of (monthly) observations
σ_F	=	the standard deviation of the returns to "long/short" factor portfolio *F*

The above procedure is repeated for a rebalancing period of three months in order to examine the effect that the payoff period may have on the 'reward' associated with each factor portfolio. A 3-month period is chosen to allow for the formation of non-overlapping portfolios while still providing adequate data points in order to apply the above t-statistic.

Lastly risk-adjusted performance evaluation is conducted on each of the factor portfolios found to offer significant outperformance through the above procedure. Both the traditional CAPM and the Van Rensburg (2002) two factor APT models are used for the risk-adjusted performance evaluation. Mathematically the procedure can be presented as follows:

CAPM:

$$R_F - R_{ft} = \alpha_F + \beta_F(R_{mt} - R_{ft}) + \varepsilon_{Ft} \qquad \ldots(6.1)$$

Two-factor APT:

$$R_F - R_{ft} = \alpha_F + \beta_{F,FINDI}(R_{FINDIt} - R_{ft}) + \beta_{F,RESI}(R_{RESIt} - R_{ft}) + \varepsilon_{Ft} \qquad \ldots(6.2)$$

where:

R_F	=	returns on factor portfolio *F* in period t
R_{ft}	=	risk-free rate in period t (proxied by the return on 3-month Treasury Bills)
R_{mt}	=	return on 'market' portfolio in period t (proxied by the JSE All-Share Index)
R_{FINDIt}	=	return on first APT factor in period t (proxied by the JSE Financial-Industrial Index)
R_{RESIt}	=	return on second APT factor in period t (proxied by the JSE Resources Index)
$\beta_F, \beta_{F,FINDI}$ *and* $\beta_{F,RESI}$	=	risk parameters to be estimated
ε_{Ft}	=	a residual error term that obeys the classic assumptions

To evaluate the risk-adjusted performance a significance test is conducted on the intercept terms (α) of the above models. This procedure is repeated for both the All-share and Large-cap samples using a one- and three-month holding period over the three different sample periods.

6.3 Single-factor portfolio results.

6.3.1. All-share sample

Table 6.1 presents the results of the evaluation of the raw returns (returns not adjusted for risk) of the factor portfolios constructed based on the methodology described in Section 6.2. All shares are included and portfolios are rebalanced monthly. Portfolios are ranked in descending order based on the absolute value of the t-statistics. The monthly mean returns that are significantly different from zero on a 95% level of confidence are indicated in bold.

Table 6.1: Evaluation of factor portfolios' raw returns: All-share sample.
This table presents the average difference in monthly returns between Portfolio_1 and Portfolio_3 constructed for each respective factor (and the difference between the long and short moving average portfolios) and rebalanced monthly. A t-statistic is calculated for the average difference in returns for each factor portfolio for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the mean monthly return difference is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 – 2002)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**2.68%**	4.80%	107	**5.781**	RETVAR12	0.44%	4.86%	96	0.890
LNP	**-1.85%**	4.01%	107	**-4.755**	MOM3	0.48%	5.58%	104	0.877
MVLOG	**-1.83%**	4.84%	107	**-3.904**	OBOS6MMA	0.51%	5.90%	102	0.875
MOM12	**2.10%**	6.09%	95	**3.367**	OBOS2MMA	-0.40%	4.93%	106	-0.832
BVTMLOG	**1.42%**	5.63%	107	**2.600**	OBOS3MMA	-0.40%	5.83%	105	-0.711
OBOS12MMA	**1.40%**	6.40%	96	**2.148**	MA2	-0.23%	3.64%	107	-0.654
DPSLOG	-0.72%	3.72%	107	**-1.995**	ICBTINV	0.54%	4.18%	21	0.589
OBOS11MMA	1.27%	6.47%	97	1.935	MA11	0.27%	5.39%	107	0.524
DE	-1.17%	2.87%	21	-1.874	MOM36	0.37%	6.64%	71	0.466
OBOS9MMA	1.15%	6.26%	99	1.827	MA6	0.23%	5.65%	107	0.420
OBOS10MMA	1.15%	6.28%	98	1.814	MA5	0.22%	5.47%	107	0.413
C24MBVTM	1.04%	5.35%	83	1.775	MA7	0.23%	5.77%	107	0.404
MOM60	-1.33%	5.26%	47	-1.728	MA9	0.23%	5.77%	107	0.404
POUTRAT	-0.72%	4.35%	107	-1.700	OBOS4MMA	0.21%	5.71%	104	0.370
OBOS8MMA	1.04%	6.25%	100	1.668	EPS	-0.11%	3.68%	107	-0.318
MOM6	1.34%	8.50%	101	1.584	MA12	0.16%	5.12%	107	0.315
C24MDPSP	-0.65%	3.82%	83	-1.542	MOM1	-0.14%	4.70%	107	-0.309
PRICEREL12	0.93%	6.36%	96	1.428	MA8	0.17%	5.62%	107	0.308
DY	-0.67%	4.95%	107	-1.398	MA10	0.16%	5.48%	107	0.303
OBOS7MMA	0.78%	6.11%	101	1.282	MA3	-0.12%	4.92%	107	-0.257
EY	0.53%	4.81%	107	1.130	EARNREV3M	0.02%	0.95%	47	0.138
BETA	0.69%	6.68%	107	1.072	C24MEPSP	-0.05%	4.04%	83	-0.123
STP	0.69%	6.76%	107	1.057	EG1	0.03%	3.82%	107	0.090
ROE	-0.49%	5.25%	107	-0.971	SPS	0.08%	4.44%	21	0.081
OBOS5MMA	0.53%	5.89%	103	0.911	MA4	0.03%	5.47%	107	0.064

Panel B: Subsample_2 (2003 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**1.40%**	3.18%	98	**4.359**	**MA5**	0.46%	3.25%	99	1.399
C24MEPSP	**1.00%**	3.09%	98	**3.191**	**OBOS3MMA**	-0.50%	3.56%	98	-1.396
C24MDPSP	**0.89%**	3.15%	98	**2.796**	**STP**	0.44%	2.52%	63	1.393
MOM6	**0.92%**	3.51%	98	**2.594**	**C24MBVTM**	**-0.43%**	3.38%	98	-1.268
EARNREV3M	**0.24%**	0.92%	98	**2.551**	**MVLOG**	-0.37%	2.93%	97	-1.256
MOM1	**-0.77%**	3.28%	98	**-2.331**	**OBOS7MMA**	0.48%	3.90%	98	1.224
OBOS2MMA	**-0.74%**	3.20%	98	**-2.277**	**RETVAR12**	-0.44%	3.64%	98	-1.206
MA11	**0.92%**	4.11%	99	**2.221**	**PRICEREL12**	0.47%	3.92%	98	1.197
MA12	**0.90%**	4.14%	99	**2.157**	**MA4**	0.36%	3.28%	99	1.099
MA10	**0.83%**	3.85%	99	**2.137**	**MOM36**	0.39%	4.02%	98	0.957
EY	**0.65%**	3.08%	98	**2.091**	**OBOS6MMA**	0.33%	3.96%	98	0.826
OBOS10MMA	0.76%	3.77%	98	**2.004**	**OBOS4MMA**	-0.29%	3.89%	98	-0.746
EPS	0.46%	2.36%	98	1.941	**MA3**	0.20%	3.25%	99	0.617
DY	0.71%	3.67%	98	1.924	**DE**	**-0.12%**	2.28%	98	-0.533
OBOS12MMA	0.75%	3.90%	98	1.911	**DPSLOG**	-0.11%	2.23%	98	-0.486
BVTMLOG	0.47%	2.55%	98	1.827	**LNP**	-0.13%	2.75%	98	-0.477
OBOS11MMA	0.70%	3.80%	98	1.815	**ICBTINV**	0.13%	2.82%	98	0.463
OBOS9MMA	0.68%	3.75%	98	1.805	**ROE**	0.16%	2.92%	63	0.428
MOM12	0.71%	3.92%	98	1.784	**MOM60**	0.11%	3.15%	98	0.344
MA8	0.62%	3.66%	99	1.682	**POUTRAT**	-0.12%	3.59%	98	-0.332
MA7	0.57%	3.48%	99	1.617	**EG1**	-0.09%	3.17%	96	-0.264
MA9	0.57%	3.48%	99	1.617	**OBOS5MMA**	0.10%	3.93%	98	0.245
SPSLOG	-0.37%	2.27%	98	-1.602	**MA2**	-0.05%	2.91%	99	-0.179
OBOS8MMA	0.59%	3.75%	98	1.547	**MOM3**	-0.05%	3.83%	98	-0.142
MA6	0.51%	3.33%	99	1.519	**BETA**	**-0.01%**	4.78%	98	-0.015

Panel C: Total_sample (1994 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**2.06%**	4.14%	206	**7.129**	**STP**	0.57%	5.56%	171	1.338
LNP	**-1.03%**	3.56%	206	**-4.149**	**SPSLOG**	-0.31%	2.76%	120	-1.227
MVLOG	**-1.14%**	4.09%	205	**-3.995**	**OBOS6MMA**	0.41%	5.02%	201	1.169
MOM12	**1.40%**	5.13%	194	**3.810**	**MA7**	0.39%	4.80%	206	1.162
BVTMLOG	**0.95%**	4.44%	206	**3.063**	**MA9**	0.39%	4.80%	206	1.162
OBOS12MMA	**1.07%**	5.27%	195	**2.828**	**MA8**	0.38%	4.77%	206	1.156
OBOS11MMA	**0.97%**	5.28%	196	**2.582**	**MA6**	0.36%	4.67%	206	1.115
OBOS10MMA	**0.95%**	5.16%	197	**2.573**	**MA5**	0.33%	4.53%	206	1.055
OBOS9MMA	**0.91%**	5.15%	198	**2.480**	**MOM60**	-0.33%	4.00%	146	-0.997
MOM6	**1.11%**	6.51%	200	**2.421**	**MOM36**	0.38%	5.25%	170	0.946
OBOS8MMA	**0.80%**	5.15%	199	**2.203**	**OBOS5MMA**	0.31%	5.02%	202	0.879
EARNREV3M	**0.17%**	0.93%	146	**2.195**	**BETA**	0.34%	5.84%	206	0.839
EY	**0.59%**	4.06%	206	**2.080**	**ROE**	-0.26%	4.51%	171	-0.749
DPSLOG	-0.43%	3.10%	206	-1.971	**EPS**	0.15%	3.12%	206	0.694
OBOS2MMA	-0.57%	4.17%	205	-1.966	**C24MBVTM**	0.22%	4.44%	182	0.663
C24MEPSP	0.51%	3.58%	182	1.913	**C24MDPSP**	0.17%	3.54%	182	0.645
PRICEREL12	0.69%	5.25%	195	1.826	**MOM3**	0.22%	4.79%	203	0.640
MA11	0.58%	4.81%	206	1.737	**MA2**	-0.14%	3.30%	206	-0.628
OBOS7MMA	0.62%	5.12%	200	1.708	**ICBTINV**	0.18%	3.09%	120	0.622
MOM1	-0.45%	4.08%	206	-1.601	**MA4**	0.19%	4.54%	206	0.606
MA12	0.51%	4.68%	206	1.570	**OBOS4MMA**	-0.05%	4.90%	203	-0.150
POUTRAT	-0.43%	4.00%	206	-1.547	**EG1**	-0.04%	3.52%	204	-0.145
MA10	0.48%	4.77%	206	1.446	**MA3**	0.03%	4.19%	206	0.115
DE	-0.31%	2.40%	120	-1.403	**DY**	-0.02%	4.42%	206	-0.070
OBOS3MMA	-0.47%	4.85%	204	-1.379	**RETVAR12**	0.00%	4.29%	195	0.001

Comparing the results of Table 6.1 to Table 5.1 (Chapter 5) it is seen that the majority of factors found to be significant in explaining the cross- section of returns over Subsample_1, Subsample_2 and Total_sample can be used to form portfolios that offer superior performance opportunities. Specifically, value (represented by CFTP and BVTMLOG), size (represented by LNP, MVLOG) and momentum (represented by MOM6, MOM12 and longer term OBOS) portfolios could be formed for Subsample_1 and Total_sample that outperform their counterparts significantly on a 95% level of confidence. For Subsample_2, value (represented by CFTP and EY), growth (represented by C24MDPSP and C24MEPSP), momentum (represented by MOM6 and longer term MA) and short- term price-reversal (represented by MOM1 and shorter term OBOS) portfolios could be formed that significantly outperformed its counterparts. These results show that, similar to the findings of the univariate cross-sectional regression approach, the value and momentum effect seem to be robust across all sample periods while the size effect disappears during Subsample_2 and is replaced by a short- term price reversal effect. In addition a growth effect is observed during the latter period.

The above procedure is repeated for a holding period of three months before rebalancing takes place. The results are reported in Table 6.2.

Table 6.2: Evaluation of factor portfolios' raw returns: All-share sample, portfolios rebalanced every 3 months.

This table presents the average difference in three-month holding period returns between Portfolio_1 and Portfolio_3 constructed for each respective factor (and the difference between the long and short moving average portfolios). Portfolios are rebalanced every 3 months. A t-statistic is calculated for the average difference in returns for each factor portfolio for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the mean three-month holding period return difference is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 – 2002)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
LNP	**-8.28%**	14.41%	36	**-3.447**	MA9	-2.58%	18.96%	36	-0.816
CFTP	**7.68%**	14.34%	36	**3.213**	MA10	-2.36%	17.55%	36	-0.805
DPSLOG	**-4.79%**	9.31%	36	**-3.090**	EPS	-2.16%	16.18%	36	-0.801
MVLOG	**-8.28%**	16.47%	36	**-3.016**	MOM6	3.13%	22.86%	34	0.799
POUTRAT	**-6.02%**	15.42%	36	**-2.342**	C24MEPSP	-2.78%	19.33%	28	-0.760
DY	**-6.98%**	19.00%	36	**-2.203**	STP	2.51%	16.82%	25	0.745
BVTMLOG	**5.18%**	14.47%	36	**2.148**	SPSLOG	1.97%	7.03%	7	0.740
C24MDPSP	**-8.07%**	20.20%	28	**-2.115**	MA11	-1.58%	15.72%	36	-0.603
BETA	3.72%	14.58%	36	1.532	MA12	-1.52%	16.81%	36	-0.544
MA4	-3.22%	13.91%	36	-1.387	ROE	1.23%	14.30%	35	0.511
MOM60	-5.34%	16.48%	16	-1.297	OBOS4MMA	-1.86%	23.51%	35	-0.469
MA2	-2.45%	12.16%	36	-1.210	OBOS12MMA	2.07%	25.00%	32	0.468
DE	-2.13%	4.66%	7	-1.207	OBOS5MMA	-1.84%	24.77%	34	-0.434
MA5	-2.97%	14.80%	36	-1.205	OBOS11MMA	1.88%	25.30%	32	0.421
C24MBVTM	3.07%	13.67%	28	1.189	MOM36	-0.78%	14.67%	24	-0.259
ICBTINV	1.78%	4.10%	7	1.148	MOM1	-0.55%	13.81%	35	-0.236
MA8	-3.25%	18.01%	36	-1.083	OBOS10MMA	0.91%	25.22%	33	0.207
MOM12	3.61%	20.48%	32	0.997	MOM3	-0.76%	21.83%	35	-0.205
RETVAR12	2.96%	16.97%	32	0.988	OBOS6MMA	-0.73%	25.09%	34	-0.169
MA6	-2.64%	16.59%	36	-0.955	OBOS8MMA	-0.57%	29.47%	33	-0.111
OBOS2MMA	-3.31%	21.38%	35	-0.917	PRICEREL12	0.37%	19.23%	32	0.110
EY	2.18%	14.32%	36	0.914	OBOS7MMA	0.40%	23.12%	34	0.100
OBOS3MMA	-3.31%	22.28%	35	-0.879	EARNREV3M	-0.21%	12.54%	16	-0.067
MA3	-1.80%	12.44%	36	-0.867	OBOS9MMA	0.26%	25.10%	33	0.059
MA7	-2.58%	18.96%	36	-0.816	EG1	-0.12%	13.40%	35	-0.051

Panel B: Subsample_2 (2003 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
SPSLOG	**-2.22%**	3.66%	32	**-3.434**	MA11	1.25%	10.06%	32	0.703
CFTP	**4.18%**	7.02%	32	**3.365**	EPS	0.66%	5.33%	32	0.697
C24MEPSP	**2.86%**	5.77%	32	**2.803**	PRICEREL12	0.95%	8.04%	32	0.672
LNP	**-1.86%**	4.08%	32	**-2.583**	MA12	1.12%	10.06%	32	0.629
MVLOG	**-1.93%**	4.38%	32	**-2.486**	MA8	1.01%	9.16%	32	0.623
C24MDPSP	**2.27%**	6.06%	32	**2.120**	MA7	0.95%	8.75%	32	0.615
BVTMLOG	**1.79%**	4.92%	32	**2.058**	MA9	0.95%	8.75%	32	0.615
EY	1.99%	5.83%	32	1.934	OBOS3MMA	-0.74%	7.02%	32	-0.595
DY	2.05%	6.91%	32	1.679	DPSLOG	-0.32%	3.12%	32	-0.579
MOM6	2.52%	8.68%	32	1.643	OBOS6MMA	0.86%	8.69%	32	0.562
MOM12	2.39%	8.56%	32	1.578	MA3	-0.81%	8.41%	32	-0.542
MA2	-1.44%	6.85%	32	-1.189	EG1	-0.42%	5.43%	31	-0.435
STP	1.17%	5.14%	21	1.039	MA6	0.60%	8.26%	32	0.411
OBOS8MMA	1.54%	8.65%	32	1.006	MOM36	0.52%	7.59%	32	0.387
OBOS9MMA	1.57%	8.85%	32	1.006	DE	0.19%	2.98%	32	0.362
MOM1	-0.88%	4.98%	32	-0.999	BETA	-0.48%	8.20%	32	-0.331
C24MBVTM	-1.27%	7.17%	32	-0.999	OBOS5MMA	0.41%	8.65%	32	0.270
OBOS12MMA	1.49%	9.00%	32	0.939	RETVAR12	-0.25%	5.61%	32	-0.251
OBOS10MMA	1.44%	8.82%	32	0.923	MOM3	0.33%	8.20%	32	0.228
ICBTINV	0.91%	5.59%	32	0.918	MOM60	-0.18%	6.21%	32	-0.161
OBOS11MMA	1.41%	8.94%	32	0.890	POUTRAT	0.19%	6.88%	32	0.160
OBOS2MMA	-0.68%	4.62%	32	-0.830	OBOS4MMA	-0.20%	7.61%	32	-0.146
MA10	1.37%	9.79%	32	0.790	MA4	-0.17%	8.10%	32	-0.119
OBOS7MMA	1.20%	8.82%	32	0.767	MA5	0.12%	7.92%	32	0.084
EARNREV3M	0.28%	2.11%	32	0.751	ROE	-0.06%	4.27%	21	-0.064

Panel C: Total_sample (1994 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**6.03%**	11.55%	68	**4.307**	OBOS11MMA	1.64%	18.82%	64	0.699
LNP	**-5.26%**	11.25%	68	**-3.855**	MA6	-1.12%	13.34%	68	-0.690
MVLOG	**-5.29%**	12.68%	68	**-3.440**	EPS	-0.83%	12.33%	68	-0.558
DPSLOG	**-2.69%**	7.40%	68	**-2.994**	MOM1	-0.71%	10.49%	67	-0.553
BVTMLOG	**3.58%**	11.11%	68	**2.661**	C24MBVTM	0.76%	10.83%	60	0.542
POUTRAT	**-3.09%**	12.48%	68	**-2.044**	MA7	-0.92%	15.05%	68	-0.503
SPSLOG	-1.47%	4.63%	39	-1.986	MA9	-0.92%	15.05%	68	-0.503
MA2	-1.98%	9.96%	68	-1.636	OBOS10MMA	1.17%	18.86%	65	0.500
EY	2.09%	11.09%	68	1.557	OBOS4MMA	-1.07%	17.68%	67	-0.494
MOM12	3.00%	15.59%	64	1.540	ROE	0.75%	11.55%	56	0.485
DY	-2.73%	15.21%	68	-1.479	DE	-0.23%	3.39%	39	-0.414
MOM6	2.84%	17.36%	66	1.328	OBOS9MMA	0.91%	18.80%	65	0.389
C24MDPSP	-2.56%	15.27%	60	-1.297	PRICEREL12	0.66%	14.62%	64	0.364
MA4	-1.78%	11.57%	68	-1.271	OBOS7MMA	0.78%	17.56%	66	0.363
ICBTINV	1.06%	5.32%	39	1.249	MA10	-0.60%	14.45%	68	-0.344
MOM60	-1.90%	10.87%	48	-1.211	OBOS5MMA	-0.75%	18.67%	66	-0.327
BETA	1.74%	12.11%	68	1.188	EG1	-0.26%	10.37%	66	-0.204
OBOS2MMA	-2.05%	15.72%	67	-1.070	OBOS8MMA	0.47%	21.71%	65	0.174
MA5	-1.52%	12.07%	68	-1.036	MA12	-0.28%	14.01%	68	-0.165
MA3	-1.33%	10.67%	68	-1.028	MA11	-0.25%	13.34%	68	-0.154
OBOS3MMA	-2.08%	16.75%	67	-1.018	C24MEPSP	0.23%	14.02%	60	0.126
STP	1.90%	12.77%	46	1.007	MOM3	-0.24%	16.66%	67	-0.117
RETVAR12	1.36%	12.64%	64	0.859	EARNREV3M	0.12%	7.29%	48	0.111
OBOS12MMA	1.78%	18.64%	64	0.765	MOM36	-0.04%	11.08%	56	-0.024
MA8	-1.25%	14.59%	68	-0.704	OBOS6MMA	0.04%	18.87%	66	0.019

From Table 6.2 it is seen that constructing portfolios based on a value or size strategy appears to be profitable across all sample periods when a three-month holding period is used. Specifically, using CFTP or BVTMLOG to construct value portfolios while using LNP or MVLOG to construct size portfolios appear to offer robust strategies to generate significant outperformance across all sample periods. Although momentum portfolios continue offering outperformance opportunities, it loses its significance over a 3-month holding period. Similarly, the short- term price reversal strategy loses its significance over a 3-month holding period. The factors and ranking order of factors that offer the most significant explanatory power of the cross- section of returns over a three-month payoff period (Chapter 5 Section 5.4.1) correlates very well with the identity and ranking order of factor portfolios that offer significant outperformance opportunities over a similar payoff period.

6.3.2. Large-cap sample

Table 6.3 presents the results for the Large-cap sample.

Table 6.3: Evaluation of factor portfolios' raw returns: Large-cap sample.
This table presents the average difference in monthly returns between Portfolio_1 and Portfolio_3 constructed for each respective factor (and the difference between the long and short moving average portfolios) and rebalanced monthly, using the 5th market cap decile as liquidity filter. A t-statistic is calculated for the average difference in returns for each characteristic portfolio for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the mean monthly return difference is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 – 2002)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**2.58%**	5.21%	107	**5.133**	POUTRAT	0.38%	4.78%	107	0.818
LNP	**-1.11%**	4.01%	107	**-2.864**	RETVAR12	-0.39%	4.91%	96	-0.777
MOM12	**1.88%**	6.50%	95	**2.819**	MA5	0.42%	5.62%	107	0.769
BVTMLOG	**1.48%**	5.96%	107	**2.566**	OBOS5MMA	0.51%	6.82%	103	0.756
BETA	1.21%	6.45%	107	1.943	DY	0.43%	6.07%	107	0.739
EPS	0.59%	3.24%	107	1.888	DPSLOG	-0.31%	4.86%	107	-0.669
OBOS12MMA	1.42%	7.42%	96	1.871	OBOS4MMA	0.41%	6.60%	104	0.630
MOM36	1.74%	8.06%	71	1.825	MOM1	-0.31%	5.28%	106	-0.599
MOM6	1.54%	8.58%	101	1.804	OBOS2MMA	-0.32%	5.51%	106	-0.594
MOM60	-1.58%	6.04%	47	-1.791	MA6	0.33%	5.89%	107	0.585
OBOS11MMA	1.35%	7.50%	97	1.767	MA10	0.25%	5.26%	107	0.486
OBOS10MMA	1.31%	7.45%	98	1.748	MA4	0.22%	5.55%	107	0.417
STP	1.26%	7.95%	107	1.644	C24MEPSP	0.15%	3.92%	83	0.339
OBOS9MMA	1.15%	7.32%	99	1.559	MA8	0.14%	5.77%	107	0.248
OBOS8MMA	1.05%	7.11%	100	1.474	OBOS3MMA	-0.15%	6.49%	105	-0.238
OBOS7MMA	0.98%	6.83%	101	1.446	SPSLOG	-0.16%	3.20%	21	-0.231
MA2	-0.56%	4.08%	107	-1.421	MA3	-0.10%	5.24%	107	-0.200
PRICEREL12	0.88%	7.06%	96	1.225	MA7	0.08%	5.84%	107	0.141
MOM3	0.74%	6.50%	104	1.161	MA9	0.08%	5.84%	107	0.141
MA11	0.57%	5.37%	107	1.101	EG1	0.06%	4.57%	107	0.139
MA12	0.51%	5.20%	107	1.016	EY	0.05%	5.95%	107	0.086
DE	-0.89%	4.14%	21	-0.984	EARNREV3M	-0.03%	3.27%	47	-0.063
OBOS6MMA	0.65%	6.90%	102	0.949	ROE	0.03%	4.39%	107	0.059
C24MBVTM	-0.63%	6.32%	83	-0.912	ICBTINV	0.04%	5.41%	21	0.034
MVLOG	-0.41%	4.94%	107	-0.856	C24MDPSP	-0.01%	4.14%	83	-0.025

Panel B: Subsample_2 (2003 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**1.33%**	3.46%	99	**3.840**	**MOM6**	0.30%	4.36%	99	0.676
EPS	**1.18%**	3.31%	99	**3.556**	**MOM60**	-0.23%	3.64%	99	-0.633
MOM1	**-1.09%**	4.03%	99	**-2.701**	**MA8**	0.23%	4.31%	99	0.532
OBOS2MMA	**-1.04%**	3.96%	99	**-2.602**	**OBOS5MMA**	-0.23%	5.07%	99	-0.454
BVTMLOG	**0.57%**	2.59%	99	**2.191**	**ICBTINV**	0.16%	3.95%	99	0.400
EARNREV3M	0.56%	3.18%	99	1.757	**OBOS8MMA**	0.20%	4.87%	99	0.399
OBOS3MMA	-0.75%	4.38%	99	-1.696	**DE**	-0.11%	3.10%	99	-0.358
DPSLOG	-0.47%	2.98%	99	-1.578	**MA4**	-0.15%	4.30%	99	-0.349
EY	0.56%	4.12%	99	1.361	**OBOS12MMA**	0.17%	4.98%	99	0.337
LNP	-0.45%	3.33%	99	-1.329	**SPSLOG**	-0.09%	2.56%	99	-0.331
C24MEPSP	0.48%	3.62%	99	1.324	**OBOS9MMA**	0.16%	4.81%	99	0.329
RETVAR12	-0.51%	3.92%	99	-1.303	**C24MBVTM**	0.13%	4.16%	99	0.311
ROE	-0.44%	2.84%	64	-1.238	**BETA**	0.16%	5.06%	99	0.309
MA3	-0.46%	3.85%	99	-1.198	**MA6**	0.12%	4.12%	99	0.298
MA12	0.51%	4.66%	99	1.098	**MOM3**	0.14%	4.88%	99	0.287
MA11	0.51%	4.62%	99	1.094	**MVLOG**	-0.10%	3.53%	98	-0.280
C24MDPSP	0.44%	4.18%	99	1.046	**OBOS7MMA**	0.13%	4.95%	99	0.252
STP	0.57%	4.42%	64	1.031	**MA7**	0.10%	4.24%	99	0.235
MOM12	0.48%	4.93%	99	0.966	**MA9**	0.10%	4.24%	99	0.235
MA2	-0.31%	3.40%	99	-0.920	**PRICEREL12**	-0.09%	4.72%	99	-0.180
OBOS4MMA	-0.43%	4.91%	99	-0.874	**POUTRAT**	0.07%	3.89%	99	0.175
EG1	0.35%	4.12%	97	0.837	**OBOS10MMA**	0.08%	4.67%	99	0.163
MOM36	-0.40%	5.06%	99	-0.793	**OBOS11MMA**	0.07%	4.84%	99	0.154
DY	0.35%	4.44%	99	0.779	**MA5**	0.03%	4.15%	99	0.063
MA10	0.33%	4.61%	99	0.719	**OBOS6MMA**	-0.02%	5.10%	99	-0.048

Panel C: Total_sample (1994 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**1.98%**	4.49%	206	**6.346**	**MOM3**	0.45%	5.76%	203	1.107
EPS	**0.88%**	3.28%	206	**3.833**	**DY**	0.39%	5.34%	206	1.055
BVTMLOG	**1.04%**	4.67%	206	**3.205**	**MOM36**	0.49%	6.54%	170	0.984
LNP	**-0.79%**	3.71%	206	**-3.063**	**PRICEREL12**	0.39%	5.99%	195	0.912
MOM12	**1.16%**	5.78%	194	**2.807**	**MVLOG**	-0.26%	4.32%	205	-0.866
MOM1	**-0.69%**	4.72%	205	**-2.083**	**MA3**	-0.28%	4.62%	206	-0.856
OBOS2MMA	**-0.66%**	4.82%	205	**-1.973**	**MA10**	0.29%	4.94%	206	0.837
STP	1.00%	6.84%	171	1.919	**EY**	0.30%	5.15%	206	0.828
MOM6	0.92%	6.84%	200	1.912	**DE**	-0.25%	3.30%	120	-0.822
MOM60	-0.66%	4.57%	146	-1.757	**C24MDPSP**	0.23%	4.15%	182	0.759
BETA	0.70%	5.83%	206	1.734	**POUTRAT**	0.23%	4.36%	206	0.754
OBOS12MMA	0.78%	6.31%	195	1.732	**OBOS6MMA**	0.32%	6.07%	201	0.739
MA2	-0.44%	3.76%	206	-1.688	**MA5**	0.23%	4.96%	206	0.665
OBOS10MMA	0.69%	6.23%	197	1.561	**MA6**	0.23%	5.11%	206	0.653
OBOS11MMA	0.70%	6.31%	196	1.560	**EG1**	0.20%	4.35%	204	0.651
MA11	0.54%	5.01%	206	1.550	**C24MBVTM**	-0.22%	5.26%	182	-0.559
MA12	0.51%	4.94%	206	1.490	**MA8**	0.18%	5.11%	206	0.513
OBOS9MMA	0.65%	6.20%	198	1.483	**ROE**	-0.15%	3.88%	171	-0.501
OBOS8MMA	0.62%	6.10%	199	1.443	**SPSLOG**	-0.10%	2.67%	120	-0.404
RETVAR12	-0.45%	4.42%	195	-1.427	**ICBTINV**	0.14%	4.21%	120	0.359
EARNREV3M	0.37%	3.21%	146	1.397	**OBOS5MMA**	0.15%	6.02%	202	0.343
DPSLOG	-0.39%	4.06%	206	-1.380	**MA7**	0.09%	5.12%	206	0.251
OBOS7MMA	0.56%	5.97%	200	1.322	**MA9**	0.09%	5.12%	206	0.251
C24MEPSP	0.33%	3.75%	182	1.181	**MA4**	0.04%	4.98%	206	0.126
OBOS3MMA	-0.44%	5.56%	204	-1.129	**OBOS4MMA**	0.00%	5.84%	203	-0.004

From Table 6.3 it is seen that portfolios constructed from Large-cap shares based on a value (CFTP and BVTMLOG), size (LNP) or momentum (MOM12) approach offer significant outperformance opportunities during Subsample_1 and Total_sample. In addition to value (CFTP and BVTMLOG) portfolios, it is also possible to construct profitable portfolios based on shorter term price reversal strategies (MOM1 and a shorter term OBOS factor) during Subsample_2. Furthermore, portfolios constructed during Subsample_1 and Total_sample based on the CAPM beta offered significant outperformance opportunities on a 90% level of confidence. These results (similar to those for the All-share sample) indicate a high correlation (in terms of the identity as well as ranking order) between factors that contribute significantly to explaining the cross- section of large cap equity returns and those that can be used to construct factor portfolios offering significant outperformance opportunities.

The results with regard to Large-cap factor portfolios when rebalancing takes place every three months, are reported in Table 6.4 below,

Table 6.4: Evaluation of factor portfolios' raw returns: Large-cap sample, portfolios rebalanced every 3 months

This table presents the average difference in three-month holding period returns between Portfolio_1 and Portfolio_3 constructed for each respective factor (and the difference between the long and short moving average portfolios) and rebalanced every 3 months, using the 5th market cap decile as liquidity filter. A t-statistic is calculated for the average difference in returns for each factor portfolio for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the mean three-monthly holding period return difference is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 – 2002)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
MOM60	**-12.76%**	15.90%	16	**-3.209**	EARNREV3M	-0.83%	4.41%	12	-0.651
MOM12	**6.15%**	13.57%	32	**2.564**	MA12	1.40%	13.66%	36	0.616
OBOS11MMA	**6.42%**	16.29%	32	**2.230**	ICBTINV	2.36%	11.10%	7	0.563
CFTP	**5.70%**	15.44%	31	**2.053**	MA10	1.22%	13.43%	36	0.543
EPS	**3.10%**	9.23%	36	2.017	OBOS5MMA	1.46%	16.43%	34	0.517
OBOS10MMA	5.82%	17.37%	33	1.924	SPSLOG	-1.51%	7.73%	7	-0.515
OBOS9MMA	5.64%	17.65%	33	1.837	MA3	1.13%	13.27%	36	0.510
OBOS12MMA	5.30%	16.63%	32	1.803	MOM1	1.14%	13.59%	35	0.496
MVLOG	-2.40%	8.65%	36	-1.667	OBOS2MMA	1.11%	13.81%	35	0.475
PRICEREL12	3.80%	13.58%	32	1.583	MA8	1.08%	14.98%	36	0.431
MOM6	4.27%	16.17%	34	1.540	MA5	0.88%	15.06%	36	0.349
LNP	-2.51%	9.99%	36	-1.506	MA4	0.72%	13.52%	36	0.319
OBOS8MMA	4.52%	17.45%	33	1.487	STP	-1.21%	17.80%	22	-0.318
BETA	3.34%	15.26%	36	1.313	DY	0.66%	13.50%	36	0.292
MA2	2.19%	10.00%	35	1.299	EG1	0.78%	16.98%	33	0.263
OBOS7MMA	3.76%	17.30%	34	1.266	MOM36	-0.89%	18.03%	24	-0.241
OBOS6MMA	3.41%	16.44%	34	1.210	MA7	0.57%	15.04%	36	0.227
DE	-2.49%	5.50%	7	-1.197	MA9	0.57%	15.04%	36	0.227
BVTMLOG	3.66%	21.47%	32	0.964	ROE	-0.55%	13.63%	29	-0.217
OBOS4MMA	2.29%	15.17%	35	0.892	POUTRAT	0.39%	12.25%	36	0.191
MOM3	1.94%	13.90%	35	0.827	C24MEPSP	-0.48%	15.78%	26	-0.154
MA11	1.71%	13.55%	36	0.756	C24MDPSP	-0.24%	10.60%	28	-0.121
DPSLOG	-1.78%	14.53%	36	-0.735	EY	0.20%	14.77%	35	0.081
C24MBVTM	2.46%	18.52%	26	0.678	MA6	-0.11%	14.91%	36	-0.043
RETVAR12	1.08%	9.25%	32	0.660	OBOS3MMA	0.08%	14.26%	35	0.031

Panel B: Subsample_2 (2003 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**4.18%**	7.32%	32	**3.235**	RETVAR12	-0.58%	6.60%	32	-0.496
EPS	**2.67%**	6.23%	32	**2.421**	OBOS2MMA	-0.47%	5.42%	32	-0.494
LNP	**-2.33%**	6.02%	32	**-2.186**	ROE	-0.48%	4.69%	21	-0.470
BVTMLOG	**1.70%**	4.45%	32	**2.163**	OBOS5MMA	-0.77%	9.79%	32	-0.445
MA2	-1.73%	6.40%	32	-1.526	MOM12	0.79%	10.06%	32	0.443
STP	2.67%	8.06%	21	1.520	MOM3	-0.67%	9.12%	32	-0.414
DY	2.11%	8.70%	32	1.375	OBOS6MMA	-0.74%	10.51%	32	-0.400
DPS	-0.92%	4.08%	32	-1.276	MA7	-0.62%	9.10%	32	-0.383
EY	1.57%	7.27%	32	1.219	MA9	-0.62%	9.10%	32	-0.383
POUTRAT	1.32%	6.76%	32	1.104	DE	-0.34%	5.59%	32	-0.347
C24MDPSP	1.50%	7.92%	32	1.074	OBOS7MMA	-0.55%	10.66%	32	-0.291
C24MEPSP	1.20%	7.08%	32	0.958	EG1	-0.27%	7.52%	31	-0.197
MVLOG	-1.09%	6.42%	32	-0.957	MA6	-0.29%	8.63%	32	-0.190
MA3	-1.38%	8.54%	32	-0.913	OBOS12MMA	0.34%	10.56%	32	0.182
MOM1	-0.96%	6.15%	32	-0.880	BETA	0.25%	9.25%	32	0.152
MOM36	-1.44%	9.25%	32	-0.879	OBOS11MMA	0.28%	10.71%	32	0.148
OBOS3MMA	-1.19%	7.86%	32	-0.854	MA11	0.18%	10.62%	32	0.096
MOM60	-0.97%	6.53%	32	-0.839	MA10	0.15%	10.53%	32	0.078
MOM6	1.23%	9.54%	32	0.727	MA12	-0.10%	10.68%	32	-0.052
MA5	-1.03%	8.72%	32	-0.668	PRICEREL12	-0.09%	10.18%	32	-0.050
MA4	-1.02%	9.04%	32	-0.638	OBOS10MMA	0.08%	10.72%	32	0.042
SPSLOG	-0.52%	4.73%	32	-0.616	MA8	-0.07%	9.67%	32	-0.040
ICBTINV	0.83%	7.71%	32	0.611	OBOS8MMA	0.06%	10.62%	32	0.031
OBOS4MMA	-0.89%	8.96%	32	-0.563	OBOS9MMA	-0.03%	10.95%	32	-0.017
C24MBVTM	0.92%	9.77%	32	0.530	EARNREV3M	-0.02%	7.32%	32	-0.015

Panel C: Total_sample (1994 – 2011)

Factor	Mean return	Standard deviation	Number of observations	t Statistic	Factor	Mean return	Standard deviation	Number of observations	t Statistic
CFTP	**4.93%**	11.95%	63	**3.273**	MOM36	-1.20%	13.58%	56	-0.662
EPS	**2.90%**	7.91%	68	**3.022**	EY	0.85%	11.74%	67	0.595
MOM60	**-4.90%**	11.85%	48	**-2.864**	C24MDPSP	0.69%	9.23%	60	0.578
LNP	**-2.42%**	8.30%	68	**-2.407**	OBOS4MMA	0.77%	12.60%	67	0.500
MOM12	**3.47%**	12.15%	64	**2.284**	MA10	0.71%	12.07%	68	0.486
MVLOG	-1.78%	7.66%	68	-1.921	MOM3	0.70%	11.85%	67	0.481
OBOS11MMA	3.35%	14.02%	64	1.912	MA12	0.70%	12.28%	68	0.467
MOM6	2.79%	13.36%	66	1.699	OBOS3MMA	-0.53%	11.59%	67	-0.373
OBOS10MMA	2.99%	14.66%	65	1.646	MA8	0.54%	12.68%	68	0.350
OBOS12MMA	2.82%	14.04%	64	1.607	ROE	-0.52%	10.73%	50	-0.343
OBOS9MMA	2.85%	14.90%	65	1.542	STP	0.69%	13.90%	43	0.325
BVTMLOG	2.68%	15.41%	64	1.390	MA2	0.32%	8.64%	67	0.305
OBOS8MMA	2.32%	14.56%	65	1.286	C24MEPSP	0.45%	11.71%	58	0.291
PRICEREL12	1.86%	12.07%	64	1.230	OBOS2MMA	0.35%	10.61%	67	0.272
BETA	1.88%	12.79%	68	1.215	RETVAR12	0.25%	8.01%	64	0.249
DPSLOG	-1.37%	10.87%	68	-1.043	EARNREV3M	-0.24%	6.61%	44	-0.241
DY	1.34%	11.44%	68	0.969	OBOS5MMA	0.38%	13.56%	66	0.226
OBOS7MMA	1.67%	14.52%	66	0.934	EG1	0.27%	13.18%	64	0.166
C24MBVTM	1.61%	14.24%	58	0.860	MA6	-0.19%	12.27%	68	-0.130
ICBTINV	1.11%	8.26%	39	0.836	MOM1	0.14%	10.68%	67	0.106
SPSLOG	-0.69%	5.27%	39	-0.821	MA4	-0.10%	11.58%	68	-0.070
DE	-0.73%	5.56%	39	-0.817	MA3	-0.05%	11.28%	68	-0.037
OBOS6MMA	1.40%	13.94%	66	0.814	MA5	-0.02%	12.43%	68	-0.014
POUTRAT	0.83%	9.99%	68	0.683	MA7	0.01%	12.52%	68	0.007
MA11	0.99%	12.19%	68	0.669	MA9	0.01%	12.52%	68	0.007

Comparing Table 6.4 to Table 6.3 it is seen that value (represented mostly by CFTP for the Large-cap sample) remains a significant portfolio construction strategy across all sample periods. Size (represented by LNP) continues offering a strategy for constructing profitable portfolios over Subsample_2 and Total_sample, while it loses its significance over Subsample_1. A momentum (represented by MOM12) approach offers profitable opportunities for the Large-cap sample during Subsample_1 and Total_sample, while the shorter term price reversal strategy is not found to be significant for the Large-cap sample. Note that the longer term price reversal strategy (represented by MOM60) becomes significant for Subsample_1 and Total_sample. Once again the factors and ranking order of its significance in terms of portfolio construction for the Large-cap sample correlate very well with that found for the same sample applying the cross- sectional regression approach using 3-month return periods as dependent variable (Chapter 5 Section 5.4.2).

6.4 Risk-adjusted performance evaluation

In this section factor portfolios found to offer significant outperformance are adjusted for risk based on the CAPM and Van Rensburg (2002) two-factor APT models by applying regressions (6.1) and (6.2) respectively. Following this risk adjustment approach allows for the examination of whether the excess performance offered by the specific factor portfolios can be explained by the respective market models. If not, these factors can be regarded as market anomalies.

6.4.1. All-share sample

Risk-adjusted performance evaluation results for the monthly rebalanced factor portfolios constructed from the All-share sample are reported in Table 6.5.

Table 6.5: Risk-adjusted factor portfolio performance evaluation: All-share sample
This table presents the risk-adjusted portfolio performance results. Intercept terms (α) in bold indicate significance on a 95% level of confidence. Each risk-adjusted factor portfolio is presented in order of significance of outperformance as presented in Table 6.1. Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C).

Panel A: Subsample_1 (1994 – 2002)

	CAPM					APT		
Factor	α	t(α)	β	t(β)	R-squared	α	t(α)	R-squared
CFTP	**0.020**	3.997	0.021	0.281	0.001	**0.026**	3.964	0.011
LNP	**-0.023**	-5.353	0.006	0.092	0.000	**-0.020**	-3.354	0.004
MVLOG	**-0.023**	-4.780	0.013	0.177	0.000	**-0.023**	-3.303	0.014
MOM12	**0.017**	2.585	-0.036	-0.359	0.001	0.008	0.833	0.010
BVTMLOG	0.006	0.972	0.054	0.572	0.004	0.015	1.825	0.002
OBOS12MMA	0.010	1.403	0.026	0.243	0.001	-0.001	-0.148	0.000

Panel B: Subsample_2 (2003 – 2011)

	CAPM					APT		
Factor	α	t(α)	β	t(β)	R-squared	α	t(α)	R-squared
CFTP	**0.010**	3.047	-0.008	-0.137	0.000	**0.010**	2.905	0.024
C24MEPSP	0.005	1.640	0.053	0.909	0.008	0.005	1.427	0.047
C24MDPSP	0.004	1.119	0.081	1.358	0.019	0.003	0.992	0.031
MOM6	0.004	1.240	0.039	0.584	0.004	0.004	1.224	0.003
EARNREV3M	-0.002	-1.608	0.005	0.261	0.001	-0.001	-1.511	0.004
MOM1	**-0.011**	-3.206	-0.085	-1.371	0.019	**-0.011**	-3.188	0.016
OBOS2MMA	**-0.010**	-3.182	-0.085	-1.414	0.020	**-0.010**	-3.153	0.018
MA11	0.004	0.977	0.092	1.183	0.014	0.005	1.143	0.035
MA12	0.004	0.868	0.111	1.424	0.020	0.004	1.012	0.037
MA10	0.004	0.891	0.068	0.925	0.009	0.004	1.036	0.025
EY	0.003	0.896	-0.013	-0.229	0.001	0.002	0.743	0.024

Panel C: Total_sample (1994 – 2011)

			CAPM			APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
CFTP	**0.015**	4.995	0.005	0.091	0.000	**0.016**	5.093	0.001
LNP	**-0.014**	-5.291	0.004	0.084	0.000	**-0.011**	-3.771	0.008
MVLOG	**-0.015**	-5.262	-0.011	-0.223	0.000	**-0.013**	-4.026	0.000
MOM12	**0.010**	2.553	0.008	0.129	0.000	0.005	1.200	0.013
BVTMLOG	0.003	0.946	0.019	0.349	0.001	0.006	1.714	0.000
OBOS12MMA	0.006	1.594	0.036	0.544	0.002	0.001	0.283	0.004
OBOS11MMA	0.006	1.400	0.033	0.499	0.001	0.001	0.132	0.004
OBOS10MMA	0.005	1.393	0.040	0.615	0.002	0.000	0.052	0.005
OBOS9MMA	0.005	1.170	0.027	0.421	0.001	-0.001	-0.155	0.006
MOM6	0.006	1.149	0.056	0.695	0.003	-0.001	-0.158	0.007
OBOS8MMA	0.003	0.880	0.029	0.454	0.001	-0.002	-0.441	0.007
EARNREV3M	**-0.003***	-3.217	0.010	0.724	0.004	**-0.002***	-3.140	0.016
EY	0.000	-0.126	0.050	1.005	0.005	0.004	1.176	0.031

Table 6.5 shows that the value effect persists, indicated by a significant alpha (α) term, irrespective of sample period or model used for risk-adjustment. The size effect persists for Subsample_1 and Total_sample while the short- term price reversal effect observed for Subsample_2 persists as well. The raw-return outperformance associated with the momentum factor (Subsample_1 and Total_sample) was found to remain significant on a risk-adjusted basis when using the CAPM while losing its significance when applying the APT model. However, looking at the significance associated with the Beta in the case of CAPM and the R-squared value regarding both the CAPM and APT, it seems that although the significance of outperformance associated with the remaining factor portfolios on a raw return basis is lost when adjusted for risk, neither of these models are able to explain the variance in the returns offered by the characteristic portfolios.

The risk-adjusted performance results associated with a 3-month payoff period is presented in Table 6.6.

Table 6.6: Risk-adjusted factor portfolio performance evaluation: All-share sample, portfolios rebalanced every 3 months.
This table presents the risk-adjusted portfolio performance results for portfolios rebalanced every three months. Intercept terms (α) in bold indicate significance on a 95% level of confidence. Each risk-adjusted factor portfolio is presented in order of significance of outperformance as presented in Table 6.2. Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C).

Panel A: Subsample_1 (1994 – 2002)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
LNP	**-0.103**	-3.556	0.190	0.746	0.019	**-0.082**	-3.018	0.055
CFTP	**0.050**	2.193	0.285	1.430	0.068	**0.091**	3.217	0.106
DPSLOG	**-0.088**	-2.549	-0.008	-0.026	0.000	-0.055	-1.429	0.023
MVLOG	**-0.113**	-3.715	0.289	1.078	0.040	**-0.094**	-3.393	0.090
POUTRAT	**-0.064**	-2.070	-0.069	-0.253	0.002	-0.019	-0.658	0.064
DY	**-0.078**	-2.084	-0.059	-0.179	0.001	-0.026	-0.744	0.105
BVTMLOG	0.027	0.982	-0.140	-0.582	0.012	0.034	1.150	0.250
C24MDPSP	**-0.098**	-2.535	0.220	0.639	0.015	**-0.066**	-2.442	0.020

Panel B: Subsample_2 (2003 – 2011)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
SPSLOG	**-0.039**	-5.785	0.106	1.750	0.093	**-0.038**	-5.727	0.154
CFTP	**0.029**	2.115	0.032	0.259	0.002	0.023	1.905	0.264
C24MEPSP	0.015	1.294	0.057	0.561	0.010	0.010	0.995	0.318
LNP	**-0.037**	-4.913	**0.150**	2.218	0.141	**-0.034**	-5.069	0.352
MVLOG	**-0.037**	-4.547	0.141	1.911	0.109	**-0.033**	-4.708	0.356
C24MDPSP	0.013	1.125	-0.052	-0.490	0.008	0.007	0.778	0.482
BVTMLOG	0.010	1.019	-0.079	-0.930	0.028	0.007	0.722	0.140

Panel C: Total_sample (1994 – 2011)

	CAPM					APT		
Factor	α	t(α)	β	t(β)	R-squared	α	t(α)	R-squared
CFTP	**0.037**	2.845	0.152	1.292	0.027	**0.049**	3.638	0.034
LNP	**-0.070**	-4.601	0.206	1.512	0.037	**-0.056**	-5.053	0.074
MVLOG	**-0.076**	-4.713	0.258	1.787	0.051	**-0.061**	-5.296	0.088
DPSLOG	**-0.048**	-2.670	0.028	0.173	0.000	-0.022	-1.561	0.034
BVTMLOG	0.019	1.317	-0.120	-0.948	0.015	**0.027**	2.143	0.124
POUTRAT	-0.033	-1.955	-0.131	-0.878	0.013	-0.006	-0.449	0.104

Similar to the results for the 1-month holding period, it is seen that the value effect persists, irrespective of sample period used (note however that the value effect remains significant only on a 90% level of confidence when applying the APT model for Subsample_2). The size effect found over all sample periods for longer holding periods is found to be significant on a risk-adjusted basis as well, irrespective of the model applied. Based on the level of significance associated with the CAPM beta as well as the R-squared values for both models, it is once again seen that neither the CAPM nor two-factor APT are able to explain the returns generated by any of the factor portfolios that offer superior returns on a raw-returns basis over a 3-month holding period. Note however, that for the first time relatively high R-squared values are obtained associated with the APT model during Subsample_2, especially with regards to the growth and size effects. It seems therefore that the two factor APT model is rather effective in explaining the returns generated by these factor portfolios. The significance associated with the alpha term with regard to the size factor portfolios however, indicate that there are still factors missing (or incorrectly specified) with regard to the Van Rensburg *et al*. (2002) two-factor APT model.

6.4.2. Large-cap sample

Risk-adjusted performance evaluation results for the monthly rebalanced factor portfolios constructed from the Large-cap sample are reported in Table 6.7.

Table 6.7: Risk-adjusted factor portfolio performance evaluation: Large-cap sample
This table presents the risk-adjusted portfolio performance results for the Large-cap sample. Intercept terms (α) in bold indicate significance on a 95% level of confidence. Each risk-adjusted factor portfolio is presented in order of significance of outperformance as presented in Table 6.3. Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C).

Panel A: Subsample_1 (1994 – 2002)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
CFTP	**0.020**	3.636	0.030	0.371	0.002	**0.026**	3.548	0.002
LNP	**-0.016**	-3.541	-0.061	-0.901	0.009	-0.010	-1.592	0.019
MOM12	**0.015**	2.193	-0.052	-0.485	0.003	0.012	1.231	0.008
BVTMLOG	0.006	0.876	0.079	0.786	0.007	0.012	1.327	0.007

Panel B: Subsample_2 (2003 – 2011)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
CFTP	**0.010**	2.729	-0.024	-0.369	0.001	**0.010**	2.666	0.004
EPS	0.006	1.894	0.126	2.028	0.041	0.006	1.662	0.095
MOM1	**-0.014**	-3.264	-0.103	-1.351	0.018	**-0.014**	-3.230	0.016
OBOS2MMA	**-0.013**	-3.216	-0.089	-1.180	0.014	**-0.013**	-3.200	0.012
BVTMLOG	0.002	0.769	-0.018	-0.359	0.001	0.002	0.656	0.011

Panel C: Total_sample (1994 – 2011)

			CAPM			APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
CFTP	**0.014**	4.502	0.003	0.057	0.000	**0.016**	4.572	0.002
EPS	0.005	1.927	0.052	1.273	0.009	**0.008**	3.060	0.023
BVTMLOG	0.004	1.046	0.037	0.636	0.002	0.006	1.523	0.002
LNP	**-0.011**	-4.134	-0.055	-1.197	0.008	**-0.009**	-2.871	0.015
MOM12	0.008	1.774	0.005	0.070	0.000	0.005	0.952	0.008
MOM1	**-0.011**	-3.056	-0.015	-0.265	0.000	**-0.011**	-2.679	0.005

With regard to the Large-cap sample, only the value effect persists across all sample periods. The size effect persists for Total_sample while the short- term price reversal effect persists for Subsample_1 and Total_sample. Note however that, as was the case for the All-share sample, neither the CAPM nor the two-factor APT models are able to explain the returns generated by any of the factor portfolios that offer superior returns on a raw-returns basis.

The risk-adjusted performance results associated with a 3-month payoff period using the Large-cap sample is presented in Table 6.8.

Table 6.8: Risk-adjusted factor portfolio performance evaluation: Large-cap sample, portfolios rebalanced every 3 months.
This table presents the risk-adjusted portfolio performance results for the Large-cap sample over three-month holding periods. Intercept terms (α) in bold indicate significance on a 95% level of confidence. Each risk-adjusted factor portfolio is presented in order of significance of outperformance as presented in Table 6.4. Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C).

Panel A: Subsample_1 (1994 – 2002)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
MOM60	**-0.140**	-3.283	-0.042	-0.109	0.001	**-0.117**	-2.511	0.095
MOM12	0.040	1.569	0.267	1.183	0.048	0.024	0.726	0.040
OBOS11MMA	0.045	1.429	0.197	0.714	0.018	0.012	0.278	0.014
CFTP	0.039	1.300	0.383	1.458	0.076	**0.073**	2.513	0.061
EPS	0.029	1.828	0.236	1.673	0.091	**0.061**	2.755	0.124

Panel B: Subsample_2 (2003 – 2011)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
CFTP	**0.035**	2.482	-0.109	-0.860	0.024	**0.029**	2.366	0.313
EPS	0.008	0.706	0.162	1.525	0.072	0.004	0.382	0.246
LNP	**-0.043**	-3.872	0.197	1.941	0.112	**-0.039**	-3.869	0.312
BVTMLOG	0.009	1.063	-0.086	-1.129	0.041	0.005	0.704	0.274

Panel C: Total_sample (1994 – 2011)

	CAPM					APT		
Factor	**α**	**t(α)**	**β**	**t(β)**	**R-squared**	**α**	**t(α)**	**R-squared**
CFTP	**0.032**	2.014	0.134	0.929	0.015	**0.049**	3.514	0.002
EPS	0.018	1.860	**0.189**	2.156	0.072	**0.027**	2.478	0.085
MOM60	**-0.069**	-3.770	0.195	1.184	0.030	**-0.063**	-3.676	0.175
LNP	**-0.043**	-4.029	**0.258**	2.719	0.110	**-0.040**	-3.312	0.099
MOM12	0.012	0.776	0.250	1.757	0.049	-0.001	-0.041	0.054

From table 6.8 it seems that, except when applying the CAPM during Subsample_1, the value effect offers significant outperformance on both a raw and risk-adjusted basis across all sample periods over a 3-month holding period. In addition, the size effect persists during Subsample_2 and Total_sample as well, while the longer term price reversal effect persists during Subsample_1 and Total_sample. Although not always significant on a risk-adjusted basis, the returns offered by the remainder of the factor portfolios can once again not be explained by either the CAPM or two-factor APT model, implied by the insignificant beta coefficients (CAPM) and low R-squared values (CAPM and APT).

6.5 Conclusion

The results obtained following a single-factor portfolio construction approach to examine the impact of firm-specific factors on the cross- section of equity returns on the JSE, correlate strongly with the results obtained following a univariate cross-sectional regression approach (Chapters 5).

A value factor portfolio (using especially CFTP) offers significant outperformance across all sample periods and holding periods, irrespective of level of liquidity applied or whether returns are adjusted for risk, making this a robust strategy. Constructing portfolios based on size factors (specifically LNP) generally offer superior returns that are insensitive to holding period and level of liquidity, but the results suggest that size factor portfolios are sensitive to time, as the significant outperformance is limited to Subsample_1 and Total_sample. When the holding period is increased to three months however, the size factor portfolios appear to be robust as it offers significant outperformance during all sample periods across all levels of liquidity.

Momentum, growth and price reversal are dependent on sample period, level of liquidity and holding period. Specifically, constructing portfolios based on momentum factors work well for Subsample_1 and Total_sample, over a one-month holding period, irrespective of level of liquidity applied, while the strategy is only profitable over the three-month holding period for the Large-cap sample during these sample periods. With regard to Subsample_2, the momentum strategy works well only for the All-share sample and a one-month holding period. Instead, portfolios constructed based on short- term price reversal works well for Subsample_2 for holding periods of one-month, irrespective of the level of liquidity.

Portfolios based on growth factors are found to offer superior returns only during Subsample_2 while using the All-share sample, irrespective of holding period. It therefore appears to be sensitive to time and liquidity. Furthermore, the returns offered by the growth approach lose their significance when adjusted for risk by either the CAPM or two-factor APT model.

Longer term price reversal portfolios, constructed using MOM60, appear to offer abnormal returns for Subsample_1 and Total_sample as long as it is constructed from the Large-cap sample and rebalanced every three months, making such a strategy dependent on time, liquidity and payoff period.

Risk-adjusted performance evaluation shows that neither the traditional CAPM nor the Van Rensburg (2002) two-factor APT models are able to explain the excess returns offered following a single-factor portfolio construction approach. The results suggest that value and size factors (most probably represented by CFTP and LNP respectively) need to form part of a multifactor return generating model for the JSE, while additional momentum and price-reversal factors may contribute to the explanatory power of such a model.

7

MULTIFACTOR ANALYSES OF FACTORS THAT EXPLAIN THE CROSS- SECTION OF RETURNS ON THE JSE

7.1 Introduction

In Chapter 5 and Chapter 6 different approaches were followed to examine the impact of firm-specific factors on the cross- section of equity returns on the JSE. A univariate cross-sectional regression approach was followed in Chapter 5 while a single-factor portfolio construction approach was applied in Chapter 6. Irrespective of the different approaches, the results of the two chapters were found to be highly correlated. Both chapters however focused on the factors from an individual point of view. To determine the impact of a combination of these factors on the cross- section of returns, multifactor analyses are performed in this chapter using those factors that were found to be either insensitive (i.e. robust) or less sensitive to the effect of time, liquidity and/or payoff period (referred to as the candidate factors) as identified in Chapter 5 and Chapter 6. A multiple cross- sectional regression approach is applied using all possible permutations of pairs of candidate factors to determine the combined significance in explaining the cross- section of returns. Although some factors were found to be more sensitive to time, liquidity and/or payoff period than others, all permutations of candidate factors were tested across all sample periods to determine whether some factors becomes less sensitive once it is combined with other factors. Furthermore, the analysis is performed using the All-share and Large-cap samples to examine the effect liquidity may have on the explanatory power of the multifactor models.

Details with regard to the methodology followed are provided in Section 7.2, followed by a discussion of the multifactor analysis results for the All-share sample (Section 7.3.1) and the Large-cap sample (Section 7.3.2). Section 7.4 concludes this chapter.

7.2 Methodology

A multiple regression approach similar to Van Rensburg and Robertson (2003) is followed to determine the combination of technical and fundamental factors that explain the cross- section of returns on the JSE.

First, all permutations of pairs of candidate factors identified in Chapter 5 and Chapter 6 are regressed in a two-factor model:

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} A_{i,t} + \gamma_{2,t+1} B_{i,t} + \varepsilon_{i,t+1} \quad ...(7.1)$$

where

$r_{i,t+1}$ = realised return on share i for month t+1

$\gamma_{0,t+1}$ = intercept term

$A_{i,t}$, $B_{i,t}$ = standardised value of candidate factors *A* and *B* respectively

$\gamma_{1,t+1}$, $\gamma_{2,t+1}$ = cross-sectional coefficients of candidate factors *A* and *B* respectively

$\varepsilon_{i,t+1}$ = error term

Next, a three-factor regression is performed in each month for all permutations of significant pairs of candidate factors together with an additional candidate factor. This process is repeated until no more candidate factors can be added to the multiple regression equation without some or all of the factors losing their joint significance. The multifactor analysis is performed for the All-share and the Large-cap samples to examine the effect liquidity may have on the results.

7.3 Multifactor testing of significant factors

For convenience, those candidate factors identified through the univariate regression analysis (Chapter 5) and single-factor portfolio construction approach (Chapter 6) that are used in further multifactor testing in this section are listed in Table 7.1.

Table 7.1: Fundamental and technical factors to be used in multifactor testing
Factors that were found to be most significant during each of the subsample periods and mostly remained significant irrespective of the liquidity filter used, are listed in this table. These are the factors that will be used in further multifactor testing.

Subsample_1 (1994-2002)		Subsample_2 (2003-2011)		Total_sample (1994 – 2011)	
Factor	**Category**	**Factor**	**Category**	**Factor**	**Category**
CFTP	Value	CFTP	Value	CFTP	Value
MOM6	Momentum	BVTMLOG		BVTMLOG	
MOM12		MOM1	Price reversal	MOM6	Momentum
OBOS12mMA		MOM6	Momentum	MOM12	
OBOS11mMA				OBOS12mMA	
LNP	Size			OBOS11mMA	
				MA12	
				MA11	
				LNP	Size

A high level of correlation between factors could (and most probably would) lead to multicollinearity within the regression equations. Care should therefore be taken to include only those factors that show a low level of correlation between each other when performing multifactor testing. Different combinations of the factors reported in Table 7.1 that show lower levels of correlation between each other could however be applied to examine the combined effect on explanatory power. Table 7.2 summarises the level of correlation between the factors in Table 7.1 and is used when selecting the combination of factors in multifactor testing.

Table 7.2: Correlation between fundamental and technical factors to be used in multifactor testing
Factors showing a high level of correlation with each other could cause multicollinearity when performing multifactor testing. Due to the nature of its construction the moving average dummy variables are omitted from the table but retained for the multifactor analysis. Values in bold indicate a high level of correlation.

	CFTP	BVTMLOG	MOM1	MOM6	MOM12	OBOS12mMA	OBOS11mMA	LNP
CFTP	1	**0.62**	-0.08	-0.17	-0.20	-0.19	-0.18	-0.29
BVTMLOG		1	-0.10	-0.23	-0.27	-0.25	-0.24	-0.34
MOM1			1	0.37	0.28	0.48	0.50	0.01
MOM6				1	**0.68**	**0.90**	**0.91**	0.03
MOM12					1	**0.81**	**0.77**	0.07
OBOS12mMA						1	**0.99**	0.03
OBOS11mMA							1	0.03
LNP								1

All permutations of paired candidate factors were tested using the two-factor cross- sectional regression approach (7.1). Note that all possible combinations across all sample periods were tested, and not only combinations of those candidate factors listed within the specific sample period as reported in Table 7.1. The reason for this is that, although some factors may appear to be more significant during a specific sample period than others as per the results from Chapter 5 and Chapter 6, when combined with less significant factors during a specific sample period it may still offer a multifactor model that is significant in explaining the cross- section of equity returns.

7.3.1. All-share sample

Table 7.3 reports the pairs of candidate factors that were found to be jointly significant for each of the three periods respectively for the All-share sample. More than one two-factor model capturing similar effects can be derived due to the high level of correlation between factors associated with the specific effect (see Table 7.2). Table 7.3 reports only one two-factor model associated with the combined effects captured by the model. The choice of model reported here is based on the combination of the most significant factors as per the results reported in Chapter 5 (Section 5.3). All possible significant two-factor models are reported in Appendix D.

Table 7.3: Significant paired permutations of candidate factors: All-share sample
Monthly two-factor cross-sectional regressions were performed for all permutations of candidate factors. Those pairs that were found to be jointly significant in explaining the cross- section of returns on the JSE are reported here. Pairs are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average Coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.011	**5.439**	5.54%	3.17%	Vale and size
LNP	-0.005	**-2.586**			
CFTP	0.011	**5.227**	8.45%	6.34%	Value and momentum
MOM12	0.007	**2.471**			
MOM1	-0.007	**-3.115**	6.28%	4.79%	Short- term price reversal and momentum
OBOS12mMA	0.036	**5.035**			
MOM12	0.009	**3.698**	6.14%	4.61%	Momentum and size
LNP	-0.011	**-6.234**			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average Coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.006	**3.777**	4.96%	3.60%	Value and momentum
MOM6	0.005	**2.422**			
CFTP	0.006	**4.011**	4.80%	3.46%	Value and short term price reversal
MOM1	-0.006	**-2.956**			
MOM1	-0.009	**-4.618**	5.56%	4.29%	Short- term price reversal and momentum
MOM6	0.008	**4.205**			

Panel C: Total_sample (1994 - 2011)

Factor	Average Coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.009	**6.583**	4.76%	2.88%	Value and size
LNP	-0.003	**-2.735**			
CFTP	0.006	**4.530**	9.85%	5.54%	Value and momentum
MOM6	0.005	**2.849**			
MOM1	-0.006	**-2.837**	8.42%	5.55%	Short- term price reversal and momentum
MOM6	0.007	**3.796**			
MOM6	0.005	**2.952**	7.34%	4.46%	Momentum and size
LNP	-0.007	**-3.974**			

From Table 7.3 it is seen that a number of two-factor models can be derived for the JSE during each respective sample period. Specifically, “value and momentum” as well as “short- term price-reversal and momentum” models can be derived for all of the sample periods. For Subsample_1 and Total_sample, “value and size” and “momentum and size” models can be derived as well, while “value and short- term price reversal” models can be derived for Subsample_2. In keeping with the results of Chapter 5 and Chapter 6 this is in line with expectations as the value and momentum effects were observed during all periods, the size effect was only observed for Subsample_1 and Total_sample while the short- term price-reversal effect was most distinct for Subsample_2. The R-squared (and adjusted R-squared) value is quoted for each possible two-factor model for the purpose of comparing the models that capture the same effect (i.e. those reported in Table 7.3 and those reported in Appendix D.1). A higher R-squared value reflects a higher percentage of the cross- sectional variation being explained by the specific pair of factors. Note however that since the cross- sectional regressions are conducted at the individual stock level, the R-squared term is, as can be expected, relatively low. This figure can however be easily manipulated higher as the research design employs larger and larger portfolios of stocks sorted by the factors concerned rather than individual stocks in the cross- sectional regressions (Van Rensburg *et al.*, 2003).

A number of three-factor models were derived by appending a third factor to the two-factor models reported in Table 7.3. The combinations of candidate factors that were found to be jointly significant for each of the three periods respectively are reported in Appendix D.2. Table 7.4 reports only one three-factor model associated with the combined effects captured by the model. The choice of model reported here is based on the combination of the most significant factors as per the results reported in Chapter 5 (Section 5.3).

Table 7.4: Significant three-factor permutations of candidate factors: All-share sample
Monthly three-factor cross-sectional regressions were performed for all permutations of significant pairs of candidate factors (Table 7.3) together with an additional candidate factor. Those permutations that were found to be jointly significant in explaining the cross- section of returns on the JSE are reported here. Three-factor models are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-Statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.011	**5.459**	10.57%	7.45%	Value, size, momentum
LNP	-0.007	**-3.846**			
MOM12	0.007	**2.817**			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-Statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.006	**3.831**	7.47%	5.47%	Value, momentum and short- term price reversal
MOM6	0.008	**4.068**			
MOM1	-0.009	**-4.870**			

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-Statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.008	**6.218**	8.92%	6.35%	Value, size, momentum
LNP	-0.004	**-3.714**			
MOM12	0.006	**3.189**			

From Table 7.4 it is seen that a "Value, size and momentum" three-factor model can be derived for both Subsample_1 and Total_sample. Appending MOM1 to any of the significant pairs in Table 7.3 (that excluded MOM1) for these two periods resulted in a loss of significance in some or all factors, meaning that the short- term price-reversal effect observed when deriving two-factor models could not be captured with a three-factor model. Furthermore, the three models derived for these two sample periods consist of exactly the same candidate factors. For Subsample_2 a "Value, momentum and short term price reversal" three-factor model can be derived. As was the case for the two-factor models, a different number of models that capture the same effect for each of the sample periods respectively can be derived (see Appendix D.2). The R-squared (and adjusted R-squared) values are quoted to facilitate comparison between the models for each respective sample period.

In summary, when making no adjustment for thin trading (liquidity) a three-factor model capturing the value, size and momentum effect can be derived for the period January 1994 through December 2002 as well as for the period January 1994 through May 2011. The value, size and momentum effects are in line with most of the research findings reported in Chapter 3, with the major difference that CFTP captures the value effect instead of price-to-earnings or price-to-book, while LNP captures the size effect instead of market capitalisation. For the period January 2003 through May 2011, a three-factor model is derived that captures the value, momentum and short- term price-reversal effects while the size effect found during the other two sample periods disappears. Therefore the value and momentum effects appear to be robust and could be used in deriving a multifactor model to explain the cross- section of returns on the JSE when all shares and a monthly payoff period are considered, which is directly in line with the results from Chapter 5 and Chapter 6.

7.3.2. Large-cap sample

To examine the effect of liquidity on the results, the multi-factor regressions (7.1) were repeated using a liquidity filter set equal to the 5th market cap decile (i.e. the Large-cap sample). The results are reported in Table 7.5 below. Note that, as with the All-share sample, only those multifactor models that consist of the most significant factors as per the univariate regression results from Section 5.3 are reported here. A complete list of all possible multifactor models that capture similar effects as those reported in this section is reported in Appendix D.3.

Table 7.5: Significant paired permutations of candidate factors: Large-cap sample.
Monthly two-factor cross-sectional regressions were done for all permutations of candidate factors. Those pairs that were found to be jointly significant in explaining the cross- section of returns on the JSE are reported here. Pairs are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.014	**6.042**	11.04%	7.80%	Value and momentum
MOM12	0.009	**3.015**			
MOM1	-0.009	**-3.376**	11.91%	9.16%	Short- term price reversal and momentum
OBOS12MMA	0.041	**3.903**			
MOM12	0.010	**3.588**	10.34%	7.51%	Momentum and size
LNP	-0.006	**-2.691**			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.007	**3.773**	7.87%	5.09%	Value and short term price reversal
MOM1	-0.008	**-3.387**			
MOM1	-0.011	**-4.590**	9.03%	6.46%	Short- term price reversal and momentum
MOM6	0.007	**2.576**			

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.010	**6.787**	8.16%	5.02%	Value and short term price reversal
MOM1	-0.004	**-2.310**			
CFTP	0.006	**3.189**	14.06%	7.17%	Value and momentum
MOM6	0.005	**1.983**			
MOM1	-0.009	**-3.985**	14.42%	8.39%	Short- term price reversal and momentum
MOM6	0.009	**3.507**			
MOM1	-0.004	**-2.319**	7.66%	4.93%	Short- term price reversal and size
LNP	-0.004	**-2.615**			
MOM12	0.006	**2.715**	9.92%	7.22%	Momentum and size
LNP	-0.004	**-2.815**			

When adjusting for liquidity, a "short- term price reversal and momentum" two-factor model can be derived irrespective of the sample period under review. In addition, "value and momentum" and "momentum and size" two-factor models can be derived for Subsample_1 and Total_sample, while "value and short- term price reversal" two-factor models can be derived for Subsample_2 and Total_sample. The "value and size" two-factor models reported in Table 7.4 for Subsample_1 and Total_sample cannot be derived for the Large-cap sample. It seems therefore that less liquid shares would have to be added to the samples for such a two-factor model to be derived. Similarly, a "value and momentum" two-factor model cannot be derived for Subsample_2 any longer. Interesting to note is the derivation of a "short- term price reversal and size" two-factor model for Total_sample. The latter two-factor model could not be derived for the All Share sample during any of the sample periods, and it thus seems that these two factors can collectively assist in explaining the cross-section of returns on the JSE if only the most liquid shares are included and the total sample period is used. Apart from the differences discussed above, the effects captured by the two-factor models derived for the All-share sample during each sample period remain robust irrespective of the liquidity adjustment made. As was the case for the All-share sample, the average R-squared (and adjusted R-squared) values are quoted for each two-factor model for comparison purposes (refer to Appendix D.3).

Three-factor models can be derived by appending a third factor to the two-factor models reported in Table 7.5. The combinations of candidate factors that were found to be jointly significant for each of the three periods respectively when the sample is adjusted for liquidity are reported in Table 7.6.

Table 7.6: Significant three-factor permutations of candidate factors: Large-cap sample
Monthly three-factor cross-sectional regressions were done for all permutations of significant pairs of candidate factors (Table 7.5) together with an additional candidate factor. Those permutations that were found to be jointly significant in explaining the cross- section of returns on the JSE are reported here. Three-factor models are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.012	**5.603**	15.19%	10.46%	Value, momentum and short-term price reversal
MOM12	0.011	**3.603**			
MOM1	-0.005	**-2.089**			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.006	**3.457**	12.37%	8.29%	Value, momentum and short-term price reversal
MOM1	-0.011	**-4.838**			
MOM6	0.007	**2.518**			

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.006	**3.200**	20.00%	9.60%	Value, momentum and short-term price reversal
MOM1	-0.012	**-4.766**			
MOM6	0.009	**3.203**			

From Table 7.6 it is seen that a “value, momentum and short- term price-reversal” three-factor model can be derived for each of the sample periods. Value is captured by CFTP while short-term price reversal is captured by MOM1 for each period under review. For Subsample_1, MOM12 captures the momentum effect while the same effect is captured by MOM6 for Subsample_2 and Total_sample. The major difference between the three-factor models derived using the All-share sample versus those derived using the Large-cap sample, lies in the disappearance of the size effect while a short-term price-reversal effect is observed during each sample period. In keeping with the results reported in Chapter 5, Section 5.3 and Section 5.4, this phenomenon should not come as a surprise. It was seen that smaller, less liquid shares need to be included in the sample for the size effect to be observed while the short- term price-reversal effect is more associated with the large-cap shares. In summary, it seems that, when focusing on the larger, more liquid shares, a robust “value, momentum and short-term price-reversal” three-factor model can be derived to explain the monthly cross-section of returns on the JSE, irrespective of the period under review. Comparing the average R-squared values, it seems that a large-cap multi-factor model can be derived that explains a higher percentage of the cross- section of large-cap returns relative to the cross- section of all-share returns explained by an all-share multifactor model on the JSE. Similar to the All-share sample is the inclusion of both value and momentum factors in a three-factor model. Therefore, when using a one-month payoff period, value and momentum seem to be insensitive to liquidity or time, confirming expectations based on the results obtained in Chapter 5 and Chapter 6.

7.4 Conclusion

Using a multiple cross- sectional regression approach, multifactor analyses are performed based on all possible combinations of candidate factors identified in Chapter 5 and Chapter 6, to examine whether multifactor models could increase the explanatory power of the cross- section in returns on the JSE.

For the All-share sample it was found that a number of two-factor models can be derived to increase the explanatory power. 'Value and momentum' and 'value and short- term price reversal' two-factor models could be derived for each of the sample periods. When a third factor was added to the significant two-factor models, a 'value, momentum and size' three-factor model could be derived for the first and total sample periods while a 'value, momentum and short- term price-reversal' model was derived for the period January 2003 through May 2011. The disappearance of the size effect during the second sample period is in line with the results obtained in Chapter 5 and Chapter 6. A fourth factor could not be added to the mix without some or all candidate factors losing their significance.

A two-factor model capturing 'momentum' and 'short- term price reversal' could be derived for all sample periods using the Large-cap sample. Furthermore, the 'value' effect could be added to derive three-factor models for each of the respective sample periods. Therefore a 'value, momentum and short- term price reversal' three-factor model appears to be significant in explaining the monthly cross- section of returns of the larger shares on the JSE. As with the All-share sample, adding a fourth factor to the three-factor models resulted in some or all of the factors to become insignificant.

8

EXTREME PERFORMANCE AND FILTER RULES ON THE JSE

8.1 Introduction

A third approach to testing the EMH was identified in Chapter 3, referred to as the ‘extreme performer’ approach. Compared to the cross- sectional regression (Chapter 5) and single-factor portfolio construction (Chapter 6) approaches, this approach is relatively unexplored, especially within the South African context.

The extreme performer approach is applied in this chapter to examine the impact of firm-specific factors on the cross- section of monthly returns on the JSE. In this chapter an extreme performer is defined as a share that experienced an increase of 6% (classified as a winner) or -5% (classified as a loser) during a 1-month period. Due to this approach being such a relatively unexplored one, the methodology followed in this chapter is the first of its kind. Specifically, a combination of cross-sectional regression and logistic regression methods are used. Based on the cross-sectional regression, factors that differ significantly between extreme performer shares and the rest are identified. Using the results of the cross- sectional regressions, the logistic regression is applied to formulate ‘filter rules’ to filter potential future extreme performers. These filtered shares are used in constructing portfolios to examine the possibility of obtaining abnormal returns.

Details of the methodology followed are described in Section 8.2. Results of the cross- sectional regressions are discussed in Section 8.3 followed by the results of the logistic regression, portfolio construction and portfolio performance evaluation in Section 8.4. The chapter is concluded in Section 8.5.

8.2 Methodology

Two subsamples are created for the shares on the JSE over the period 1994 through 2011 by applying a cross- sectional split of the data over all time-series. The first subsample is used to identify common factors amongst extreme performers, while the second is used to test whether these factors hold up in an independent sample. The analysis is performed using a 1-month holding period. This allows for the creation of non-overlapping portfolios to determine whether a filter-rule approach to portfolio construction may offer superior returns in a statistically and economically significant fashion. From Chapter 3 it was seen that extreme performers are defined in an arbitrary fashion in the literature. In line with the studies by Reinganum (1988), Tunstall, Stein and Carris (2004) and Kornik (2006) an extreme winner is defined in this thesis as a share that experienced at least a 100% return during a 12-month period, while an extreme loser is defined as a share that experienced a negative return of at least 50% over a 12-month period. Geometrically converting these values into monthly values results in a monthly increase of 5.95% and a monthly decrease of -5.61%. To make a clear distinction between the winner and loser shares and in keeping with the difference in magnitude of the annual increase versus annual decrease, it was decided to define an extreme winner as a share that experienced an increase of at least 6% during a 1-month period and an extreme loser as a share that experienced a decrease of at least 5% in a 1-month period. To ensure that each subsample is similar in size and representative of the economic groups (financial, industrial and resources sectors) on the JSE, the first subsample (Sample_A) is formed by including the first half of each economic group alphabetically while the second half is categorised into the second subsample (Sample_B). Note that the analyses performed in this chapter are based on the All-share sample only. This ensures that enough shares are available to perform the portfolio construction using the filter rules derived from the first part of the analyses.

To determine whether the specific factor differs significantly between winner (loser) shares and the rest of the sample, the following regressions are performed:

$$C_i = \alpha_i + \beta_{iW} DW_{i,1} + \varepsilon_i \qquad \text{…(8.1)}$$

$$C_i = \alpha_i + \beta_{iL} DL_{i,1} + \varepsilon_i \qquad \text{…(8.2)}$$

where

C_i	=	factor *i* in period of buy (sell) signal (where the latter is at the beginning of the 1-month period during which the share price increases (decreases))
α_i	=	constant term associated with factor *i*
$DW_{i,1}; DL_{i,1}$	=	Dummy variables for 1-month holding period, set equal to 1 if share *i* is classified as a winner (DW_i) or loser (DL_i) and 0 otherwise
β_{iW}, β_{iL}	=	coefficient associated with the winner and loser dummy variables respectively for factor *i* in period of buy (sell) signal
ε_i	=	residual term for factor *i*

Regressions (8.1) and (8.2) are performed for all three sample periods, namely 1994 through 2002 (Subsample_1), 2003 through May 2011(Subsample_2) and 1994 through May 2011 (Total_sample).

The t-statistic associated with the dummy coefficients (β_{iW}, β_{iL}) is used to determine whether the factor (C_i) differs significantly between winner (loser) shares and the rest of the shares in the sample (from here on referred to as REST) in the period of a buy (sell) signal. Those factors found to have a significant dummy coefficient are used in further analyses to formulate filter rules for share selection and subsequent portfolio construction in Section 8.4. Descriptive statistics are calculated and presented together with a histogram for each factor to allow for the examination of the statistical differences found within a factor when it is associated with a winner share, loser share or a share that falls into the ‘remainder’ category. The histograms and descriptive statistics are reported in Appendix E.1.

8.3 Results: Evaluation of extreme performer factors

Table 8.1 presents the results of the evaluation of the extreme performer factors for winner shares using a 1-month holding period.

Table 8.1: Evaluation of winner factors over a 1-month period using Sample_A

This table presents the constant term (α_i), its associated t-statistic, dummy variable coefficient (β_{iW}), its t-statistic and standard error (σ_{ε_i}). Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the t-statistic associated with the dummy variable is significantly different from zero at the ninety-five percent level of confidence. Factors are ranked according to the absolute value of the dummy coefficient t-statistic.

Panel A: Subsample_1 (1994 – 2002)
Proportion winners = 20.48%

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
MA2	0.280	59.136	0.232	**22.148**	0.460
BETA	0.661	228.868	0.032	**5.819**	0.228
RETVAR12	0.020	63.035	0.003	**4.904**	0.022
CFTP	0.157	66.873	0.020	**4.690**	0.152
MOM12	0.178	21.994	0.054	**3.704**	0.533
LNP	2.241	112.865	-0.127	**-3.572**	1.458
EG1	0.687	28.041	0.143	**3.270**	1.277
PRICEREL12	0.813	288.419	-0.016	**-3.169**	0.192
EARNREV3M	0.010	6.564	0.009	**2.930**	0.082
MA10	0.493	72.410	-0.031	**-2.549**	0.500
MA8	0.510	74.929	-0.031	**-2.528**	0.500
DPSLOG	-1.135	-56.436	-0.093	**-2.520**	1.314
ROE	17.510	58.162	-1.330	**-2.427**	16.724
MVLOG	7.127	293.597	-0.104	**-2.374**	1.790
MA12	0.476	70.022	-0.025	**-2.044**	0.499
C24MEPSP	0.009	10.905	-0.003	**-1.973**	0.052
BVTMLOG	-0.515	-40.399	0.044	1.924	0.828
MOM36	0.626	22.684	0.094	1.902	1.490
DY	3.202	63.774	-0.171	-1.899	3.498
MA6	0.523	76.890	-0.023	-1.891	0.500
MA7	0.512	75.219	-0.023	-1.887	0.500
MA9	0.512	75.219	-0.023	-1.887	0.500
POUTRAT	34.495	89.230	-1.281	-1.848	26.025
OBOS12MMA	0.038	9.088	0.014	1.838	0.285
OBOS11MMA	0.035	8.934	0.011	1.622	0.268
MA11	0.482	70.877	-0.019	-1.548	0.499
MOM1	0.012	6.954	0.004	1.378	0.127
MA5	0.524	77.005	-0.016	-1.345	0.500
EY	0.105	90.406	0.003	1.339	0.083
STP	3.184	31.649	2.264	1.272	4.321
OBOS3MMA	0.009	5.889	-0.003	-1.213	0.108
OBOS10MMA	0.032	8.932	0.008	1.157	0.252
EPS	1.567	45.320	0.073	1.143	2.615
ICBTIN	0.309	14.867	-0.040	-1.042	0.389
C24MDPSP	0.004	11.663	-0.001	-0.978	0.022
MOM6	0.076	11.526	0.011	0.886	0.327
C24MBVTM	0.457	19.459	0.037	0.879	1.215
MA4	0.526	77.298	-0.009	-0.757	0.500
OBOS4MMA	0.013	6.808	-0.002	-0.716	0.135
MOM60	1.177	19.508	-0.076	-0.704	2.438
OBOS9MMA	0.030	8.973	0.004	0.652	0.235
SPSLOG	2.106	40.302	-0.056	-0.588	1.405
OBOS5MMA	0.017	7.597	-0.002	-0.531	0.158
OBOS6MMA	0.021	8.220	-0.002	-0.423	0.180
OBOS8MMA	0.027	8.791	0.002	0.319	0.218
DE	30.907	21.011	-0.532	-0.193	33.187
OBOS2MMA	0.004	3.542	0.000	-0.140	0.072
MOM3	0.050	15.209	0.000	0.059	0.227
MA3	0.515	75.669	0.001	0.058	0.500
OBOS7MMA	0.024	8.467	0.000	0.040	0.199

Panel B: Subsample_2 (2003 – 2011)
Proportion winners = 21.04%

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
MA2	0.349	67.943	0.216	**19.332**	0.481
CFTP	0.124	83.748	0.020	**7.182**	0.105
RETVAR12	0.009	62.849	0.001	**5.247**	0.010
EY	0.095	99.364	0.009	**4.972**	0.069
MVLOG	8.428	386.092	-0.192	**-4.762**	1.624
LNP	3.014	172.061	-0.138	**-4.323**	1.296
BETA	0.595	188.217	0.024	**4.174**	0.227
BVTMLOG	-0.775	-81.321	0.071	**4.025**	0.686
PRICEREL12	0.843	268.735	0.022	**3.784**	0.230
C24MDPSP	0.007	20.969	0.002	**3.346**	0.025
POUTRAT	45.135	103.683	-2.349	**-2.952**	28.714
EARNREV3M	0.004	3.732	0.006	**2.851**	0.084
STP	3.458	32.194	5.444	**2.832**	4.951
MA10	0.645	100.238	0.030	**2.585**	0.476
MA11	0.650	101.321	0.022	1.888	0.475
C24MEPSP	0.014	15.570	0.003	1.845	0.064
ROE	22.274	48.874	-1.495	-1.826	21.785
MOM60	2.581	58.472	-0.139	-1.719	3.010
MA5	0.616	94.062	0.020	1.668	0.485
MA7	0.633	97.455	0.019	1.633	0.480
MA9	0.633	97.455	0.019	1.633	0.480
MA8	0.637	98.224	0.019	1.581	0.479
MA12	0.655	102.265	0.018	1.539	0.474
MA6	0.626	96.044	0.018	1.496	0.482
MA3	0.592	89.370	0.017	1.398	0.490
OBOS6MMA	0.030	4.571	0.016	1.379	0.477
EG1	0.352	19.374	0.043	1.280	1.006
MOM6	0.125	36.277	0.008	1.265	0.260
MOM36	1.204	51.469	0.052	1.211	1.669
MOM1	0.021	16.555	-0.003	-1.169	0.093
OBOS2MMA	0.007	3.867	-0.004	-1.072	0.134
DPSLOG	-0.275	-15.336	-0.035	-1.055	1.240
MA4	0.607	92.032	0.013	1.041	0.488
OBOS7MMA	0.046	6.084	0.014	0.995	0.551
OBOS5MMA	0.024	4.483	0.009	0.945	0.394
MOM12	0.299	48.469	0.010	0.901	0.443
C24MBVTM	0.152	10.863	0.019	0.720	0.975
SPSLOG	2.528	110.577	0.029	0.689	1.405
OBOS4MMA	0.018	4.222	0.005	0.674	0.310
OBOS8MMA	0.062	7.254	0.010	0.632	0.625
OBOS9MMA	0.077	8.092	0.007	0.424	0.699
EPS	3.039	50.813	0.042	0.381	4.233
DE	34.949	49.489	-0.433	-0.330	42.618
OBOS3MMA	0.012	3.800	0.002	0.315	0.224
ICBTIN	0.247	33.793	0.003	0.254	0.389
OBOS10MMA	0.092	8.771	0.005	0.245	0.773
MOM3	0.068	29.250	0.000	0.100	0.167
DY	4.042	88.914	0.006	0.066	3.168
OBOS11MMA	0.108	9.360	0.001	0.063	0.846
OBOS12MMA	0.122	9.775	0.000	-0.014	0.912

Panel C: Total_sample (1994 – 2011)
Proportion of winners = 20.75%

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
MA2	0.313	89.657	0.225	**29.318**	0.471
CFTP	0.139	102.769	0.020	**8.243**	0.130
RETVAR12	0.014	79.917	0.002	**6.739**	0.018
BETA	0.631	292.789	0.025	**6.261**	0.230
LNP	2.630	191.476	-0.144	**-5.773**	1.432
MVLOG	7.783	446.941	-0.170	**-5.364**	1.824
BVTMLOG	-0.658	-83.509	0.063	**4.398**	0.764
EY	0.100	132.821	0.006	**4.271**	0.076
EARNREV3M	0.006	6.779	0.007	**3.974**	0.084
POUTRAT	39.706	134.403	-1.938	**-3.625**	27.844
EG1	0.510	33.468	0.098	**3.541**	1.157
MOM12	0.244	48.498	0.030	**3.259**	0.489
STP	3.331	44.928	3.916	**2.968**	4.671
ROE	19.537	74.587	-1.358	**-2.865**	19.196
DPSLOG	-0.681	-48.041	-0.070	**-2.683**	1.349
MOM60	2.216	59.867	-0.142	**-2.109**	2.934
C24MDPSP	0.006	23.664	0.001	1.881	0.024
MOM36	0.994	54.594	0.060	1.817	1.628
DY	3.623	105.944	-0.106	-1.701	3.369
MOM6	0.110	35.160	0.008	1.379	0.283
C24MBVTM	0.261	20.981	0.028	1.246	1.077
OBOS6MMA	0.025	7.125	0.007	1.125	0.364
OBOS2MMA	0.005	5.089	-0.002	-1.024	0.108
MA8	0.574	120.834	-0.008	-0.971	0.495
EPS	2.254	65.917	0.061	0.967	3.543
PRICEREL12	0.829	387.349	0.004	0.924	0.214
OBOS7MMA	0.035	8.542	0.007	0.921	0.420
MA3	0.554	116.237	0.008	0.878	0.497
MA12	0.566	118.948	-0.006	-0.742	0.496
OBOS8MMA	0.045	9.671	0.006	0.666	0.476
OBOS5MMA	0.020	6.952	0.004	0.659	0.303
OBOS9MMA	0.055	10.442	0.005	0.575	0.532
OBOS10MMA	0.064	11.012	0.006	0.538	0.588
MA6	0.575	121.215	-0.004	-0.522	0.495
OBOS11MMA	0.074	11.522	0.006	0.478	0.644
MA7	0.573	120.675	-0.004	-0.460	0.495
MA9	0.573	120.675	-0.004	-0.460	0.495
OBOS12MMA	0.083	11.928	0.006	0.457	0.695
MOM1	0.017	15.453	0.001	0.371	0.111
MA10	0.569	119.760	-0.003	-0.362	0.495
DE	34.454	53.359	-0.433	-0.361	41.601
SPSLOG	2.460	116.672	0.013	0.345	1.414
OBOS4MMA	0.015	6.559	0.001	0.316	0.240
C24MEPSP	0.012	18.997	0.000	0.271	0.059
OBOS3MMA	0.010	5.964	-0.001	-0.258	0.176
MA11	0.567	119.197	-0.001	-0.132	0.496
ICBTIN	0.254	36.783	-0.001	-0.098	0.389
MOM3	0.059	29.804	0.000	0.052	0.199
MA4	0.567	119.166	0.000	0.035	0.496
MA5	0.571	120.130	0.000	0.014	0.495

From Table 8.1 it is seen that on average 15 of the factors generally differ significantly between winner shares and the REST while approximately 20% of the observations are categorised as winners.

From a first glance at Table 8.1 it seems that the majority of significant t-statistics are associated with factors that are very similar in identity and ranking order to the factors that explain the cross- section of returns on the JSE (Chapters 5) and that can be used to construct ‘factor’ portfolios that could potentially offer superior returns (Chapter 6). Specifically, the factors associated with size (MVLOG and LNP), value (CFTP and BVTMLOG) and momentum (MOM12) generally fall into this significant category and are the same factors identified earlier. Note however that BVTMLOG is significant for Subperiod_1 on a 90% level of significance and that MOM12 is insignificant for Subperiod_2. The coefficient associated with the size factors (MVLOG and LNP) are negative, which means that winner shares are generally associated with lower market cap or price levels compared to the REST, confirming the size effect. Momentum and value factor dummy coefficients are positive, meaning that winner shares generally have higher value (CFTP and BVTMLOG) and momentum (MOM12) values compared to the REST. In keeping with the value factors being the inverse of what is normally applied (i.e. Price-to-book and Price-to-cash flow) these results further confirm the value and momentum effects on the JSE.

Three notable ‘additions’ are reported in Table 8.1 which were not observed in earlier chapters.

Firstly, the 2-month moving average variable (MA2) is associated with a significant, positive dummy coefficient across all sample periods. In fact, it is found to be the most significant factor. Based on the positive slope of the dummy coefficient, it seems that winner shares trade more often at a price above their 2-month moving average price compared to the REST. In keeping with the fact that a cross -sectional split is applied across all sample periods and the construction of the moving average dummy variable (refer to Chapter 4), a different, perhaps more meaningful interpretation can be made regarding the MA2 factor. Specifically, the alpha value (which is greater than 0.3) together with the dummy variable coefficient (which is greater than 0.2) imply that winner shares trade above their 2-month moving average more than 50% of the time, while the REST trade at such a level roughly a third of the time.

Secondly, the two variance factors Retvar12 and Beta are significant and positively related to winner shares, implicated by their respective positive dummy coefficients. In earlier chapters (Chapter 6) it was found that Beta may be a function of sample liquidity, and that the expected positive relationship between Beta and share performance as portrayed by the CAPM may, in the South African case, be dependent on the level of liquidity of the share (although still not applicable in isolation). The results in Table 8.1 do not necessarily contradict this finding, as the analysis is based on the All-share sample which of course includes the more liquid shares as well. However, up to this point the CAPM Beta was never really considered a relatively important factor when it comes to stock performance on the JSE. Furthermore Retvar12 was generally not found to be significant in explaining the cross- section of returns on the JSE or as a factor to form profitable 'factor' portfolios, yet is significantly associated with winner shares according to the findings in Table 8.1.

Lastly, the 3-month percentage change in 1-year forward- looking earnings per share growth factor (EARNREV3M) is found to be significantly higher when associated with winner shares relative to the REST.

Results of the evaluation of the extreme performer factors for loser shares using a 1-month holding period are presented in Table 8.2.

Table 8.2: Evaluation of loser factors over a 1-month period using Sample_A

This table presents the constant term (α_i), its associated t-statistic, dummy variable coefficient (β_{iL}), its t-statistic and standard error (σ_{ε_i}). Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the t-statistic associated with the dummy variable is significantly different from zero at the ninety-five percent level of confidence. Factors are ranked according to the absolute value of the dummy coefficient t-statistic.

Panel A: Subsample_1 (1994 – 2002)
Proportion losers = 17.76%

Factor	α_i	t-stat (α_i)	β_{iL}	t-stat (β_{iL})	σ_{ε_i}
MA2	0.296	62.950	0.177	**15.905**	0.464
PRICEREL12	0.820	298.867	-0.042	**-8.075**	0.192
RETVAR12	0.020	63.621	0.004	**7.210**	0.022
CFTP	0.171	74.868	-0.030	**-6.845**	0.152
MOM12	0.218	27.662	-0.086	**-5.690**	0.532
POUTRAT	34.930	93.514	-3.159	**-4.344**	25.994
DY	3.249	66.784	-0.375	**-3.984**	3.495
MOM1	0.017	9.891	-0.012	**-3.701**	0.127
OBOS12MMA	0.050	12.235	-0.028	**-3.609**	0.285
MA11	0.488	73.838	-0.042	**-3.309**	0.499
MOM60	1.055	18.194	0.374	**3.291**	2.433
OBOS11MMA	0.045	11.790	-0.024	**-3.284**	0.268
OBOS10MMA	0.040	11.423	-0.021	**-3.105**	0.251
BVTMLOG	-0.481	-38.669	-0.073	**-3.069**	0.827
BETA	0.666	236.395	0.017	**2.799**	0.228
MA12	0.477	72.351	-0.035	**-2.736**	0.499
MOM6	0.088	13.742	-0.034	**-2.701**	0.327
C24MBVTM	0.436	19.018	0.119	**2.694**	1.214
OBOS9MMA	0.036	10.941	-0.017	**-2.673**	0.235
C24MEPSP	0.009	11.376	-0.004	**-2.492**	0.052
MA4	0.532	80.460	-0.032	**-2.476**	0.499
MA7	0.513	77.653	-0.031	**-2.473**	0.500
MA9	0.513	77.653	-0.031	**-2.473**	0.500
MA10	0.491	74.357	-0.031	**-2.454**	0.500
STP	3.374	34.792	-4.392	**-2.349**	4.318
OBOS8MMA	0.031	10.394	-0.013	**-2.320**	0.218
MOM3	0.054	16.918	-0.014	**-2.295**	0.227
MA3	0.523	79.136	-0.029	**-2.262**	0.500
MA8	0.508	76.850	-0.029	**-2.246**	0.500
OBOS7MMA	0.027	9.869	-0.012	**-2.241**	0.199
MA6	0.523	79.163	-0.027	**-2.089**	0.500
OBOS5MMA	0.018	8.536	-0.008	**-1.991**	0.158
EG1	0.756	31.875	-0.091	-1.962	1.278
OBOS6MMA	0.023	9.145	-0.009	-1.848	0.180
OBOS4MMA	0.014	7.531	-0.006	-1.817	0.135
MA5	0.525	79.437	-0.023	-1.780	0.500
MOM36	0.680	25.254	-0.090	-1.761	1.490
OBOS2MMA	0.004	4.406	-0.003	-1.616	0.072
DE	31.655	22.663	-4.301	-1.409	33.142
ROE	17.297	58.430	-0.679	-1.207	16.732
OBOS3MMA	0.009	5.959	-0.003	-1.149	0.108
C24MDPSP	0.004	11.877	-0.001	-0.904	0.022
EARNREV3M	0.013	8.603	-0.002	-0.626	0.082
ICBTIN	0.292	14.978	0.027	0.601	0.389
DPSLOG	-1.157	-59.352	-0.022	-0.557	1.315
EY	0.106	93.601	0.001	0.490	0.083
SPSLOG	2.082	42.652	0.037	0.342	1.406
MVLOG	7.099	300.882	-0.014	-0.297	1.791
EPS	1.592	47.262	-0.015	-0.218	2.615
LNP	2.199	113.942	0.008	0.214	1.459

Panel B: Subsample_2 (2003 – 2011)
Proportion losers = 13.13%

Factor	α_i	t-stat (α_i)	β_{iL}	t-stat (β_{iL})	σ_{ε_i}
MA12	0.692	117.441	-0.168	**-12.327**	0.469
MA10	0.685	115.698	-0.166	**-12.111**	0.471
MA11	0.688	116.450	-0.165	**-12.055**	0.470
MA8	0.669	111.987	-0.145	**-10.479**	0.476
BETA	0.590	202.676	0.070	**10.411**	0.225
MA7	0.663	110.473	-0.128	**-9.223**	0.478
MA9	0.663	110.473	-0.128	**-9.223**	0.478
MOM12	0.325	56.972	-0.119	**-9.075**	0.440
MA5	0.646	106.681	-0.126	**-8.972**	0.482
MA6	0.654	108.466	-0.118	**-8.496**	0.480
RETVAR12	0.009	67.304	0.003	**8.227**	0.010
MA2	0.380	76.539	0.111	**8.117**	0.487
PRICEREL12	0.860	296.192	-0.054	**-8.105**	0.229
MA4	0.631	103.497	-0.110	**-7.810**	0.486
MA3	0.617	100.648	-0.106	**-7.474**	0.489
MOM6	0.137	42.890	-0.056	**-7.432**	0.259
MOM3	0.075	34.924	-0.037	**-7.429**	0.167
DY	4.176	99.050	-0.726	**-7.357**	3.156
CFTP	0.133	96.305	-0.018	**-5.644**	0.105
EARNREV3M	0.008	7.413	-0.012	**-4.639**	0.084
MOM1	0.022	19.056	-0.012	**-4.371**	0.093
C24MBVTM	0.135	10.350	0.121	**4.031**	0.974
MOM36	1.257	57.853	-0.195	**-3.903**	1.668
OBOS5MMA	0.035	7.010	-0.043	**-3.743**	0.394
MVLOG	8.340	410.580	0.174	**3.674**	1.625
OBOS11MMA	0.125	11.700	-0.090	**-3.628**	0.846
OBOS12MMA	0.140	12.089	-0.096	**-3.603**	0.912
OBOS10MMA	0.109	11.163	-0.081	**-3.602**	0.772
OBOS9MMA	0.093	10.499	-0.072	**-3.520**	0.699
POUTRAT	45.034	111.749	-3.296	**-3.497**	28.706
BVTMLOG	-0.741	-83.299	-0.071	**-3.457**	0.686
OBOS8MMA	0.076	9.676	-0.062	**-3.424**	0.624
OBOS4MMA	0.025	6.367	-0.030	**-3.279**	0.310
OBOS7MMA	0.059	8.560	-0.053	**-3.272**	0.550
OBOS3MMA	0.016	5.693	-0.021	**-3.264**	0.224
SPSLOG	2.508	118.284	0.158	**3.182**	1.404
OBOS6MMA	0.043	7.105	-0.044	**-3.156**	0.476
ICBTIN	0.257	37.469	-0.047	**-3.002**	0.389
EG1	0.345	20.451	0.104	**2.660**	1.005
DE	35.534	53.990	-3.857	**-2.515**	42.593
LNP	2.955	181.560	0.093	**2.463**	1.297
EY	0.099	110.776	-0.005	**-2.163**	0.069
C24MDPSP	0.008	25.371	-0.001	-1.942	0.025
ROE	22.061	52.579	-1.350	-1.385	21.790
C24MEPSP	0.014	17.285	0.002	1.280	0.064
MOM60	2.521	61.203	0.096	1.029	3.010
STP	3.585	36.221	2.271	0.996	4.957
DPSLOG	-0.291	-17.434	0.031	0.774	1.240
OBOS2MMA	0.006	3.718	-0.002	-0.425	0.134
EPS	3.050	54.927	0.007	0.055	4.234

Panel C: Total_sample (1994 – 2011)
Proportion losers = 15.52%

Factor	α_i	t-stat (α_i)	β_{iL}	t-stat (β_{iL})	σ_{ε_i}
MA2	0.337	98.558	0.143	**16.438**	0.477
RETVAR12	0.014	81.773	0.005	**13.815**	0.018
PRICEREL12	0.842	416.329	-0.053	**-12.371**	0.213
MA11	0.593	132.015	-0.116	**-12.310**	0.493
MA12	0.590	131.306	-0.114	**-12.158**	0.494
MA10	0.593	132.063	-0.109	**-11.590**	0.493
MOM12	0.278	58.641	-0.113	**-11.358**	0.487
MA8	0.593	132.005	-0.095	**-10.110**	0.493
BETA	0.629	307.501	0.043	**9.702**	0.229
MA7	0.592	131.745	-0.088	**-9.405**	0.493
MA9	0.592	131.745	-0.088	**-9.405**	0.493
DY	3.732	115.244	-0.627	**-9.197**	3.359
MA6	0.592	131.754	-0.079	**-8.452**	0.493
MA5	0.589	130.888	-0.079	**-8.390**	0.494
MOM6	0.123	41.794	-0.053	**-8.112**	0.282
MA4	0.584	129.669	-0.075	**-7.996**	0.495
MA3	0.573	126.829	-0.071	**-7.560**	0.496
POUTRAT	40.100	143.654	-4.388	**-7.449**	27.798
CFTP	0.150	116.166	-0.020	**-7.369**	0.130
MOM3	0.065	34.702	-0.026	**-6.629**	0.198
C24MBVTM	0.236	20.055	0.154	**6.119**	1.076
MOM1	0.020	19.359	-0.013	**-5.914**	0.111
MOM36	1.060	61.662	-0.215	**-5.905**	1.626
OBOS12MMA	0.100	15.206	-0.069	**-4.986**	0.694
OBOS11MMA	0.090	14.750	-0.062	**-4.891**	0.643
OBOS10MMA	0.079	14.193	-0.056	**-4.787**	0.587
OBOS9MMA	0.067	13.489	-0.047	**-4.538**	0.531
OBOS8MMA	0.056	12.611	-0.040	**-4.277**	0.475
OBOS5MMA	0.027	9.726	-0.025	**-4.223**	0.303
OBOS7MMA	0.045	11.453	-0.033	**-4.033**	0.419
EARNREV3M	0.009	10.924	-0.008	**-3.832**	0.084
OBOS4MMA	0.020	8.882	-0.017	**-3.745**	0.240
OBOS6MMA	0.033	9.905	-0.026	**-3.671**	0.364
OBOS3MMA	0.013	7.765	-0.012	**-3.410**	0.176
DPSLOG	-0.682	-50.771	-0.092	**-3.165**	1.348
C24MDPSP	0.007	27.487	-0.002	**-2.975**	0.024
ROE	19.477	77.885	-1.493	**-2.913**	19.196
SPSLOG	2.440	124.622	0.130	**2.869**	1.413
DE	35.074	58.154	-3.985	**-2.860**	41.572
ICBTIN	0.261	40.282	-0.039	**-2.618**	0.389
BVTMLOG	-0.630	-83.944	-0.040	**-2.531**	0.764
MVLOG	7.752	468.279	-0.088	**-2.516**	1.825
EPS	2.308	70.893	-0.163	**-2.339**	3.542
LNP	2.597	199.021	-0.046	-1.693	1.433
EG1	0.530	36.770	0.040	1.319	1.158
OBOS2MMA	0.005	5.389	-0.003	-1.300	0.108
C24MEPSP	0.012	20.773	-0.001	-1.172	0.059
STP	3.492	50.066	-1.679	-1.144	4.674
MOM60	2.158	61.961	0.071	0.940	2.934
EY	0.102	142.525	0.000	-0.251	0.076

Although the average proportion of observations associated with loser shares (approximately 15%) are much lower than that associated with winners (approximately 20%), substantially more factors differ significantly between loser shares and the REST as opposed to between winner shares and the REST, as can be seen from Table 8.2.

The value factors CFTP and BVTMLOG are once again significant during each sample period. The negative coefficients imply that loser shares generally have lower CFTP and BVTMLOG values compared to the REST as opposed to the positive coefficients associated with the winner shares. This finding suggests that the value factors CFTP and BVTMLOG may be used not only to identify potential extreme performers but also to classify them as either winners or losers. Note that a third value factor, DY, is generally found to be more significantly (and negatively) associated with loser shares than the former two value factors. Therefore DY may be used as an additional value filtering factor to identify potential loser shares.

Compared to the winner shares, the size effect seems to be less important in identifying loser shares. This is implicated by the relatively lower level of significance associated with especially LNP and MVLOG factors. Note further that both positive and negative signs are associated with the dummy variable coefficients regarding the different size factors depending on the specific factor and sample period used. Therefore no definitive conclusion regarding the association between loser shares and size can be drawn.

From Table 8.2 it appears that loser shares are, as was the case for winner shares, significantly associated with momentum factors. MOM12 is highly significant during each sample period, and the negative dummy coefficient indicates that loser shares generally have lower prior 12-month returns compared to the REST during the period of a sell signal. In keeping with the results in Table 8.1 and noting that the majority of longer term moving average (MA), over-bought over-sold (OBOS) and relative price (PRICEREL12) factors have significant negative dummy coefficients, it is clear that a strong momentum effect exists on the JSE, and that this effect appears to be associated more significantly (and negative) with loser shares.

The significant, positive relationship observed between winner shares and MA2 in Table 8.1 is repeated for loser shares in Table 8.2. Loser shares however are trading at a price above its 2-month moving average slightly less frequently, as indicated by the lower dummy coefficient relative to that of the winner shares. But just like winner shares, the results in Table 8.2 imply that loser shares trade at such a level more

frequently than the REST. Therefore, while it may be possible to use MA2 as a filter to isolate potential extreme performers from the REST, it may be difficult to use as a filter to identify potential winners and losers from the pool of extreme performers.
Similarly, significant positive dummy coefficients are also obtained for volatility factors Retvar12 and Beta, as was the case for winners. The volatility level associated with losers is however higher than that associated with winners, indicated by the comparatively larger coefficients in Table 8.2. Hence, as can be expected, extreme performing shares have higher levels of volatility. However, those with the highest levels of volatility are mostly associated with losers, a finding that contradicts Modern Portfolio Theory (refer to Chapter 2).

In summary, it appears that a momentum factor (MA2) and two volatility factors (Retvar12 and/or Beta) could be used as entry level filters to identify possible extreme performers over a 1-month period, as both winners and losers have significantly higher values associated with these factors relative to the REST. Due to the fact that relatively higher levels of these factors are significantly associated with both winners and losers, and given the almost negligible difference in the distribution of these between winners and losers (refer to Appendix E.1), further analysis is needed to determine the most effective way of applying these in a filtering process to isolate winners and losers. The latter will be conducted in Section 8.4. Apart from these three factors, the type and order of filters to be applied to create a winner and loser portfolio respectively will differ slightly. To construct a winner portfolio, value filters will be applied first, followed by size and lastly momentum filters. Relatively higher values with regard to the value and momentum factors and lower levels with regard to the size factors are associated with winner shares. Regarding the construction of a loser portfolio, momentum filters will be applied first, followed by value filters. In contrast to winners, loser shares are associated more with lower prior returns (momentum factors) as well as lower levels regarding value factors. Note that a size filter may be ignored with regard to the loser portfolio as no clear evidence of a significant association between loser shares and size factors was obtained. This filter sequence, applied to construct the winner and loser portfolios respectively, will ensure that the filtering process reflects the level of significance associated with the specific factors.

8.4 Deriving filter rules

The process of deriving filter rules using the factors that are significantly associated with winner or loser shares (Section 8.3) is complicated by the fact that some factors are significantly associated with both categories and also of the same sign. Due to the binary nature of the dummy variable created to distinguish winner and loser shares from the REST, a possible approach in creating filter rules may however be to derive a model that would maximise the probability of selecting either a winner or a loser share, given the factors identified earlier. A logistic regression model (or logit model) does exactly that, i.e. provides a model to determine the probability of the binary dependent variable (in this case the dummy variable) being equal to either one (winner or loser) or zero (the REST) given the independent variables (the factors identified that differ significantly between winner, loser and the REST). Before the logistic regression approach is applied however, a brief theoretical background regarding the logit model (as discussed in Wooldridge 2009: 574 – 587) is provided in the next section for a better understanding of how the process is used in this thesis.

8.4.1 Logit models for binary response

8.4.1.1 Specifying a logit model

Consider a class of binary response models of the form

$$P(y = 1|\boldsymbol{x}) = \mathrm{G}(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) = \mathrm{G}(\beta_0 + \boldsymbol{x\beta}) \qquad \text{....(8.3)}$$

where

P(.)	=	Probability function
y	=	Dependent (binary) variable
$\boldsymbol{x}$	=	Vector of independent variables with typical element x_j, j = 1,..,k
G	=	Function taking on values strictly between zero and one: 0 < G(z) < 1 for all real numbers z
β_0	=	Logistic regression constant term
$\boldsymbol{\beta}$	=	Vector of logistic regression coefficients

In the logit model, *G* is the logistic function:

$$G(z) = \frac{e^{(z)}}{[1+e^{(z)}]} \quad ...(8.4)$$

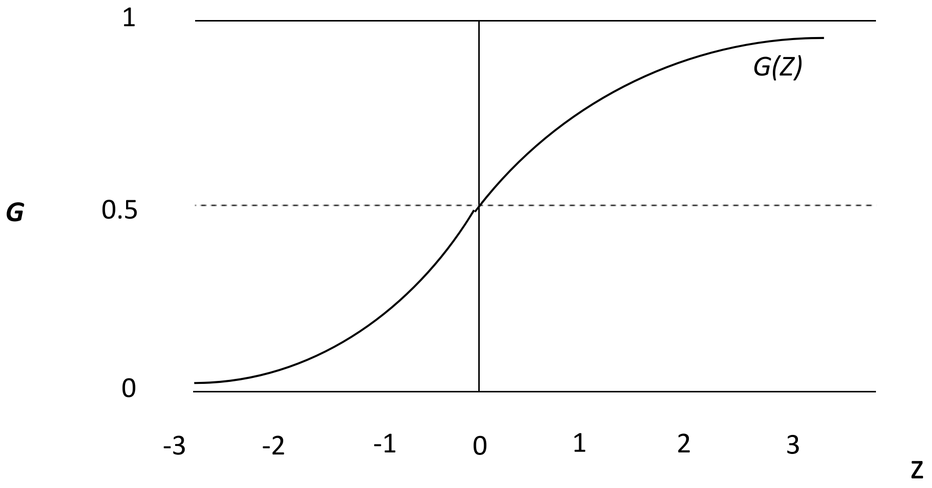
where

e = 2.718

$G(z) \rightarrow 0\ as\ z \rightarrow -\infty\ and\ G(z) \rightarrow 1\ as\ z \rightarrow +\infty$, thus *G(z)* is constrained by the values 0 and 1 and is the cumulative distribution function (cdf) for a standard logistic random variable, illustrated in Figure 8.1.

Figure 8.1: Graphical illustration of the logistic function

$$G(z) = \frac{e^{(z)}}{[1+e^{(z)}]}$$



Logit models can be derived from an underlying latent variable model. Mathematically, this can be expressed as follows:

Let y^* be an unobserved (latent) variable, determined by

$$y^* = \beta_0 + \boldsymbol{x\beta} + \varepsilon, \quad y = 1[y^* > 0] \quad ...(8.5)$$

where the notation 1[.] is an indicator function and defines a binary outcome. The indicator function takes on a value of one if the event in brackets is true, and zero otherwise. Therefore, according to (8.5), y = 1 if $y^* > 0$ and y = 0 if $y^* \leq 0$. ε is assumed to be independent of $\boldsymbol{x}$ and has either the standard normal distribution or the standard logistic distribution. Irrespective, this assumption implies that ε is symmetrically distributed about zero, which means that 1 – *G(-z)* = *G(z).*

From (8.5) and the assumptions discussed above, the response probability for *y* can be derived as follows:

$$P(y=1|\boldsymbol{x}) = \mathrm{P}(\mathrm{y}^* > 0|\boldsymbol{x}) = \mathrm{P}[e > -(\beta_0 + \boldsymbol{x\beta})|\boldsymbol{x}] = 1 - G[-(\beta_0 + \boldsymbol{x\beta})] = \mathrm{G}(\beta_0 + \boldsymbol{x\beta})$$

which is exactly the same as (8.3), namely

$$P(y=1|\boldsymbol{x}) = \mathrm{G}(\beta_0 + \beta_1 \mathrm{x}_1 + \cdots + \beta_\mathrm{k} \mathrm{x}_\mathrm{k}) = \mathrm{G}(\beta_0 + \boldsymbol{x\beta}) \qquad \text{....(8.3)}$$

In most applications of binary response models, the primary goal is to explain the effects of x_j on the response probability $P(y=1|\boldsymbol{x})$**.** The latent variable formulation tends to give the impression that we are primarily interested in the effects of each x_j on y^*. For logit models the direction of the effect of x_j on E(y^*|**x**) = $\beta_0 + \boldsymbol{x\beta}$ and on E(*y*|**x**) = $P(y=1|\boldsymbol{x})$ = $\mathrm{G}(\beta_0 + \boldsymbol{x\beta})$ is always the same. However, the latent variable (y^*) rarely has a well-defined unit of measurement. Therefore the magnitudes of each β_j are not, by themselves, particularly useful as is the case for linear probability models. Mostly the goal is to estimate the effect of x_j on the probability of success $P(y=1|\boldsymbol{x})$, but this is complicated by the nonlinear nature of *G*(.)

Using calculus, it is possible however to find the partial effect of a roughly continuous variable on the response probability. Specifically, if x_j is roughly continuous, its partial effect on p(***x***) = $P(y=1|\boldsymbol{x})$ is obtained from the partial derivative:

$$\frac{\partial p(x)}{\partial x_j} = g(\beta_0 + \boldsymbol{x\beta})\beta_j, where\ g(z) \equiv \frac{\partial G}{\partial z}(z) \qquad \text{...(8.6)}$$

Due to the fact that *G* is the cdf of a continuous random variable, g is a probability density function. In the logit case, *G*(.) is a strictly increasing function, and so g(z) > 0 for all *z*. Hence, the partial effect of x_j on p(***x***) depends on ***x*** through the positive quantity $g(\beta_0 + \boldsymbol{x\beta})$, which means that the partial effect always has the same sign as β_j. Hence the coefficients obtained through the logistic regression approach (reported in 8.4.2) cannot be interpreted as normal linear regression coefficients, but the partial effect of a specific factor on p(x) can be determined using the above approach.

8.4.1.2 Maximum Likelihood Estimation of logit Models

Assume a random sample of size *n*. To obtain the maximum likelihood estimator, conditional on the explanatory variables, the density of y_i given $\boldsymbol{x_i}$ is needed. This can be written as:

$$f(y|\boldsymbol{x}_i;\boldsymbol{\beta}) = [G(\boldsymbol{x}_i\boldsymbol{\beta})]^y[1 - G(\boldsymbol{x}_i\boldsymbol{\beta})]^{1-y}, y = 0,1 \qquad \text{...(8.7)}$$

For simplicity, the intercept is absorbed into the vector $\boldsymbol{x_i}$. From (8.7), when y = 1 we get $G(\boldsymbol{x}_i\boldsymbol{\beta})$, and when y = 0 we get $1 - G(\boldsymbol{x}_i\boldsymbol{\beta})$. The log-likelihood functionℓ_i, for observation *i,* is a function of the parameters and the data ($\boldsymbol{x_i}$,*y*) and is obtained by taking the log of (8.7):

$$\ell_i(\boldsymbol{\beta}) = y_i log[G(\boldsymbol{x}_i\boldsymbol{\beta})] + (1 - y_i)\log[1 - G(\boldsymbol{x}_i\boldsymbol{\beta})] \qquad \text{...(8.8)}$$

Due to G(.) being strictly between zero and one, $\ell_i(\boldsymbol{\beta})$ is well defined for all values of $\boldsymbol{\beta}$.

The log-likelihood for a sample size of n, $\mathcal{L}$, is obtained by summing (8.8) across all observations: $\mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{n} \ell_i(\boldsymbol{\beta})$.

The maximum likelihood estimation of $\boldsymbol{\beta}$, denoted by $\widehat{\boldsymbol{\beta}}$, maximizes this log-likelihood and is referred to as the logit estimator.

Due to the nonlinear nature of the maximization problem, it is not possible to write a formula for the logit maximum likelihood estimates (Wooldridge, 2009:579). Nonetheless, the general theory of maximum likelihood estimation for random samples implies that, under very general conditions, it is consistent, asymptotically normal and asymptotically efficient. When the logit model is estimated, the following null hypothesis can be performed (similar to ordinary least squares) to test for the significance of the estimates:

H_0: $\beta_j = 0$

The t-statistic to use for this test is calculated as

$$\frac{\widehat{\beta}_j}{SE_{\widehat{\beta}_j}} \qquad \text{...(8.9)}$$

where $SE_{\widehat{\beta}_j}$ is the asymptotic standard error of $\hat{\beta}_j$. The latter is calculated as follows:

Given the binary response model $P(y=1|\boldsymbol{x}) = G(\boldsymbol{x\beta})$ where *G(.)* is the logit function and $\boldsymbol{\beta}$ the $k \times 1$ vector of parameters, the $k \times k$ asymptotic variance matrix of $\widehat{\boldsymbol{\beta}}$ is estimated as

$$\widehat{Avar}(\widehat{\boldsymbol{\beta}}) \equiv \left(\sum_{i=1}^{n} \frac{[g(\boldsymbol{x}_i\widehat{\boldsymbol{\beta}})]^2 \boldsymbol{x}_i'\boldsymbol{x}_i}{G(\boldsymbol{x}_i\widehat{\boldsymbol{\beta}})[1-G(\boldsymbol{x}_i\widehat{\boldsymbol{\beta}})]}\right)^{-1} \quad ...(8.10)$$

The asymptotic standard errors of the $\hat{\beta}_j$ are the square roots of the diagonal elements of (8.10).

As is the case with multiple linear regression, it is possible to test multiple restrictions in logit models. An appropriate test to use for testing multiple restrictions regarding logit models is the likelihood ratio (LR) test, which is based on the same concept as the F-test in a linear model. Specifically, the LR test is based on the following idea: As discussed earlier, the maximum likelihood estimation maximizes the log-likelihood function. Therefore, dropping variables generally leads to a smaller log-likelihood. The question is whether the difference in the log-likelihood before and after the variable has been removed, is large enough to conclude that the variable is important. This decision is of course based on a test statistic and a set of critical values. The likelihood ratio statistic is twice the difference in the log-likelihoods:

$$LR = 2(\mathcal{L}_{ur} - \mathcal{L}_r) \quad ...(8.11)$$

where

LR = Likelihood ratio statistic

$\mathcal{L}_{ur}$ = Log-likelihood value for the unrestricted model

$\mathcal{L}_r$ = Log-likelihood value for the restricted model

Due to the fact that $\mathcal{L}_{ur} \geq \mathcal{L}_r$, LR is nonnegative and usually strictly positive. In keeping with the fact that y_i is either zero or one and that both variables inside the log function in equation (8.8) is strictly between zero and one (which implies that their natural logs are negative), it is clear that the log-likelihood will always be a negative number. This is however not a problem in calculating (8.11) as the negative signs are simply preserved. The multiplication by two in (8.11) is needed to ensure that LR has an approximate chi-square distribution under H_0. Testing for example *q* exclusion restrictions at the 5% level, the critical value to be used is therefore the 95th percentile in the X^2-distribution with q degrees of freedom.

8.4.1.3 Goodness-of-fit for logit models

Two methods in determining the goodness-of-fit regarding logit models include the "percent correctly predicted" approach and the "pseudo R-squared" measures. With regard to the percent correctly predicted approach, the binary predictor of y_i is defined to be one if the predicted probability is at least 0.5 and zero, otherwise (Wooldridge, 2009:581). Mathematically it can be expressed as follows: $\tilde{y}_i = 1 \; if \; \mathrm{G}(\hat{\beta}_0 + \boldsymbol{x_i}\hat{\boldsymbol{\beta}}) \geq 0.5$ and $\tilde{y}_i = 0 \; if \; \mathrm{G}(\hat{\beta}_0 + \boldsymbol{x_i}\hat{\boldsymbol{\beta}}) < 0.5$. Given $\{\tilde{y}_i$: i = 1,2,...n$\}$ it is therefore possible to determine how well $\tilde{y}_i$ predicts y_i across all observations. The percentage correctly predicted is the percentage of times that $\tilde{y}_i = y_i$.

Using a threshold value of 0.5 for the goodness-of-fit (or prediction rule) has been criticized, especially when one of the outcomes is less likely. In such a case, setting the fraction of successes in the sample equal to the threshold could be a better approach. Yet another approach is to choose the threshold so that the fraction of $\tilde{y}_i$ = 1 in the sample is approximately equal to $\bar{y}$. In other words, search over threshold values, 0< τ < 1, such that if $\tilde{y}_i$ = 1 when $\mathrm{G}(\hat{\beta}_0 + \boldsymbol{x_i}\hat{\boldsymbol{\beta}}) \geq \tau$, then $\sum_{i=1}^{n} \tilde{y}_i \approx \sum_{i=1}^{n} y_i$. Given this set of $\tilde{y}_i$, the percentage correctly predicted for each of the two outcomes as well as the overall percentage correctly predicted, can be calculated. The objective therefore becomes to find a threshold τ that will maximise the percentage of correctly predicted outcomes.

Unlike linear regression models, probability models have no disturbance term as an independent source of nuisance variation. This means that there is no true equivalent of the linear regression R^2 (Cramer, 1991:103). Nevertheless, various pseudo R-squared measures have been suggested for binary response models (Wooldridge, 2009:581). Two such pseudo R-squared measures include the Cox and Snell (1989) and the Nagelkerke (1991) measures.

Cox and Snell (1989) suggest the following R^2 for logit models:

$$R^2 = 1 - \exp\left[-\frac{2}{n}\{\mathcal{L}_{\hat{\beta}} - \mathcal{L}_0\}\right] = 1 - \{\frac{\mathcal{L}_0}{\mathcal{L}_{\hat{\beta}}}\}^{\frac{2}{n}} \quad \text{...(8.12)}$$

where

n = sample size

$\mathcal{L}_{\hat{\beta}}$ = log-likelihood of the fitted model

$\mathcal{L}_0$ = log-likelihood of the “null” model, i.e. a model with only an intercept

From (8.12) it is clear that the more explanatory power the covariates have, the larger the R^2 value will be. Nagelkerke (1991) notes that the Cox and Snell R^2 can never be equal to 1, and will in fact reach a maximum of only 0.75 when 50% of y_i is equal to one and 50% of y_i is equal to zero. He suggests the following refinement to the Cox and Snell (1989) R^2:

$$\bar{R}^2 = \frac{R^2}{\max(R^2)} \quad \text{...(8.13)}$$

where

R^2 = Cox and Snell R^2

$max(R^2)$ = Maximum value that the Cox and Snell R^2 can take on for the specific model

8.4.2 Applying logit models to predict winner and loser shares

Using the shares in Sample_A and the results obtained in Section 8.3, a logit model is developed for the winner and loser shares respectively. Due to the large number of candidate factors identified in Section 8.3 (which are the potential independent variables for the logit model), factors were chosen from each variable category (i.e. value, growth, size, momentum and volatility) based on the level of significance associated with the dummy variables while taking the correlation between factors into consideration. Following this approach not only simplifies the logistic regression process but further assists in avoiding possible multicollinearity within the logit model that could potentially be caused by high correlations between factors. Once the factors have been chosen, a forward stepwise logistic regression approach is followed to determine which of these variables should form part of the ultimate model. The forward stepwise logistic regression algorithm (as applied in SPSS statistical software) includes the following steps:

i. The necessary information is calculated for the initial model, including the maximum likelihood estimate (or logit estimator) of the parameter(s), predicted probability and likelihood function.
ii. Based on the maximum likelihood estimates of the current model, the score statistic for every variable eligible for inclusion (i.e. those variables specified by the user, which in this case will be as many of the factors found to be significant in Section 8.3 as possible) is calculated and a significance is determined for the specific variable.
iii. The variable with the smallest significance is chosen and compared to the probability of a variable entering the model. If it is less than this probability, the next step is performed. If not, the process stops.
iv. The logit model is updated with the new variable.
v. The likelihood ratio statistic (or Wald statistic[1]) is calculated for each variable in the current model together with its corresponding significance.
vi. The variable with the largest significance is chosen and the level of significance is compared to the probability for variable removal. If the significance is less than this probability, the process goes back to step ii. If the current model with the variable deleted is the same as the previous, the process stops. Otherwise the process moves on to the next step.
vii. The current model is modified by removing the variable with the largest significance from the previous model. Parameters are estimated for the current model and the process goes back to step v.

The results of this approach (as obtained for each successive step) for winner shares are reported in Table 8.3 followed by the goodness- of- fit measures in Table 8.4.

Table 8.3: Forward stepwise regression results for 1-month period: Winner shares
This table presents the results of the forward stepwise logistic regression approach. The variables included at each step (until the process is terminated) are listed below the table. The variable coefficient (B) and standard error (S.E.) are reported after each successive step. The significance of each variable is determined by comparing the Wald statistic to the critical value obtained from the chi-squared distribution table with the appropriate degrees of freedom. The associated p-value is reported as well (Sig.)

[1] The Wald statistic is used in a similar fashion to the t-statistic defined in equation (8.9). The Wald statistic is calculated as $\frac{\hat{\beta}_j^{\,2}}{\sigma_{\hat{\beta}_j}^{\,2}}$ and has an asymptotic chi-square distribution with degrees of freedom equal to the number of restrictions being tested.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CFTP	1.520	.255	35.599	1	.000	4.573
	Constant	-1.032	.050	419.491	1	.000	.356
Step 2[b]	CFTP	1.441	.256	31.743	1	.000	4.226
	BETA	.468	.142	10.867	1	.001	1.597
	Constant	-1.340	.107	157.486	1	.000	.262
Step 3[c]	CFTP	1.371	.258	28.293	1	.000	3.941
	RETVAR12	5.216	2.442	4.561	1	.033	184.181
	BETA	.383	.147	6.755	1	.009	1.467
	Constant	-1.335	.107	156.255	1	.000	.263

a. Variable(s) entered on step 1: CFTP.

b. Variable(s) entered on step 2: BETA.

c. Variable(s) entered on step 3: RETVAR12.

It can be seen that all variables included are statistically significant at the 5% level. Based on the construction process of the logit model, a positive (negative) coefficient implies an increase (decrease) in the probability of the binary dependent variable taking on the value one for a one unit increase in the associated independent variable. Specifically, the exponent of the coefficient value (reported in the last column) is interpreted as an "odds ratio". Therefore, the probability of the binary dependent variable taking on the value of one is exp(B) times as likely for a one unit increase in the value of the independent variable. For example, the Exp(B) of 3.941 associated with CFTP reported in step 3 means that the probability that a share is classified as a winner is approximately 4 times as likely with a one unit increase in CFTP. The large value associated with RETVAR12 is due to the format (squared term) used in the data set.

Table 8.4: Goodness of fit
This table reports the goodness-of-fit measures for each logit model after every successive step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	6008.854[a]	.007	.010
2	5998.015[a]	.009	.013
3	5993.525[a]	.010	.015

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

From Table 8.4 it is seen that the different measures improve for each successive model. The pseudo R-squared values are quite low, however this may be due to the fact that the logistic regression models are based on single shares. These values could easily be increased by using portfolios of shares instead.

The same process is followed for the loser shares, and the results are reported in Appendix E.2.

From Table 8.3 and Appendix E.2 the respective winner and loser logit models can be formulated in equation format:

$$logit(winner) = -1.335 + 1.371CFTP + 5.216RETVAR12 + 0.383BETA \quad ...(8.14)$$

$$logit(loser) = -1.488 + 0.171MA2 + 12.150RETVAR12 - 0.373PRICEREL12 - 0.345MOM12 + 0.913BETA - 1.535CFTP \quad ...(8.15)$$

The significant variables included in the final logit models are very much in line with the results in Section 8.3. Firstly, the two volatility variables Retvar12 and Beta are both significantly and positively associated with winner and loser shares. The logit process however allows for the identification of the different levels of these variables that are associated with the respective winner and loser shares, which wasn't very clear when examining the respective distributions only (Appendix E.1). With regard to the winner logit model, the value factor (CFTP) turned out to be a significant filter (as expected according to Section 8.3), while no momentum and size factors were found to be significant. Although the 2-month moving average (MA2) factor was found to be significantly associated with both winner and loser shares in Section 8.3, it was found to be significant in only the loser logit model. Similar to the results in Section 8.3 however, value (CFTP) and momentum (MOM12) factors appear to be significant in filtering loser shares while the size factor did not have any significant effect.

In keeping with the fact that the dependent (binary) variable is defined to identify extreme performer shares one would expect that the event of being classified as an extreme performer (winner or loser) should be lower (or less likely) than being classified as a "normal" (REST) share. Therefore a different threshold value (than the default level of 0.5) will have to be identified by means of the "*percent correctly predicted*" approach (Section 8.4.1.3) to use the logit model(s) for filtering purposes. The process of determining a threshold value (τ) that would maximise the percentage of outcomes correctly predicted by the respective logit models was applied using the following steps:

i. The winner and loser logit models [(8.14) and (8.15)] are applied to the shares in Sample_A, resulting in a time series of monthly logit values for each share for every month in the period under review.

ii. Formula (8.4) is used to convert these logit values into outright probabilities. By default, when the probability is at least 50% the predicted value ($\tilde{y}_i$) is set equal to one, and zero otherwise. Therefore a share is classified as a winner (loser) when the calculated probability in step i. is at least 50%, and as part of the REST when the probability is less than 50%.

iii. A calibrating process is applied to align the calculated probabilities with the true values of the binary dependent variable y_i with respect to Sample_A. This is done by creating two time-series: one consists of the probability values when the true dependent variable is equal to one [(i.e. when the share is classified as a winner (loser)] and the other consists of the probability values when the true dependent variable is equal to zero (i.e. when the share is classified under the REST). The percentage of correctly predicted values is calculated as the total number of times the predicted value ($\tilde{y}_i$) is equal to one divided by the total number of times the true value (y_i) is equal to one. This results in percentage correctly predicted values for winner (loser) shares. Similarly, the number of times the predicted value was equal to zero is divided by the total number of times the true value was equal to zero, resulting in the percentage of time a share is correctly predicted as being part of the REST.

iv. The default threshold value of 0.5 is replaced by the average of the probabilities calculated in the first part of step ii which is associated with the observations where the true dependent variable takes on the value one.

v. Based on this new threshold value, the second part of step ii. is repeated to classify shares as winners (losers) or REST. In other words a share is classified as a winner (loser) if the calculated probability in step ii is at least equal to the new threshold value, and as part of the REST when the probability is less than the new threshold value.

vi. Similar to step iii the percentage correctly predicted values is calculated.

vii. The latest threshold value is adjusted by changing the value only marginally in either direction. The percentage correctly predicted values are calculated in the same way as was done in step iii. These percentages are compared to the immediate preceding percentage correctly predicted values obtained. If there was an increase in the accuracy of correctly predicted values the threshold value to be used in the next step is set equal to this latest (adjusted) value.

viii. Step vii. is repeated until no other threshold value offers better results in terms of an increase in the percentage correctly predicted values. The latest threshold value is regarded as the optimal value to be used in applying the logit models for prediction purposes.

Following the above iteration process, a threshold value of 0.301 was obtained for the winner logit model (8.14). The percentage correctly predicted values using the threshold value of 0.301 are reported in Table 8.5 for each successive step.

Table 8.5: Percentage correctly predicted values
This table reports percentage correctly predicted values based on the specific logit model created during each successive step and the threshold value ("cut value") used. The objective is to obtain a threshold value such that the percentage correctly predicted for both values of the binary dependent variable is optimised for the specific step. (Note that the percentage correctly predicted value should not be compared between the steps as the objective is to optimise the percentage correctly predicted values within each specific step representing a specific logit model).

Classification Table[a]

Observed			Predicted		
			DUM1MWIN		Percentage Correct
			0	1	
Step 1	DUM1MWIN	0	1817	1552	53.9
		1	686	827	54.7
	Overall Percentage				54.2
Step 2	DUM1MWIN	0	1726	1643	51.2
		1	644	869	57.4
	Overall Percentage				53.2
Step 3	DUM1MWIN	0	1790	1579	53.1
		1	668	845	55.8
	Overall Percentage				54.0

a. The cut value is .301

The values within the cells indicate the number of times the binary dependent variable was observed to be 1 or 0 versus the number of times it was predicted to be 1 or 0 for each step. Taking Step 3 for example, the binary dependent variable was predicted to be zero 1790 times while the actual number of times it was equal to zero is 1790 + 1579 = 3 369. Hence the percentage of binary variables correctly predicted to be zero equals 1790/3369 = 53.1%. Similarly, the binary dependent variable value was predicted to equal one 845 times while the actual number of times it was equal to one is 668+845 = 1513. Hence the percentage of binary variables correctly predicted to equal one is 845/1513 = 55.8%.

Following the same iteration process, a threshold value of 0.217 (see Appendix E.2) was obtained for the loser logit model (8.15).

To determine whether the logit models obtained will hold up in an independent sample, models (8.14) and (8.15) are applied to the shares in Sample_B, using the threshold values obtained above. Monthly equally weighted winner and loser portfolios are created over the period January 1994 through May 2011. The respective winner and loser portfolios are created in such a way to ensure that a share can only be included in either the winner or loser portfolio, not in both. A benchmark portfolio is created by weighing all the shares in Sample_B equally on a monthly basis over the same period. The portfolio characteristics of the winner, loser and benchmark portfolios are reported in Table 8.6.

Table 8.6: Comparison of winner, loser and benchmark portfolio characteristics using Sample_B and rebalancing monthly.
This table presents portfolio characteristics of the winner, loser and benchmark portfolios for the period January 1994 through March 2011. Stocks are selected from Sample_B to create the respective portfolios. A paired mean comparison test was performed to test for significantly different mean monthly returns between the winner (loser) and benchmark portfolios. The t-stat obtained is reported below the average monthly return value.

	Winner	**Benchmark**	**Loser**
Average monthly return	2.54% (t-stat = 2.75)	1.58%	0.59% (t-stat = -3.58)
Annualised return	35.18%	20.65%	7.29%
Monthly standard deviation	6.85%	5.65%	6.74%
Annualised standard deviation	23.74%	19.58%	23.36%
Sharpe ratio**	1.25	0.78	0.08
Average number of shares	14	83	13

** The Sharpe ratio is calculated using the annualised figures and an annualised 3-month T-bill rate of 5.41%

From Table 8.6 it is seen that the winner (loser) portfolio significantly outperforms (underperforms) the benchmark portfolio. The level of risk as measured by the standard deviation is relatively higher for these portfolios compared to the benchmark portfolio. This could however be expected, as the winner and loser portfolios are constructed using shares that, according to the filtering (logit) model, should have a relatively higher probability of being an extreme performer which, by definition, should experience a higher level of volatility. To account for this relatively higher level of risk, the Sharpe ratio is also reported. The winner portfolio shows a higher Sharpe ratio, implying that the additional risk associated with the winner portfolio is compensated for by the additional marginal returns obtained. The loser portfolio on the other hand has a lower Sharpe ratio, indicating that much lower returns (relative to the winner and benchmark portfolios) were obtained even though a higher level of risk (relative to the benchmark portfolio) is associated with this portfolio.

8.4.3 Refining the logit models for winner and loser shares

In an attempt to refine the filtering process further, formula (8.1) can be adjusted and reapplied to identify which factors differ significantly between winner and loser shares instead of comparing winner and loser factors to those associated with the REST. Once the factors that differ statistically significantly between winner and loser shares have been identified, a similar process to the one followed above can be applied to derive a logit model for winner and loser shares respectively with the added benefit that the probability of a share being classified as both a winner and loser during a specific month may be reduced, resulting in a possible increase in the number of shares to be included in each portfolio as well as potentially improved portfolio characteristics.

To examine the effect of this refinement process, the sample of shares on which the logit model is based is reduced to include only those shares that are defined as either a winner or loser shares, ignoring the REST. Formula (8.1) is then applied to this sample after the following adjustment:

$$C_{iE} = \alpha_i + \beta_{iW} DW_{i,1} + \varepsilon_i \tag{8.16}$$

where

C_{iE}	=	factor *i* of share classified as an extreme performer in period of buy (sell) signal (where the latter is at the beginning of the 1-month period during which the share price increases (decreases))
α_i	=	constant term associated with factor *i*
$DW_{i,1}$	=	Dummy variable, set equal to 1 if the share is classified as a winner and 0 otherwise
β_{iW}	=	coefficient associated with the winner dummy variable for factor *i* in period of buy signal. Interpreted as the extra value of C_{iE} for a winner over a loser.
ε_i	=	residual term for factor *i* in period of buy signal

The t-statistic associated with the dummy coefficient (β_{iW}) is used to determine whether the extreme performer factor (C_{iE}) differs significantly between winner and loser shares in the period of a buy signal. Those factors found to have a significant dummy coefficient are used in further analyses to formulate filter rules for share selection and portfolio construction by means of the logistic regression approach discussed above. Note that if regression (8.16) is applied using the dummy variable associated with loser shares instead of winner shares, only the sign associated with the dummy coefficient will be different. Therefore the logistic regression approach to refine the filter rules in forming winner and loser portfolios respectively will make use of the exact same factors identified through (8.16). However, the resulting logit model may differ between winner and loser shares due to the difference in frequency associated with shares being classified as winners or losers respectively. The results of regression (8.16) are presented in Table 8.7.

Table 8.7: Evaluation of winner vs. loser factors over a 1-month period using Sample_A
This table presents the constant term (α_{iW}), its associated t-statistic, dummy variable coefficient (β_{iW}), its t-statistic and standard error ($\sigma_{\varepsilon_{iW}}$). Results are reported for the period 1994 to 2011. Results in bold indicate where the t-statistic associated with the dummy variable is significantly different from zero at the ninety-five percent level of confidence. Factors are ranked according to the absolute value of the dummy coefficient t-statistic.

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
CFTP	0.130	52.574	0.029	**8.972**	0.137
PRICEREL12	0.790	216.851	0.043	**8.949**	0.208
MOM12	0.165	17.600	0.108	**8.733**	0.521
MA11	0.477	57.315	0.088	**8.037**	0.497
MA12	0.476	57.099	0.084	**7.606**	0.498
MA10	0.484	58.146	0.082	**7.438**	0.497
MA8	0.498	59.777	0.068	**6.132**	0.498
MA7	0.504	60.483	0.065	**5.950**	0.497
MA9	0.504	60.483	0.065	**5.950**	0.497
MOM6	0.071	11.188	0.048	**5.760**	0.308
MA5	0.510	61.245	0.061	**5.545**	0.497
MA3	0.501	60.147	0.060	**5.481**	0.498
DY	3.105	53.154	0.412	**5.334**	3.268
MA4	0.509	61.072	0.058	**5.300**	0.497
MA6	0.512	61.585	0.058	**5.290**	0.497
MA2	0.480	57.486	0.057	**5.195**	0.499
RETVAR12	0.019	54.019	-0.002	**-4.909**	0.020
MOM36	0.844	25.890	0.209	**4.871**	1.651
OBOS12MMA	0.031	3.182	0.057	**4.415**	0.560
OBOS11MMA	0.027	3.021	0.052	**4.371**	0.517
OBOS10MMA	0.023	2.794	0.047	**4.310**	0.473
EARNREV3M	0.001	0.713	0.011	**4.234**	0.096
OBOS9MMA	0.020	2.680	0.040	**4.109**	0.430
MOM3	0.039	10.331	0.020	**4.104**	0.215
BVTMLOG	-0.670	-46.843	0.075	**3.947**	0.792
OBOS8MMA	0.016	2.446	0.035	**3.944**	0.386
OBOS7MMA	0.012	2.004	0.030	**3.901**	0.342
MOM1	0.007	3.417	0.010	**3.799**	0.121
OBOS5MMA	0.002	0.574	0.022	**3.773**	0.254
OBOS6MMA	0.008	1.477	0.025	**3.722**	0.298
C24MBVTM	0.390	16.471	-0.101	**-3.235**	1.143
BETA	0.673	171.178	-0.016	**-3.135**	0.227
OBOS4MMA	0.002	0.665	0.014	**3.129**	0.204
POUTRAT	35.711	70.576	2.057	**3.086**	27.112
C24MDPSP	0.005	11.413	0.002	**2.995**	0.024
OBOS3MMA	0.001	0.387	0.008	**2.432**	0.154
EY	0.102	72.853	0.004	**2.383**	0.080
STP	3.324	24.836	3.978	**2.269**	4.848
EPS	2.145	34.422	0.171	**2.075**	3.581
LNP	2.551	103.316	-0.064	**-1.964**	1.475
SPSLOG	2.570	63.118	-0.097	-1.864	1.404
DE	31.089	25.086	2.932	1.844	41.009
MOM60	2.229	32.656	-0.155	-1.746	2.976
ICBTIN	0.222	15.896	0.030	1.688	0.408
MVLOG	7.664	244.116	-0.051	-1.228	1.870
EG1	0.571	20.166	0.037	0.987	1.218
C24MEPSP	0.011	9.467	0.001	0.893	0.061
DPSLOG	-0.774	-28.950	0.023	0.649	1.398
OBOS2MMA	0.003	1.671	0.001	0.354	0.093
ROE	17.984	38.838	0.195	0.315	19.863

From Table 8.7 it is seen that the majority of factors differ significantly between winner and loser shares, however the most significant differences are found within value (represented specifically by CFTP) and momentum (represented by the majority of factors classified as momentum factors).

A similar process to that followed in the previous section to reduce the number of candidate factors and to avoid possible multicollinearity is followed here. Once again the forward stepwise logistic regression approach is followed to formulate the logit models. The results of the stepwise regression process are reported in Appendix E.3 and Appendix E.4. The final (refined) winner and loser logit models are presented in formula (8.17) and (8.18) respectively:

$$logit(winner) = -1.232 + 1.207CFTP + 0.190MOM12 + 4.212RETVAR12 - 0.654MOM1 + 0.424BETA + 3.516C24MDPSP - 0.056LNP \quad ...(8.17)$$

$$logit(loser) = -1.465 - 1.562CFTP - 0.361PRICEREL12 - 0.349MOM12 + 0.149MA3 + 11.31RETVAR12 + 0.903BETA \quad ...(8.18)$$

All independent variables are significant at the 5% level (see Appendix E.3 and E.4). From (8.17) and (8.18) it is seen that, in line with the results reported in Table 8.7, the value and momentum effects (captured by CFTP and MOM12 respectively) are used in the final refined logit models to filter winner and loser shares. Once again the volatility factors (RETVAR12 and BETA) are included in both logit models. However, based on the refined process followed, the levels of volatility associated with each of the winner and loser categories should now be even more distinct. A size effect (captured by LNP) is also included to filter potential winners, which is in line with the results reported in Table 8.7. Interestingly the shorter term price reversal effect observed in earlier chapters is included in the refined logit models (captured by MOM1 in the winner and MA3 in the loser logit model) to further distinguish winner from loser shares, despite the fact that these factors appear to be relatively less significantly different between the two categories. Furthermore, from Table 8.7 it is seen that both MOM1 and MA3 have significantly higher average values with regard to winner shares, yet the probability of a share turning out to be a winner decreases for higher values of MOM1 while the probability of being classified as a loser share increases for higher levels of MA3, supporting short- term price reversal. Lastly it appears that a growth factor (captured by C24MDPSP) forms part of the filtering process to isolate potential winners.

Similar to the previous section, the “percent correctly predicted” approach was followed to obtain threshold values (τ) to be used in the filtering process. Respective values of 0.30 and 0.218 were obtained for the winner and loser logit models. Using these threshold values, models (8.17) and (8.18) were applied to the independent sample of shares (Sample_B) to construct monthly equally weighted winner, loser and benchmark portfolios. The portfolio characteristics of the respective portfolios are reported in Table 8.8.

Table 8.8: Comparison of characteristics of monthly rebalanced portfolios constructed using the refined logit models over a 1-month period based on Sample_B

This table presents portfolio characteristics of the winner, loser and benchmark portfolios that were created using the refined logit models. Stocks are selected from Sample_B to create the respective portfolios. A paired mean comparison test was performed to test for significantly different mean monthly returns between the winner (loser) and benchmark portfolios. The t-stat obtained is reported below the average monthly return values.

	Winner	Benchmark	Loser
Average monthly return	2.67% (t-stat = 2.83)	1.58%	0.32% (t-stat = -5.02)
Annualised return	37.11%	20.65%	3.89%
Monthly standard deviation	6.83%	5.65%	6.51%
Annualised standard deviation	23.65%	19.58%	22.55%
Sharpe ratio**	1.34	0.78	-0.07
Average number of shares	16	83	15

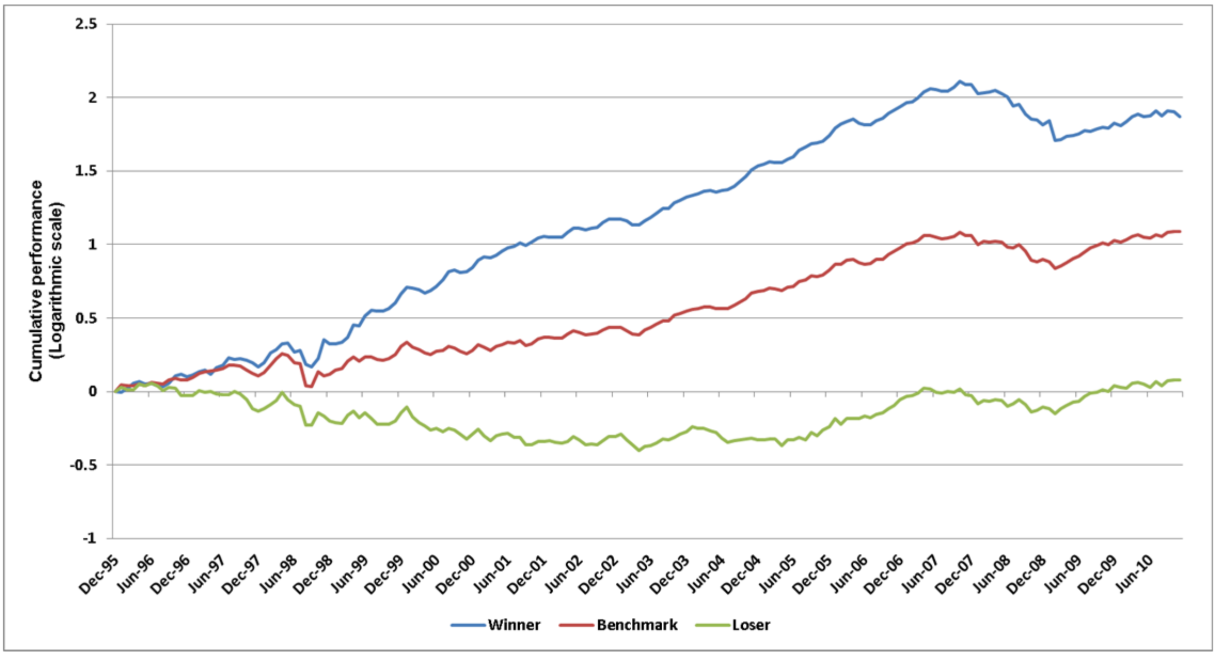
** The Sharpe ratio is calculated using the annualised figures and an annualised 3-month T-bill rate of 5.41%

Compared to Table 8.6, it is seen that all the reported portfolio characteristics improved after the logit derivation process was refined. The winner (loser) portfolio show an increase (decrease) in average monthly return and a decrease in risk (as measured by standard deviation), resulting in the increased (decreased) t-statistic values as well as Sharpe ratios. Furthermore it appears that the refined process allows for more (though not significantly so) shares to be filtered for winner and loser portfolios.

The cumulative performance of the winner, loser and benchmark portfolios are graphically presented in Figure 8.2.

Figure 8.2 Cumulative performances.

This graph illustrates the value of R1 invested at the end of December 1995 in the winner, loser and benchmark portfolios respectively. A logarithmic scale is used to present the cumulative performance.



In keeping with the above findings and the fact that an independent sample (Sample_B) was used for the application of the derived models, it appears that a logistic regression approach can be followed to formulate filter rules based on the factors that are significantly different between winner (loser) shares and the REST (or the refined alternative) to construct portfolios that may offer superior (inferior) returns relative to the benchmark at similar levels of risk. Furthermore it appears that the factors used to create these filter rules for portfolio construction on the JSE are generally the same factors that explain the cross- sectional variation in returns (Chapter 5) and that can be used to construct profitable 'factor' portfolios (Chapter 6) on the JSE.

8.4.4 Risk-adjusted performance evaluation

To examine whether the excess return associated with the winner portfolio can be explained by well-known market models, return is adjusted for risk based on the CAPM and Van Rensburg *et al*. (2002) two-factor APT models. This is done in a similar fashion to that in Chapter 6 (specifically, regressions (6.1) and (6.2) are applied using the winner excess returns as the dependent variable). The results are reported in Table 8.9.

Table 8.9: Risk-adjusted winner portfolio performance evaluation
This table presents the risk-adjusted portfolio performance results. Intercept terms (α) in bold indicate significance on a 95% level of confidence.

CAPM					APT		
α	t(α)	β	t(β)	R-squared	α	t(α)	R-squared
0.016	3.85	0.68	10.02	0.36	**0.016**	3.56	0.39

From Table 8.9 it is seen that neither the CAPM nor the APT market models can explain the monthly excess returns obtained by the winner portfolio, indicated by the significant alpha (α) coefficients and the relatively low R-squared values. As was the case with constructing single-factor portfolios (Chapter 6), it appears that firm-specific factors can be used to construct portfolios that offer abnormal returns which cannot be explained by market models, implying the existence of market anomalies on the JSE.

8.5 Conclusion

Extreme performer shares were identified and categorised as winners (those that increased at least 6% in a month) and losers (those that decreased at least 5% in a month). A cross-sectional regression approach was applied to determine which firm-specific factors differ significantly between winner or loser shares and the rest. A binary dummy variable was created for winner and loser shares respectively to distinguish it from the rest of the shares. This binary dummy variable was used as dependent variable and the significant factors identified through the cross- sectional regression as independent variables to create logistic regression models for predicting potential winner and loser shares. Value (CFTP) and two volatility (Retvar12 and Beta) factors were included in the final winner and loser logit models. The positive relation between the value factor and potential winner shares together with the negative relation between the same value factor and potential loser shares once again confirm a strong value effect on the JSE, similar to earlier chapters. Both volatility factors are positively related to potential winner and loser shares, indicating that, as can be expected, higher levels of volatility are associated with potential extreme performer shares. Volatility levels are however relatively higher for potential loser shares compared to winners, contradicting modern portfolio theory. The value and volatility factors were the only factors found to be significant with regard to the winner logit model. In addition to the value and volatility factors, momentum factors (Pricerel12, MOM12 and MA2) also form part of the loser logit model. The negative relationship between the 'longer term' momentum factors (Pricerel12 and MOM12) and potential loser shares supports the momentum effect observed in earlier chapters, while the positive relationship between MA2 and potential loser shares confirms a short-term price reversal effect.

The logistic regression model was applied to filter potential winner and loser shares from an independent sample of shares. Based on the filtered shares, equally weighted winner and loser portfolios were constructed and rebalanced monthly over the period January 1994 through May 2011. The results revealed that the winner portfolio significantly outperformed while the loser portfolio significantly underperformed the benchmark portfolio. As can be expected, relatively higher levels of volatility are associated with the winner and loser portfolios compared to the benchmark portfolio. Regarding the winner portfolio, the Sharpe ratio however, indicates that the higher risk taken is compensated for by a significant increase in return.

A second cross- sectional regression approach was applied to refine the distinction between potential winner and loser shares, wherein the dummy variable was constructed in such a way as to distinguish between winner and loser shares, ignoring the remainder of shares. Based on this refined approach and sample consisting only of extreme performers, refined winner and loser logit models were developed. Once again the logit models were applied to filter shares from the independent sample to construct winner and loser portfolios which were rebalanced monthly. Based on the portfolio performance evaluation it was seen that this refined process resulted in improved portfolio characteristics. Furthermore, a risk-adjusted performance evaluation revealed that the excess return offered by the winner portfolio cannot be explained by either the CAPM or two-factor APT model.

9

EXTREME PERFORMANCE AND FILTER RULES FOR A 12-MONTH PAYOFF PERIOD

9.1 Introduction

In Chapter 8 an extreme performer approach was applied to examine the impact of technical and fundamental factors on the cross- section of returns on the JSE. The focus however was on extreme performance during a 1-month holding period. To examine the effect payoff period may have on the results, in this chapter the extreme performer approach is applied based on a 12-month holding period. To be considered an extreme performer a share should have at least doubled or halved in price during a 12-month period. The methodology applied is similar to that applied in Chapter 8, in that a cross- sectional regression approach is followed first to determine which factors differ significantly between extreme performers and the rest of the shares. The process is refined by applying the cross- sectional regressions on the sample of extreme performers only, allowing for the identification of factors that differ significantly between winner and loser shares. To construct winner and loser logit models, logistic regressions are then applied, based on these factors.. The logit models are used to filter potential extreme performers from an independent sample and categorised into winner and loser portfolios. Portfolio characteristics are examined to determine if such an extreme performer approach could offer superior performance over a 12-month holding period, based on a raw as well as a risk-adjusted return basis.

The methodology followed is detailed in Section 9.2, followed by the evaluation of extreme performer factors over a 12-month holding period in Section 9.3. In Section 9.4 logit models are developed and used for portfolio construction and subsequent performance evaluation. The chapter is concluded in Section 9.5.

9.2 Methodology

The two subsamples created in Chapter 8 (Sample_A and Sample_B) are used for the analysis in this chapter. As before, Sample_A is used to identify common factors amongst extreme performers, while Sample_B will be used to test whether these factors hold up in an independent sample. For the analysis over a 12-month holding period, an extreme winner is defined as a share that experienced at least a 100% return during a 12-month period, while an extreme loser is defined as a share that experienced a negative return of at least 50% over a 12-month period.

To determine whether the specific factor differs significantly between winner (loser) shares and the rest of the sample, the following regressions are performed:

$$C_i = \alpha_i + \beta_{iW} DW_{i,12} + \varepsilon_i \tag{9.1}$$

$$C_i = \alpha_i + \beta_{iL} DL_{i,12} + \varepsilon_i \tag{9.2}$$

where

C_i	=	factor *i* in period of buy (sell) signal (where the latter is at the beginning of the 12-month period during which the share price increases (decreases))
α_i	=	constant term associated with factor *i*
$DW_{i,12}; DL_{i,12}$	=	Dummy variables for 12-month holding period, set equal to 1 if share *i* is classified as a winner (DW_i) or loser (DL_i) and 0 otherwise
β_{iW}, β_{iL}	=	coefficient associated with the winner and loser dummy variables respectively for factor *i* in period of buy (sell) signal
ε_i	=	residual term for factor *i* in period of buy (sell) signal

Regressions (9.1) and (9.2) are performed for three sample periods, namely 1994 through 2002 (Subsample_1), 2003 through May 2011(Subsample_2) and 1994 through May 2011 (Total_sample).

The t-statistic associated with the dummy coefficients (β_{iW}, β_{iL}) is used to determine whether the factor (C_i) differs significantly between winner (loser) shares and the rest (REST) of the shares in the sample in the period of a buy (sell) signal.

In Chapter 8 (Section 8.4.2) logistic regression models were derived using the results of the regression approach (similar to that described above). These models were applied to filter winner and loser shares for portfolio construction. The derived models were then refined (Section 8.4.3) by using those factors that differ significantly between winner and loser shares (and ignoring the REST) as potential independent variables for the logit process. This refinement process offered a filtering approach that enabled the construction of portfolios that appeared to be superior compared to those constructed based on the original regression (and subsequent logistic regression) approach. For this reason the refinement process will be applied before the logit models for winner and loser shares over a 12-month holding period are developed. Specifically, and similar to Section 8.4.3 (Chapter 8), to determine which factors (C_i) differ significantly between winner and loser shares (i.e. ignoring the REST), the regression process is repeated by adjusting formula (9.1) as follows:

$$C_{iE} = \alpha_i + \beta_{iW} DW_{i,12} + \varepsilon_i \qquad (9.3)$$

where

C_{iE}	=	factor *i* of share classified as an extreme performer in period of buy (sell) signal (where the latter is at the beginning of the 12-month period during which the share price increases (decreases))
α_i	=	constant term associated with factor *i*
$DW_{i,12}$	=	Dummy variable, set equal to 1 if the share is classified as a winner and 0 otherwise
β_{iW}	=	coefficient associated with the winner dummy variable for factor *i* in period of buy signal. Interpreted as the extra value of C_{iE} for a winner over a loser.
ε_i	=	residual term for factor *i*

The t-statistic associated with the dummy coefficient (β_{iW}) is used to determine whether the extreme performer factor (C_{iE}) differs significantly between winner and loser shares in the period of a buy signal. Those factors found to have a significant dummy coefficient are used to derive the winner and loser logit models for share filtering and portfolio construction purposes. The logit models are developed by means of a forward stepwise logistic regression approach (see Chapter 8, Section 8.4.2) and are reported in Section 9.4.

9.3 Results: Evaluation of extreme performer factors using a 12-month holding period

To examine the effect that a longer holding period may have on the significance of the differences between the factors associated with extreme performers and the REST, regressions (9.1) and (9.2) are applied using a 12-month holding period return to inform the values of *DW* and *DL*. The results are reported in Table 9.1. Descriptive statistics are calculated and presented together with a histogram for each factor, to allow for the examination of the statistical differences found within a factor when it is associated with a winner share, loser share or a share that falls into the 'remainder' category (see Appendix F.1).

Table 9.1: Evaluation of winner factors over a 12-month period using Sample_A
This table presents the constant term (α_i), its associated t-statistic, dummy variable coefficient (β_{iW}), its t-statistic and standard error ($\sigma_{\varepsilon_{iw}}$). Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the t-statistic associated with the dummy variable is significantly different from zero at the ninety-five percent level of confidence. Factors are ranked according to the absolute value of the dummy coefficient t-statistic.

Panel A: Subsample_1 (1994 – 2002)
Proportion of winners = 2.67%

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
MVLOG	7.141	349.283	-1.131	**-11.105**	1.777
MA2	0.321	73.828	0.225	**8.431**	0.468
LNP	2.229	132.883	-0.669	**-8.032**	1.453
ROE	17.368	68.468	-10.453	**-6.500**	16.656
CFTP	0.161	81.439	0.070	**6.209**	0.152
DPSLOG	-1.143	-66.682	-0.512	**-5.796**	1.311
MOM12	0.188	27.312	0.182	**5.230**	0.533
MOM60	1.200	23.727	-1.409	**-5.076**	2.425
MOM6	0.072	12.678	0.103	**4.762**	0.326
BVTMLOG	-0.510	-47.477	0.285	**4.588**	0.827
OBOS12MMA	0.039	11.049	0.081	**4.453**	0.285
OBOS11MMA	0.036	10.742	0.075	**4.404**	0.268
BETA	0.668	265.064	0.058	**4.376**	0.228
OBOS10MMA	0.032	10.457	0.068	**4.270**	0.251
OBOS9MMA	0.029	10.172	0.062	**4.235**	0.235
RETVAR12	0.021	76.532	0.006	**4.036**	0.022
STP	3.198	38.042	1.918	**3.992**	4.310
OBOS8MMA	0.026	9.822	0.052	**3.844**	0.218
OBOS7MMA	0.022	9.325	0.042	**3.454**	0.199
MOM36	0.669	28.822	-0.450	**-3.446**	1.488
MOM3	0.048	17.321	0.043	**3.177**	0.227
OBOS6MMA	0.019	8.805	0.033	**3.029**	0.180
C24MEPSP	0.009	12.176	-0.011	**-2.953**	0.052
MA5	0.516	89.434	0.084	**2.928**	0.499
C24MBVTM	0.478	24.035	-0.307	**-2.824**	1.214
MA7	0.502	86.990	0.079	**2.744**	0.500
MA9	0.502	86.990	0.079	**2.744**	0.500
MA6	0.513	88.969	0.077	**2.685**	0.500
OBOS5MMA	0.015	8.103	0.024	**2.545**	0.158
MA3	0.512	88.867	0.071	**2.483**	0.500
MA4	0.520	90.258	0.070	**2.435**	0.499
MOM1	0.013	8.646	0.018	**2.384**	0.127
C24MDPSP	0.004	13.595	-0.004	**-2.228**	0.022
DE	31.297	24.744	-13.789	**-2.162**	33.080
OBOS4MMA	0.011	7.125	0.017	**2.157**	0.135
MA8	0.498	86.363	0.054	1.874	0.500
EY	0.105	107.144	0.009	1.816	0.083
OBOS3MMA	0.007	5.799	0.011	1.742	0.108
OBOS2MMA	0.003	3.824	0.005	1.313	0.072
MA11	0.475	82.381	0.033	1.152	0.499
MA12	0.467	81.045	0.032	1.106	0.499
EARNREV3M	0.012	9.051	0.009	1.091	0.082
MA10	0.482	83.535	0.029	1.020	0.500
EPS	1.584	53.313	0.114	0.758	2.615
PRICEREL12	0.808	337.133	0.009	0.741	0.193
POUTRAT	34.053	104.025	1.102	0.664	26.031
EG1	0.730	35.413	0.063	0.489	1.278
ICBTIN	0.296	16.717	0.058	0.486	0.389
SPSLOG	2.095	46.536	-0.086	-0.463	1.405
DY	3.150	73.941	-0.012	-0.056	3.499

Panel B: Subsample_2 (2003 – 2011)
Proportion of winners = 3.60%

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
CFTP	0.125	99.202	0.096	**17.695**	0.103
MVLOG	8.429	452.301	-1.128	**-13.675**	1.607
MOM12	0.286	54.649	0.307	**13.399**	0.437
LNP	3.016	202.241	-0.855	**-12.977**	1.284
MOM6	0.119	40.325	0.157	**11.914**	0.258
EY	0.096	116.684	0.036	**10.153**	0.068
BVTMLOG	-0.772	-94.528	0.366	**9.941**	0.682
MA2	0.386	82.112	0.216	**8.710**	0.487
POUTRAT	45.092	121.149	-13.263	**-7.949**	28.589
DPSLOG	-0.260	-16.864	-0.556	**-7.730**	1.234
MOM3	0.065	32.684	0.059	**6.814**	0.167
MA12	0.652	118.835	0.150	**6.184**	0.473
MA10	0.646	117.115	0.149	**6.114**	0.475
MA11	0.649	117.960	0.148	**6.097**	0.474
RETVAR12	0.009	74.977	0.003	**5.901**	0.010
BETA	0.599	221.093	0.068	**5.857**	0.226
MA8	0.635	114.230	0.137	**5.595**	0.478
STP	3.513	38.546	2.219	**5.540**	4.933
PRICEREL12	0.847	314.067	0.061	**5.195**	0.230
MA7	0.632	113.442	0.125	**5.087**	0.480
MA9	0.632	113.442	0.125	**5.087**	0.480
SPSLOG	2.560	129.974	-0.419	**-5.051**	1.402
MA6	0.626	111.769	0.117	**4.726**	0.482
ICBTIN	0.242	38.286	0.128	**4.447**	0.388
MOM36	1.200	59.832	0.382	**4.287**	1.667
ROE	22.185	57.101	-6.889	**-4.134**	21.740
MA5	0.618	109.717	0.095	**3.820**	0.484
MOM1	0.019	17.693	0.018	**3.701**	0.093
DY	4.074	104.006	-0.644	**-3.575**	3.165
EPS	3.090	59.767	-0.714	**-3.212**	4.230
MA3	0.594	104.249	0.074	**2.930**	0.490
MA4	0.607	107.145	0.071	**2.823**	0.487
OBOS6MMA	0.032	5.710	0.052	**2.141**	0.477
OBOS7MMA	0.047	7.250	0.058	**2.035**	0.551
C24MBVTM	0.163	13.518	-0.109	-2.005	0.975
OBOS5MMA	0.025	5.372	0.040	1.969	0.394
OBOS8MMA	0.061	8.403	0.062	1.945	0.625
EARNREV3M	0.005	5.498	0.008	1.892	0.084
OBOS9MMA	0.076	9.259	0.068	1.882	0.699
OBOS10MMA	0.090	9.950	0.072	1.818	0.773
OBOS4MMA	0.018	4.933	0.029	1.810	0.310
C24MEPSP	0.014	18.864	0.006	1.795	0.064
OBOS11MMA	0.104	10.529	0.077	1.762	0.846
OBOS12MMA	0.117	10.968	0.081	1.734	0.912
OBOS3MMA	0.011	4.260	0.018	1.602	0.224
OBOS2MMA	0.006	3.557	0.008	1.149	0.134
C24MDPSP	0.008	26.265	0.001	0.975	0.025
MOM60	2.546	67.211	-0.135	-0.762	3.010
DE	34.919	57.262	-1.957	-0.708	42.617
EG1	0.366	23.581	-0.042	-0.519	1.006

Panel C: Total_sample (1994 – 2011)
Proportion of winners = 3.12%

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
MVLOG	7.780	525.526	-1.050	**-15.152**	1.813
CFTP	0.142	123.257	0.082	**14.882**	0.130
MOM12	0.240	56.362	0.266	**13.372**	0.486
LNP	2.620	224.471	-0.725	**-13.300**	1.425
MA2	0.353	110.012	0.225	**12.389**	0.478
MOM6	0.105	38.920	0.133	**11.661**	0.281
BVTMLOG	-0.652	-97.077	0.306	**9.172**	0.762
DPSLOG	-0.681	-56.079	-0.492	**-8.296**	1.345
EY	0.101	156.627	0.024	**8.000**	0.076
STP	3.364	53.885	2.158	**7.074**	4.654
MOM3	0.057	33.516	0.053	**6.826**	0.198
BETA	0.636	341.037	0.056	**6.380**	0.230
ROE	19.395	87.341	-7.278	**-6.347**	19.156
MA7	0.567	139.982	0.113	**5.960**	0.494
MA9	0.567	139.982	0.113	**5.960**	0.494
MA12	0.559	137.804	0.109	**5.758**	0.495
MA8	0.566	139.868	0.109	**5.755**	0.494
MA11	0.561	138.503	0.108	**5.704**	0.495
MA6	0.569	140.630	0.106	**5.617**	0.494
MA10	0.563	139.029	0.106	**5.608**	0.495
PRICEREL12	0.828	453.022	0.044	**5.165**	0.214
MA5	0.566	139.793	0.096	**5.093**	0.495
POUTRAT	39.381	156.445	-6.045	**-5.048**	27.830
SPSLOG	2.485	136.765	-0.366	**-4.801**	1.412
RETVAR12	0.015	96.649	0.003	**4.459**	0.018
ICBTIN	0.248	41.652	0.121	**4.324**	0.389
MOM1	0.016	17.460	0.018	**4.220**	0.111
MA3	0.553	135.959	0.078	**4.086**	0.497
MA4	0.563	138.869	0.076	**3.989**	0.495
C24MBVTM	0.278	26.085	-0.191	**-3.755**	1.077
OBOS9MMA	0.053	11.890	0.069	**3.288**	0.531
OBOS8MMA	0.044	11.060	0.061	**3.248**	0.475
OBOS10MMA	0.062	12.551	0.076	**3.221**	0.588
OBOS7MMA	0.035	9.907	0.053	**3.217**	0.420
OBOS11MMA	0.072	13.119	0.082	**3.183**	0.644
OBOS6MMA	0.025	8.385	0.045	**3.174**	0.364
OBOS12MMA	0.081	13.580	0.088	**3.154**	0.695
MOM36	1.002	64.614	0.216	**2.912**	1.628
OBOS5MMA	0.020	7.954	0.034	**2.869**	0.303
OBOS4MMA	0.015	7.328	0.024	**2.604**	0.240
OBOS3MMA	0.009	6.334	0.015	**2.270**	0.176
DY	3.604	123.274	-0.313	**-2.252**	3.369
MOM60	2.187	69.176	-0.316	**-2.060**	2.934
EARNREV3M	0.008	9.654	0.008	1.966	0.084
OBOS2MMA	0.004	4.938	0.007	1.690	0.108
EPS	2.282	77.420	-0.213	-1.549	3.543
DE	34.474	61.843	-3.068	-1.200	41.596
EG1	0.540	41.832	-0.035	-0.490	1.158
C24MEPSP	0.012	22.377	0.001	0.281	0.059
C24MDPSP	0.006	28.953	0.000	-0.013	0.024

From Table 9.1 it is seen that, compared to using a 1-month holding period (Chapter 8, Table 8.1), the proportion of winner observations is considerably less (3.13% on average) but substantially more factors differ significantly between winner shares and the REST. Looking at the size of the t-statistic however, it seems that the difference in a factor between the winners and the REST are more ‘extreme’ for certain factors. These are, as was the case for the 1-month holding period, very similar in identity and ranking order to the formerly identified factors that explain the cross- section of returns on the JSE (Chapters 5) and offer profitable single-factor portfolios (Chapter 6). Specifically, the factors associated with size (MVLOG and LNP), value (BVTMLOG and CFTP) and momentum (MOM6 and MOM12) fall into this more ‘extreme’ category and are the same factors identified earlier. Furthermore these six factors fall into the ‘extreme’ category during *each* sample period, emphasising that these are robust factors. The interpretation with regard to these factors is therefore very similar to that presented in Chapter 8 (Section 8.3) namely that winners are generally associated with lower size levels, higher value levels (as the inverse of the normal value multiples are used) and higher momentum values.

Based on the significant positive dummy coefficient associated with the 2-month moving average (MA2), it appears that winner shares trade more often at a price above their 2-month moving average price compared to the REST, irrespective of holding period used (this was also observed for the 1-month holding period). Another factor constantly falling into the ‘extreme’ category using a 12-month holding period (but not observed for the 1-month holding period) is DPSLOG, representing the growth category. The coefficient associated with the DPSLOG dummy variable is negative. This indicates that shares that doubled in price during a 12-month period during any sub-period between 1994 through 2011, generally had lower growth (represented by DPSLOG) values than the REST.

Apart from the aforementioned factors, the ranking order and consistency of falling into the ‘extreme’ category associated with the remainder of factors are dependent on the sample period used, i.e. sensitive to time. Therefore care should be taken when interpreting (and applying) these results, especially when examining the use of significant factors to formulate filter rules for portfolio construction. Nevertheless, the following additional observations are noted from Table 9.1:

The majority of longer term OBOS dummy variables are significant and positive during Subsample_1 and Total_sample, indicating that winner shares generally have higher longer term OBOS levels compared to the REST, in further support of the momentum effect. The significant positive dummy coefficients associated with the longer term MA variables during Subsample_2 and Total_sample indicate that winner shares trade at a price above its longer term moving average more often in the period of the buy signal compared to the REST, again supporting the momentum effect. The longer term price-reversal effect (represented by MOM60 in earlier chapters) is also confirmed here, however mainly for Subsample_1. The significant negative dummy variable coefficient indicates that winner shares tend to have a lower prior 5-year return relative to the REST during the buy signal period.

Results of the evaluation of the extreme performer factors for loser shares are presented in Table 9.2.

Table 9.2: Evaluation of loser factors over a 12-month period using Sample_A

This table presents the t-statistics associated with the constant term (α_i) and the value of the coefficient associated with the dummy variable (β_{iL}). Results are reported for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C). Results in bold indicate where the t-statistic associated with the dummy variable is significantly different from zero at the ninety-five percent level of confidence. Factors are ranked according to the absolute value of the dummy coefficient t-statistic.

Panel A: Subsample_1 (1994 – 2002) Proportion losers = 1.84%					
Factor	**α_i**	**t-stat (α_i)**	**β_{iL}**	**t-stat (β_{iL})**	**σ_{ε_i}**
POUTRAT	34.537	106.713	-16.398	**-8.310**	25.896
MOM60	1.103	22.117	2.782	**7.502**	2.410
BVTMLOG	-0.489	-45.595	-0.414	**-6.722**	0.825
PRICEREL12	0.811	340.760	-0.087	**-6.314**	0.192
CFTP	0.165	83.549	-0.068	**-5.959**	0.152
LNP	2.185	130.896	0.589	**5.888**	1.456
MA5	0.524	91.508	-0.166	**-4.836**	0.499
MA4	0.528	92.251	-0.165	**-4.822**	0.499
DY	3.184	75.344	-1.187	**-4.795**	3.493
MA6	0.520	90.919	-0.153	**-4.474**	0.499
MA8	0.505	88.136	-0.152	**-4.417**	0.499
MA7	0.509	88.891	-0.147	**-4.275**	0.499
MA9	0.509	88.891	-0.147	**-4.275**	0.499
MOM6	0.085	15.016	-0.099	**-4.167**	0.326
MA10	0.487	85.046	-0.138	**-4.031**	0.499
MOM3	0.052	18.790	-0.064	**-3.990**	0.227
RETVAR12	0.021	76.961	0.006	**3.923**	0.022
EY	0.106	108.808	-0.022	**-3.699**	0.083
MA11	0.480	83.838	-0.127	**-3.691**	0.499
MA3	0.519	90.599	-0.124	**-3.623**	0.499
BETA	0.668	266.649	0.055	**3.506**	0.228
MA12	0.471	82.378	-0.109	**-3.173**	0.499
OBOS5MMA	0.017	9.187	-0.034	**-3.104**	0.158
OBOS6MMA	0.021	9.970	-0.038	**-3.023**	0.180
C24MBVTM	0.479	24.019	-0.292	**-2.835**	1.214
OBOS4MMA	0.013	8.077	-0.026	**-2.810**	0.134
OBOS7MMA	0.025	10.528	-0.039	**-2.799**	0.199
OBOS8MMA	0.029	11.053	-0.039	**-2.583**	0.218
MA2	0.326	74.973	0.083	**2.575**	0.469
MOM12	0.197	28.847	-0.095	**-2.395**	0.533
MOM1	0.014	9.574	-0.021	**-2.352**	0.127
OBOS10MMA	0.036	11.718	-0.042	**-2.331**	0.251
OBOS9MMA	0.033	11.425	-0.038	**-2.316**	0.235
DPSLOG	-1.168	-68.570	0.272	**2.305**	1.314
ROE	17.209	67.254	-3.005	**-2.149**	16.727
STP	3.277	39.247	-1.534	**-2.117**	4.319
OBOS11MMA	0.040	11.991	-0.040	**-2.104**	0.268
OBOS12MMA	0.043	12.298	-0.042	**-2.042**	0.285
OBOS3MMA	0.008	6.521	-0.015	-1.983	0.108
EPS	1.596	54.121	-0.305	-1.637	2.615
OBOS2MMA	0.004	4.366	-0.007	-1.505	0.072
C24MDPSP	0.004	12.958	0.003	1.457	0.022
EARNREV3M	0.012	9.434	-0.020	-1.411	0.082
SPSLOG	2.088	47.819	1.540	1.096	1.405
DE	30.798	24.759	-30.798	-0.928	33.168
ICBTIN	0.298	17.002	-0.293	-0.752	0.389
EG1	0.730	35.495	0.101	0.699	1.278
MVLOG	7.093	346.539	0.060	0.488	1.791
C24MEPSP	0.008	11.704	-0.001	-0.303	0.052
MOM36	0.656	28.237	-0.033	-0.246	1.490

Panel B: Subsample_2 (2003 – 2011)
Proportion losers = 0.95%

Factor	α_i	t-stat (α_i)	β_{iL}	t-stat (β_{iL})	σ_{ε_i}
RETVAR12	0.009	77.021	0.009	**9.033**	0.010
BVTMLOG	-0.746	-92.813	-0.598	**-8.910**	0.683
DY	4.077	106.320	-2.649	**-7.739**	3.154
CFTP	0.131	104.478	-0.077	**-7.412**	0.105
POUTRAT	44.671	122.208	-21.817	**-6.246**	28.644
BETA	0.601	226.434	0.117	**5.177**	0.226
EY	0.098	121.312	-0.032	**-4.313**	0.069
ICBTIN	0.251	40.381	-0.183	**-3.847**	0.388
EG1	0.358	23.395	0.515	**3.781**	1.004
SPSLOG	2.530	131.177	0.522	**3.047**	1.404
MOM60	2.527	67.836	0.892	**2.884**	3.008
MOM1	0.020	19.199	-0.024	**-2.673**	0.093
MOM3	0.068	35.144	-0.044	**-2.672**	0.167
C24MBVTM	0.161	13.623	-0.256	**-2.584**	0.974
MA3	0.599	107.204	-0.104	**-2.153**	0.490
STP	3.653	40.612	-1.378	**-2.080**	4.954
LNP	2.969	200.891	0.264	**2.073**	1.297
MA7	0.640	116.930	-0.097	**-2.058**	0.480
MA9	0.640	116.930	-0.097	**-2.058**	0.480
MOM6	0.128	43.665	-0.049	-1.910	0.260
MA6	0.633	115.147	-0.090	-1.898	0.482
MA4	0.612	110.062	-0.078	-1.632	0.488
MA8	0.643	117.733	-0.072	-1.521	0.479
MOM36	1.217	61.734	0.230	1.366	1.669
MA2	0.394	84.500	0.064	1.325	0.489
MVLOG	8.369	452.569	0.184	1.151	1.626
MA5	0.623	112.791	-0.052	-1.084	0.485
MOM12	0.303	58.265	-0.044	-1.019	0.443
C24MDPSP	0.008	27.133	-0.002	-0.985	0.025
EPS	3.057	60.368	-0.441	-0.981	4.233
MA10	0.654	120.665	-0.045	-0.957	0.476
MA12	0.661	122.417	-0.042	-0.896	0.474
MA11	0.657	121.505	-0.038	-0.821	0.475
OBOS2MMA	0.006	3.984	-0.010	-0.790	0.134
OBOS3MMA	0.012	4.799	-0.016	-0.728	0.224
ROE	21.774	56.983	2.069	0.717	21.794
OBOS12MMA	0.123	11.671	-0.062	-0.692	0.912
OBOS4MMA	0.020	5.526	-0.020	-0.671	0.310
OBOS11MMA	0.109	11.228	-0.056	-0.670	0.846
OBOS10MMA	0.095	10.645	-0.048	-0.638	0.773
OBOS9MMA	0.080	9.951	-0.042	-0.609	0.699
OBOS8MMA	0.065	9.088	-0.035	-0.576	0.625
OBOS5MMA	0.027	5.998	-0.022	-0.558	0.394
OBOS7MMA	0.050	7.926	-0.028	-0.519	0.551
OBOS6MMA	0.035	6.372	-0.022	-0.461	0.477
DPSLOG	-0.286	-18.823	0.054	0.348	1.240
PRICEREL12	0.850	320.982	0.006	0.266	0.230
EARNREV3M	0.006	6.012	0.002	0.196	0.084
DE	34.831	58.170	-0.590	-0.113	42.619
C24MEPSP	0.015	19.643	0.000	0.059	0.064

Panel C: Total_sample (1994 – 2011)
Proportion losers = 1.41%

Factor	α_i	t-stat (α_i)	β_{iL}	t-stat (β_{iL})	σ_{ε_i}
POUTRAT	39.498	159.571	-20.051	**-11.212**	27.722
BVTMLOG	-0.630	-94.783	-0.432	**-9.562**	0.762
RETVAR12	0.015	97.711	0.009	**9.162**	0.018
DY	3.628	125.945	-1.800	**-9.042**	3.360
CFTP	0.147	128.259	-0.065	**-8.401**	0.130
BETA	0.637	345.805	0.085	**6.520**	0.230
MOM6	0.115	43.113	-0.097	**-5.926**	0.283
MOM60	2.151	69.124	1.412	**5.639**	2.929
MA7	0.575	143.886	-0.154	**-5.536**	0.494
MA9	0.575	143.886	-0.154	**-5.536**	0.494
MA6	0.577	144.479	-0.153	**-5.501**	0.494
MA4	0.570	142.403	-0.152	**-5.456**	0.495
MA8	0.574	143.711	-0.150	**-5.402**	0.494
MOM3	0.060	36.230	-0.060	**-5.307**	0.198
MA5	0.574	143.498	-0.146	**-5.264**	0.495
EY	0.102	160.978	-0.024	**-5.183**	0.076
PRICEREL12	0.832	460.554	-0.062	**-5.022**	0.214
MA10	0.571	142.750	-0.138	**-4.946**	0.495
MA3	0.559	139.334	-0.132	**-4.724**	0.496
MA11	0.569	142.177	-0.129	**-4.650**	0.495
MA12	0.567	141.420	-0.121	**-4.331**	0.496
LNP	2.579	222.788	0.344	**4.267**	1.433
ICBTIN	0.256	43.722	-0.189	**-4.007**	0.389
MOM1	0.017	19.126	-0.023	**-3.666**	0.111
SPSLOG	2.458	138.404	0.603	**3.523**	1.413
MOM12	0.255	60.111	-0.096	**-3.308**	0.489
EG1	0.534	41.706	0.314	**3.127**	1.157
STP	3.477	56.239	-1.407	**-2.882**	4.671
C24MBVTM	0.274	26.002	-0.201	**-2.870**	1.077
EPS	2.283	78.567	-0.584	**-2.790**	3.542
MA2	0.359	112.538	0.065	**2.435**	0.480
OBOS4MMA	0.016	8.258	-0.026	-1.879	0.240
OBOS5MMA	0.022	8.946	-0.032	-1.855	0.303
OBOS6MMA	0.028	9.423	-0.035	-1.694	0.364
OBOS7MMA	0.038	10.967	-0.040	-1.679	0.420
ROE	19.182	86.660	-2.264	-1.670	19.203
OBOS8MMA	0.048	12.135	-0.045	-1.658	0.476
OBOS10MMA	0.067	13.634	-0.055	-1.634	0.588
OBOS3MMA	0.010	7.140	-0.016	-1.599	0.176
OBOS9MMA	0.057	12.974	-0.049	-1.596	0.532
OBOS11MMA	0.077	14.196	-0.059	-1.590	0.644
OBOS12MMA	0.086	14.658	-0.064	-1.585	0.695
OBOS2MMA	0.005	5.580	-0.009	-1.462	0.108
MVLOG	7.735	525.484	-0.126	-1.230	1.826
EARNREV3M	0.008	10.271	-0.005	-0.627	0.084
C24MEPSP	0.012	22.797	-0.002	-0.470	0.059
DPSLOG	-0.702	-58.470	0.029	0.293	1.349
MOM36	1.012	66.041	-0.027	-0.244	1.629
DE	34.335	62.731	-0.590	-0.117	41.601
C24MDPSP	0.006	29.324	0.000	-0.072	0.024

From Table 9.2 it is seen that, on average, 1.4% of observations are associated with loser shares when using a 12-month holding period. Furthermore, as was the case with the winners, most factors generally differ significantly between loser shares and the REST. Focusing again on the more 'extreme' cases, the value effect is once again observed amongst shares classified as losers across all sample periods, indicated by the large, significant t-statistics associated with the negative dummy variable coefficients with regard to BVTMLOG and CFTP. In keeping with the results of Chapter 8, this finding suggests that value factors may be used to identify potential extreme performers and further classify them as either winners or losers irrespective of holding period used. The strength of the value effect with regard to losers is further supported by two additional value factors, EY (earnings-to-price) and STP (sales-to-price), also showing negative dummy coefficients. These two factors are however not consistently classified into the more 'extreme' category as is the case with BVTMLOG and CFTP. Note that the fifth value factor, DY, also forms part of the 'extreme' cases across all sample periods for loser shares, similar to the findings for a 1-month holding period. The dummy variable coefficient associated with DY is once again negative, indicating that loser shares generally have lower DY compared to the REST. DY was not as significant for winner shares and could therefore possibly be applied to specifically filter potential loser shares.

Compared to the winner shares, the size and momentum effects seem to be less important in identifying loser shares. For the 1-month holding period no definitive conclusion could be drawn regarding the association between size and loser shares, while the results in Table 9.2 support the size effect with respect to loser shares, although to a much lesser extent compared to the winner shares. In contrast to the 1-month holding period, the momentum effect appears to be less significantly associated with loser shares compared to winner shares when using a 12-month holding period, while the opposite was observed for the 1-month holding period.

A notable additional observation compared to the results discussed thus far, is the significance associated with the growth factor POUTRAT (pay-out ratio) regarding loser shares. The negative dummy coefficient indicates that loser shares normally have lower levels of POUTRAT compared to the REST. Compared to the results in Chapter 8 (Table 8.3), it therefore seems that lower levels of growth factors may be an indication of winner or loser shares, and that the type of growth factor is the determining factor. Specifically, two separate growth factors (DPSLOG and

POUTRAT) may be used to identify extreme performers, where DPSLOG may be used to construct filter levels for identifying winners, and POUTRAT for losers.

The significance associated with the price reversal effect (MOM60) is more significant for loser shares than for winners over a 12-month holding period. It is seen from Table 9.2, as indicated by the significant positive dummy coefficient, that loser shares normally have a higher prior 5-year return than the REST, in the sell signal period..

Similar to a 1-month holding period, the association between both winner and loser shares and the level of volatility (represented by Beta and Retvar12) is significant and positive. Once again the size of the coefficients is generally larger for loser shares, indicating that shares with higher volatility levels are more significantly associated with loser shares, than with winner shares.

Regarding the longer term OBOS and MA factors, although not consistently significant, a negative coefficient is associated with the dummy variables compared to the positive coefficients associated with winner shares, supporting (once again) a momentum effect on the JSE.

9.4 Deriving filter rules for portfolio construction

9.4.1. Winner and loser logit models

For reasons discussed earlier, a similar “refinement” process to that in Chapter 8 will be applied here before the logit models for winner and loser shares over a 12-month holding period are derived, to distinguish between winners and losers while ignoring the REST. Subsequently regression (9.3) is applied to Sample_A and the results are reported in Table 9.3.

Table 9.3: Evaluation of winner vs. loser factors over a 12-month period using Sample_A.
This table presents the constant term (α_i), its associated t-statistic, dummy variable coefficient (β_{iW}), its t-statistic and standard error (σ_{ε_i}). Results are reported for the period 1994 to 2011. Results in bold indicate where the t-statistic associated with the dummy variable is significantly different from zero at the ninety-five percent level of confidence. Factors are ranked according to the absolute value of the dummy coefficient t-statistic.

Factor	α_i	t-stat (α_i)	β_{iW}	t-stat (β_{iW})	σ_{ε_i}
CFTP	0.082	8.694	0.142	**12.355**	0.160
BVTMLOG	-1.062	-22.528	0.717	**12.275**	0.803
LNP	2.923	37.219	-1.028	**-10.870**	1.412
MOM6	0.018	0.895	0.220	**8.954**	0.354
MA7	0.421	15.905	0.258	**8.097**	0.476
MA9	0.421	15.905	0.258	**8.097**	0.476
MA6	0.424	15.981	0.251	**7.849**	0.477
MA8	0.424	15.981	0.251	**7.849**	0.477
MOM12	0.159	4.330	0.348	**7.845**	0.624
POUTRAT	19.448	13.003	13.889	**7.756**	23.410
PRICEREL12	0.769	67.524	0.103	**7.504**	0.198
MA10	0.433	16.269	0.236	**7.356**	0.479
EY	0.078	14.737	0.047	**7.351**	0.089
MA5	0.427	15.990	0.235	**7.310**	0.480
MA11	0.440	16.492	0.230	**7.159**	0.479
MVLOG	7.608	74.163	-0.878	**-7.109**	1.844
MOM3	0.000	0.026	0.109	**6.990**	0.229
MA12	0.446	16.705	0.222	**6.914**	0.480
MA4	0.418	15.492	0.221	**6.796**	0.485
OBOS10MMA	0.012	0.779	0.126	**6.782**	0.270
OBOS12MMA	0.022	1.227	0.147	**6.773**	0.311
DY	1.829	10.254	1.463	**6.763**	3.042
OBOS11MMA	0.018	1.073	0.136	**6.748**	0.292
OBOS9MMA	0.009	0.634	0.114	**6.662**	0.249
OBOS8MMA	0.003	0.230	0.102	**6.584**	0.227
OBOS7MMA	-0.002	-0.173	0.090	**6.440**	0.205
OBOS6MMA	-0.007	-0.661	0.077	**6.268**	0.182
MA3	0.427	15.770	0.203	**6.226**	0.487
OBOS5MMA	-0.010	-1.085	0.063	**5.930**	0.158
SPSLOG	3.060	20.314	-0.942	**-5.730**	1.251
OBOS4MMA	-0.009	-1.259	0.048	**5.381**	0.132
MOM60	3.563	12.547	-1.692	**-5.104**	3.348
MOM1	-0.006	-0.836	0.040	**4.779**	0.124
ICBTIN	0.067	1.216	0.301	**4.705**	0.459
STP	2.070	3.265	3.450	**4.632**	6.113
MA2	0.424	15.415	0.153	**4.625**	0.495
RETVAR12	0.024	21.422	-0.006	**-4.541**	0.020
OBOS3MMA	-0.006	-0.964	0.030	**4.284**	0.105
DPSLOG	-0.674	-6.609	-0.499	**-4.208**	1.409
OBOS2MMA	-0.004	-1.003	0.015	**3.200**	0.071
EG1	0.848	8.807	-0.343	**-2.901**	1.119
ROE	16.918	10.888	-4.801	**-2.363**	22.301
BETA	0.722	61.919	-0.029	**-2.069**	0.208
EPS	1.699	9.887	0.370	1.808	2.937
MOM36	0.986	8.576	0.233	1.683	1.732
EARNREV3M	0.003	0.268	0.012	1.129	0.102
C24MEPSP	0.010	2.783	0.002	0.539	0.059
DE	33.745	7.000	-2.339	-0.434	40.044
C24MBVTM	0.073	1.207	0.014	0.187	0.938
C24MDPSP	0.006	4.114	0.000	0.051	0.024

Similar to the 1-month holding period, it is seen from Table 9.3 that the majority of factors differ significantly between winner and loser shares over a 12-month holding period, while the most significant differences are once again found within the value factors (represented by CFTP and BVTMLOG). A notable difference however, is the high level of significance associated with the size factor (LNP) which appears to be the second most significantly different categorical factor between winner and loser shares over a 12-month period, followed by momentum (represented by the majority of factors classified as momentum factors). The significance of the size factor is in line with the results in Chapter 5, where it was found that size becomes highly significant for longer payoff periods. Comparing the results in Table 9.3 to that of Table 9.1 and Table 9.2, it is seen that the refinement process caused the possible additional filtering variables (MA2, DPSLOG, POUTRAT and MOM60) to become less important to consider when deriving the final logit models.

A similar process to that followed in Chapter 8 to reduce the number of candidate factors and to avoid possible multicollinearity is followed in this chapter to derive the winner and loser logit models (i.e. taking the correlation between factors into consideration while focusing on the more 'extreme' cases in Table 9.3). The forward stepwise logistic regression approach is followed to formulate the final models. The results of the stepwise process are reported in Appendix F.2 (winners) and Appendix F.3 (losers). The final winner and loser logit models are presented in formulae (9.4) and (9.5) respectively:

$$logit(winner) = -2.880 + 3.367CFTP - 0.345LNP + 1.681MOM6 \qquad ...(9.4)$$

$$logit(loser) = -3.556 - 4.492CFTP + 0.202LNP - 1.322MOM6 \qquad ...(9.5)$$

All independent variables are significant at the 1% level (see Appendix F.2 and F.3). From (9.4) and (9.5) it is seen that the winner and loser logit models contain the exact same variables. Specifically, it appears that value (captured by CFTP), size (captured by LNP) and momentum (captured by MOM6) are the most significant factors to be used in predicting potential winner and loser shares over a 12-month period. In addition to the three factors included in the final models, POUTRAT was also found to be significant in the winner logit model. However, the coefficient associated with POUTRAT was extremely small (-0.005), resulting in the exponent of this coefficient to be 0.995. This means that the probability of a share being classified as a winner is approximately just as likely for a one unit increase in POUTRAT as it was before the increase. The additional value obtained by including POUTRAT in the logit model for prediction purposes is therefore negligible, and it is removed from the model. After it has been removed, the logistic regression process was repeated to obtain the final variable coefficients reported in (9.4).

The factors used in the final logit models are the same as those that ranked amongst the most significant factors in explaining the cross- section of returns over a 12-month payoff period across all sample periods (Chapter 5, Section 5.4). To determine the most accurate threshold values for the filtering process, the “percent correctly predicted” approach (Chapter 8 Section 8.4.1.3) is followed. Threshold values of 0.0485 and 0.03 were obtained for the respective winner and loser logit models.

9.4.2. Portfolio construction for rolling 12-month periods

Using the threshold values above, logit models (9.4) and (9.5) were applied to the independent sample of shares (Sample_B) to construct rolling 12-month equally weighted winner, loser and benchmark portfolios. In other words, shares were selected and categorised into the respective winner and loser portfolios based on the associated threshold values as at the beginning of every month during the period under review. Each of these portfolios was held for a period of 12 months and the returns calculated on an equally weighted basis. Similar to Chapter 8, the portfolios are constructed subject to the constraint that each share can only be included in either the winner or loser portfolio. The benchmark portfolio is an equally weighted portfolio consisting of all the shares in Sample_B. The portfolio characteristics of the respective portfolios are reported in Table 9.4. Note that, due to the construction of rolling portfolios, no statistical significance can be claimed regarding the differences in performance between these portfolios. A different approach that will allow for statistical tests is examined in the next section.

Table 9.4: Comparison of portfolio characteristics of rolling 12-month portfolios using Sample_B

This table presents portfolio characteristics of the rolling 12-month winner, loser and benchmark portfolios that were created using the logit models developed. Stocks are selected from Sample_B to create the respective portfolios.

	Winner	Benchmark	Loser
Average rolling 12-month return	29%	23%	10%
Standard deviation (based on rolling 12-month returns)	35%	25%	25%
Sharpe ratio*	0.66	0.73	0.18
Average number of shares	16	50	14
Percentage of positive (negative) rolling 12-month alphas**	72%	NA	84%

* The Sharpe ratio is calculated using the average rolling 12-month return and an annualised 3-month T-bill rate of 5.41%

**With regard to the loser portfolio

From Table 9.4 it is seen that, as was the case for 1-month holding periods, the derived logit models can be used to filter winner (loser) shares to create portfolios that outperform (underperform) the benchmark portfolio. The winner portfolio outperforms the benchmark portfolio by an average of 6% over any rolling 12-month period, while the loser portfolio underperforms the benchmark by an average of 13% during any rolling 12-month period. Note that the winner portfolio has substantially higher risk associated with it (as measured by the standard deviation) relative to the benchmark, resulting in the relatively lower Sharpe ratio. This substantially higher standard deviation is however due to the fact that the winner logit model is developed to predict which shares could potentially double in price during the next 12 months, meaning that these are typically the kind of shares that one would expect to experience substantially higher levels of volatility. The loser logit model predicts those shares that could potentially halve in price during the next 12 months, and although these shares should also be expected to show higher levels of volatility relative to the benchmark, it should not necessarily be at similar (high) levels to that of the winner portfolio. From Table 9.4 it is seen that the standard deviation of the loser portfolio is in fact equal to that of the benchmark portfolio, which may be an indication that the filtering level used when applying the loser logit model is too low, resulting in shares that should rather be classified as part of the REST to filter through and be included in the loser portfolio. Increasing the filtering level may result in a level of risk that is more in line with expectations. This will be examined shortly.

The success of the filtering process is further supported by the fact that the winner portfolio outperformed the benchmark portfolio 72% of the time while the loser portfolio underperformed the benchmark portfolio 84% of the time (based on rolling 12-month periods).

The reason for the relatively low average number of shares included in the benchmark is mainly due to the longer holding period used (i.e. a share has to have at least 12 months of forward data to be included) while half of the shares were used to construct the logit models, leaving the other half for testing purposes. This relatively low number of shares could also be the reason for the rather high level of risk associated with the benchmark. Having said that, and noting that the average number of shares included in the respective winner and loser portfolios is relatively high (16 and 14 respectively, meaning that on average only 20 shares in total is not categorised into either the winner or loser portfolio), it appears that the application of the derived logit models could be refined to filter more strictly by increasing the filter level (i.e. the threshold). This should result in a lower number of shares to be filtered and included in the winner and loser portfolios, but at the same time increase (decrease) the relative performance of the portfolio as those shares filtered now have an even higher probability of turning out to be an actual extreme performer. To examine the effect of increasing the filter level on the performance and risk of the portfolios, logit models (9.4) and (9.5) were reapplied using an increased threshold of 0.06 instead of 0.0485 for the winner and 0.04 instead of 0.03 for the loser model. The results are reported in Table 9.5.

Table 9.5: Comparison of portfolio characteristics of rolling 12-month portfolios using increased filtering levels and Sample_B

This table presents portfolio characteristics of the rolling 12-month winner, loser and benchmark portfolios that were created using the derived logit models and an increased filtering level. Stocks are selected from Sample_B to create the respective portfolios.

	Winner	Benchmark	Loser
Average rolling 12-month return	35%	23%	7%
Standard deviation (based on rolling 12-month returns)	39%	24%	32%
Sharpe ratio*	0.75	0.76	0.05
Average number of shares	12	50	7
Percentage of positive (negative) rolling 12-month alphas**	78%	NA	78%

* The Sharpe ratio is calculated using the average rolling 12-month return and an annualised 3-month T-bill rate of 5.41%

**With regard to the loser portfolio

Note that there is a slight difference between the benchmark portfolio characteristics reported in Table 9.5 relative to that reported in Table 9.4. The reason for this is that, due to the stricter filtering level, there were fewer months during which a winner and loser portfolio could be constructed (i.e. there were months during which none of the shares met the filtering criteria). As a result the benchmark portfolio was also not constructed during those periods to ensure fair comparison, leading to the slight difference in reported results.

From Table 9.5 it is seen that the increased filtering level resulted, as expected, in the return of the winner portfolio to increase to 35% (from 29%), implying an average outperformance relative to the benchmark of 12% (from 6%) during any rolling 12-month period. The risk (standard deviation) increased to 39% (compared to 35%), which is again substantially higher relative to the benchmark due to the reasons explained above. The Sharpe ratio increased to 0.75, and the difference between the Sharpe ratio of the winner portfolio and the benchmark portfolio is now negligible. The average number of shares decreased to 12 (from 16) whereas the frequency of rolling 12-month positive alphas increased to 78%.

With respect to the loser portfolio, the increased filter level resulted in a decrease in the average rolling 12-month return to 7% (from 10%), an increase in the standard deviation to 32% (as was expected based on the earlier discussion), a decrease in the Sharpe ratio to 0.05 (previously 0.18) and, interestingly, a slight decrease in the frequency of relative rolling 12-month underperformance to 78% (from 84%). The average number of shares in the loser portfolio decreased to 7 (from 14).

Continuing to increase the filter level will generally result in enhanced relative portfolio performance with regard to the winner portfolio and worse relative performance regarding the loser portfolio. Although such an increased filter level will provide performance results that are more in line with the general expectation associated with extreme performers (i.e. significantly higher (lower) relative returns), it does not come without a cost. As seen from Table 9.5, although performance increased (decreased) substantially with a slight increase in the filtering level, so did the risk while the size of the portfolios decreased. In fact, some months didn't allow for a portfolio to be created at all. Nevertheless, an average outperformance (underperformance) of +12% (-16%) over any rolling 12-month period during an 18 year investment horizon certainly shows that it is possible to create filter rules based on technical and fundamental factors to identify potential extreme performing shares on the JSE to ultimately construct superior (inferior) performing portfolios.

9.4.3. Converting 12-month holding period returns into monthly returns

In order to evaluate the performance of the portfolios on a statistical basis in addition to the evaluation on an economic basis as above, the monthly performance of the portfolios created using the logit models were extracted to form a time-series of non-overlapping monthly returns. Specifically, the process followed to create such a time series is as follows:

At the beginning of month one, shares are filtered based on the respective winner and loser logit models. The shares are equally weighted and the portfolios' monthly returns are recorded for a period of 12 months. At the beginning of month two, a second winner (loser) portfolio is created and the performance is followed for the next twelve months. This means that two winner (loser) portfolios are available during month two. The return for month two is averaged between the two winner (loser) portfolios to record the monthly return for the second month. At the beginning of month three, a third winner (loser) portfolio is created and the monthly return is recorded for the next twelve months. Therefore three winner (loser) portfolios are available in month three, and the monthly return for month three is calculated as the average of the monthly return for the three respective portfolios. This process continues until month twelve, during which twelve winner (loser) portfolios are available. The return for month twelve is therefore the average return of the twelve winner (loser) portfolios available in month twelve. At the beginning of month thirteen, the winner (loser) portfolio that was created at the beginning of month one is dropped, and a new winner (loser) portfolio is created based on the logit results as at the beginning of that month. This means that, again, twelve winner (loser) portfolios are available during month thirteen, and the monthly return for that month is calculated as the average of the twelve winner (loser) portfolios. Each subsequent month the winner (loser) portfolio that was created twelve months earlier is dropped and a new portfolio is created based on the logit model results. This process continues for the remainder of the period under review, resulting in a time series of monthly, non-overlapping winner (loser) portfolio returns. The benchmark portfolio is created in the same manner as before, with monthly returns calculated to form a time series of monthly benchmark portfolio returns to be used in the portfolio performance evaluation process. The performance evaluation based on monthly returns is reported in Table 9.6

Table 9.6: Performance evaluation of 12-month holding period winner and loser portfolios based on monthly returns and Sample_B

This table presents portfolio factors of the winner, loser and benchmark portfolios that were created using the derived 12-month holding period logit model. Stocks are selected from Sample_B to create the respective portfolios. A paired mean comparison test was performed to test for significantly different mean monthly returns between the winner (loser) and benchmark portfolios on a 95% level of significance. The t-stat obtained is reported below the average monthly return value.

	Winner	Benchmark	Loser
Average monthly return	1.95% (t-stat = 0.93)	1.71%	0.68% (t-stat = -3.81)
Annualised return	26.14%	22.61%	8.52%
Annualised standard deviation	23.75%	20.81%	23.95%
Sharpe ratio*	0.87	0.83	0.13
Average number of shares	16	50	11

** The Sharpe ratio is calculated using the average rolling 12-month return and an annualised 3-month T-bill rate of 5.41%

From Table 9.6 it is seen that the winner (loser) portfolio outperforms (underperforms) the benchmark portfolio. The relatively higher level of risk as measured by the standard deviation is compensated for by the increased return as indicated by the higher (lower) Sharpe ratio. Note that the outperformance of the winner portfolio is not statistically significant on the 95% level of confidence, while the underperformance associated with the loser is significant. Similar to using rolling 12-month returns, a relatively large number of shares are included in the respective winner and loser portfolios. Once again this allows for examining the effect of increasing the filter (threshold) level to filter more strictly. The respective threshold levels were increased to 0.06 for the winner and 0.04 for the loser portfolios. The results are reported in Table 9.7.

Table 9.7: Performance evaluation of 12-month holding period winner and loser portfolios based on monthly returns and Sample_B and increased threshold levels

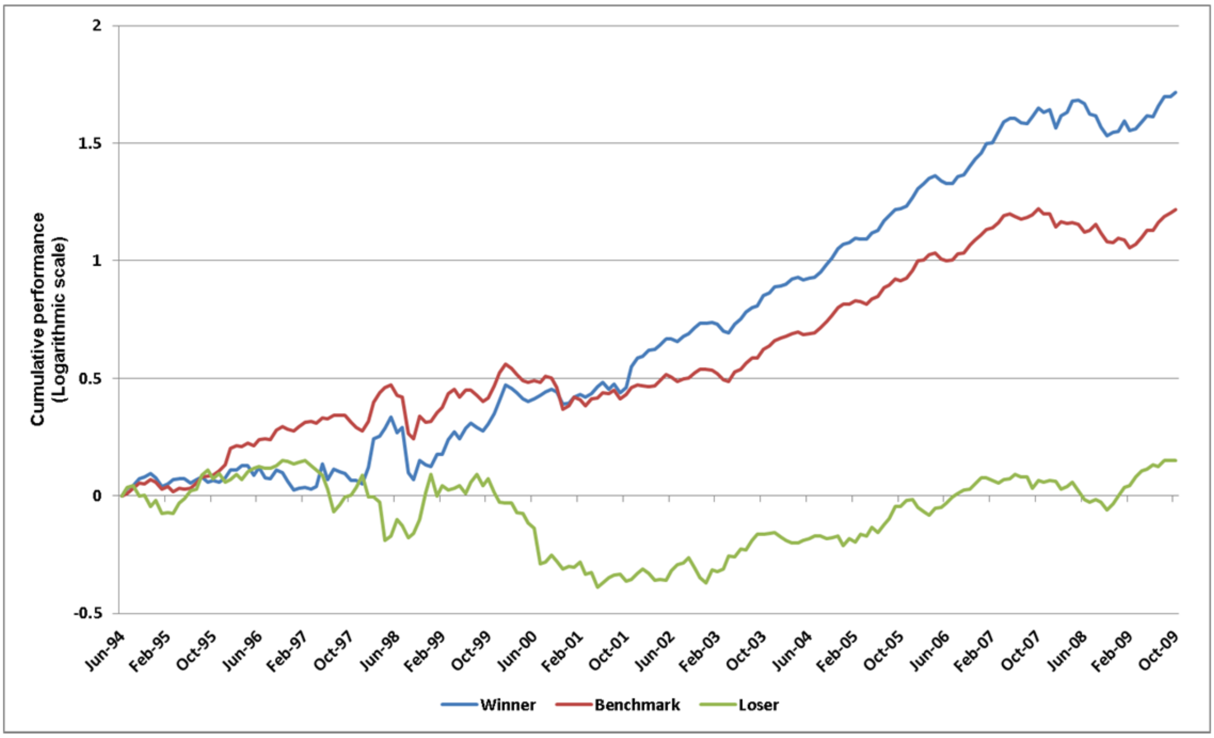
This table presents portfolio factors of the winner, loser and benchmark portfolios that were created using the derived 12-month holding period logit model with increased threshold levels. Stocks are selected from Sample_B to create the respective portfolios. A paired mean comparison test was performed to test for significantly different mean monthly returns between the winner (loser) and benchmark portfolios on a 95% level of significance. The t-stat obtained is reported below the average monthly return value.

	Winner	Benchmark	Loser
Average monthly return	2.43% (t-stat = 2.3)	1.71%	0.50% (t-stat = -2.98)
Annualised return	33.44%	22.61%	6.21%
Annualised standard deviation	25.64%	20.81%	27.12%
Sharpe ratio*	1.09	0.83	0.03
Average number of shares	11	50	6

** The Sharpe ratio is calculated using the average rolling 12-month return and an annualised 3-month T-bill rate of 5.41%

The increased threshold level resulted in an increase (decrease) in the outperformance (underperformance) of the winner (loser) portfolio relative to the benchmark portfolio. The improvement (decline) in relative performance is accompanied by an increase in risk and a decrease in the average number of shares included in the respective portfolios. Furthermore a significant increase (decrease) is seen in the Sharpe ratio of the winner (loser) portfolio. Note that the increased threshold level resulted in the relative outperformance to be statistically significant on a 95% level of confidence. Note that although the relative underperformance is still statistically significant, it is less significant compared to the results obtained using the original threshold level. This is due to a relatively larger increase in the standard deviation compared to the decrease in average monthly return for the loser portfolio. The cumulative performance is presented in Figure 9.1.

Figure 9.1 Cumulative performances.
This graph illustrates the value of R1 invested at the end of December 1995 in the winner, loser and benchmark portfolios respectively. A logarithmic scale is used to present the cumulative performance.



9.4.4. Risk-adjusted performance evaluation

To examine whether the excess return associated with the winner portfolio can be explained by well-known market models, the raw-returns are adjusted for risk based on the CAPM and Van Rensburg (2002) two-factor APT models. This is done in a similar fashion to that in Chapter 6 (specifically, regressions (6.1) and (6.2) are applied using the winner excess returns as the dependent variable). The results are reported in Table 9.8.

Table 9.8: Risk-adjusted winner portfolio performance evaluation
This table presents the risk-adjusted portfolio performance results. Intercept terms (α) in bold indicate significance on a 95% level of confidence.

	CAPM					APT		
	α	t(α)	β	t(β)	R-squared	α	t(α)	R-squared
Winner	**0.013**	2.98	0.85	12.08	0.46	**0.016**	3.94	0.56

From Table 9.8 it is seen that neither of the risk-adjusted models could explain the excess returns obtained by the winner portfolio, as indicated by the statistically significant intercept terms and the relatively low R-squared values. Similar to the results of single-factor portfolios (Chapter 6) and 1-month logit models (Chapter 8), it appears that technical and fundamental factors can be used to construct portfolios that offer abnormal returns which cannot be explained by market models over longer payoff periods.

9.5 Conclusion

Shares that experienced an increase of 100% or a decrease of 50% during a 12-month holding period were categorised as extreme performer shares and further sub-classified as winners or losers. Using a cross-sectional regression approach and a binary dummy variable to distinguish extreme performers from the rest, technical and fundamental factors that differ significantly between extreme performers and the rest were identified. A second cross- sectional regression approach, wherein the dummy variable was constructed in such a way as to distinguish between winner and loser shares (and ignoring the rest) was applied to refine the process to determine which factors specifically discriminate winners from losers. Using the winner/loser dummy variable and the factors found that significantly differentiate between winners and losers, logistic regression models were developed for predicting potential winner and loser shares. Value (CFTP), size (LNP) and momentum (MOM6) factors were included in the final winner and loser logit models. The positive (negative) relation between the value and momentum factors and potential winners (losers) indicates that a value and momentum effect can be integrated into a logit model to discriminate between potential winner and loser shares over a 12-month holding period. The negative (positive) relation between the size factor and winners (losers) indicates that a size effect further contributes to distinguish between potential winners and losers over the longer payoff period. The factors used in the final logit models are similar to those found to be amongst the most significant in explaining the cross- section of returns over a 12-month holding period in Chapter 5.

The logistic regression models were applied to filter potential winner and loser shares from an independent sample of shares. Based on the filtered shares, equally weighted winner and loser portfolios were constructed monthly and rebalanced every 12 months. The returns were converted into monthly returns for performance evaluation purposes. It was found that the winner portfolio significantly outperformed while the loser portfolio significantly underperformed the benchmark portfolio. The risk-adjusted performance evaluation revealed that the excess return offered by the winner portfolio cannot be explained by either the CAPM or two-factor APT model.

10

CONCLUSION

According to Modern Portfolio Theory (MPT), investors attempt to maximise their economic utility while being risk- averse. This implies that, for a given level of risk, investors seek the highest level of return (or similarly the lowest risk for a given level of return). Portfolios offering such combinations of risk and return are known as efficient portfolios. The search for these efficient portfolios results in fierce competition amongst investors, causing them to act quickly on new information. As a result, current prices reflect all information and investors should therefore not be able to outperform their peers in a consistent fashion, a theory generally referred to as the efficient market hypothesis (EMH). Markowitz's (1952) efficient frontier concept was extended by Tobin (1958) and Sharpe (1964) who introduced the concept of a risk free asset, resulting in the well-known separation theorem. According to the latter, investors should allocate capital between the risky market portfolio and the risk-free asset in such a manner that it reflects the investor's risk appetite. Underpinned by these theoretical foundations laid by Markowitz (1952) and Tobin (1958), Sharpe (1964), Lintner (1965) and Mossin (1966) developed the capital asset pricing model (CAPM) to price assets in an efficient market. According to the CAPM, the only risk that investors should be compensated for is that of the portfolio relative to the completely diversified market portfolio. Roll (1976) criticised the concept of an observable market portfolio that is completely diversified which led him to develop an alternative, multifactor asset pricing model. The latter is based on the law of one price, i.e. securities bearing the same level of risk should sell at the same price. This multifactor model is known as the Arbitrage Pricing Theory (APT) model.

In contrast with the assumptions underlying MPT, EMH, CAPM and APT, behavioural finance takes into consideration how various psychological qualities affect the actions investors, analysts and portfolio managers take, individually as well as in groups. These psychological qualities could lead to irrational behaviour in contrast to that assumed by MPT and cause markets to be less efficient than that proposed by the EMH. According to Scott, Stumpp and Xu (1999), behavioural finance -theory and biases can be split into two general categories, namely overconfidence and prospect theory. The first refers to the phenomenon of humans assigning an excessively high probability of success to their own forecasts (Kahneman & Tversky, 1972), while under prospect theory investor utility depends on deviations from moving reference points rather than absolute wealth as suggested by expected utility theory (Kahneman & Tversky, 1979). Prospect theory is indicative of a tendency towards loss- aversion, meaning that the extent of disutility derived from making losses is greater than that of an equal amount of gains.

For the purposes of this thesis, the focus of the literature review is on EMH tests specifically concerning the weak and semi-strong form as defined by Fama (1970). The weak form states that future prices cannot be predicted by historic prices as it follows a 'random walk' while the semi-strong form states that prices adjust quickly to reflect all publicly available data. The literature review spans more than 60 years and is discussed in detail in Chapter 3.

Tests regarding the weak form EMH include autocorrelation tests of independence of returns, tests of the overreaction theorem and tests involving technical trading rules. Various contradicting results are reported, however it does seem from the latest research that most researchers find evidence of a price-reversal effect over very short (daily or weekly) as well as longer (three to five year) investment periods, while a momentum effect is apparent over medium terms. No final conclusion regarding the period to use when applying momentum and/or contrarian strategies are obtained however, as the periods reported by the different researchers vary considerably.

Tests regarding the semi-strong form EMH are dominated by those concerned with the identification of firm- specific characteristics that explain future stock returns or the cross- section of returns. Since the early 2000's, the results of these studies converged to suggest mainly two style factors, namely size and value, as the most prominent explanatory variables of expected returns. With regard to value, the two indicators mostly researched are price-to-earnings (P/E) and book-to-market (B/M), with the latter receiving most attention in current international literature, especially after Fama and French (1992) suggested that size and B/M collectively subsumes the effect of P/E. Not surprisingly, the focus of the more recent studies has therefore shifted towards determining whether the size and value (specifically B/M) indicators together with a technical indicator (specifically momentum) are capital market anomalies that could be exploited to provide abnormal returns, or simply common risk factors that should be included in equilibrium asset pricing models.

From the literature review three approaches in testing the EMH were identified, namely a cross- sectional regression approach, a factor-portfolio approach and an extreme performer approach. All three approaches are applied in this thesis.

In total fifty fundamental and technical factors are applied in this thesis, following the combination of factors identified through the literature review as well as own-defined factors that make sense from a South African point of view. The data selected for this thesis cover the period from January 1994 through May 2011. This specific period was selected to avoid any possible distortions in the results obtained due to economic and political events that occurred in South Africa prior to the transition period of 1994. Furthermore this period allows for the formation of two independent subsamples of approximately equal length, both covering full investment cycles. Additionally, the research can be conducted over the full 17.5 year period, providing three sets of results to be compared. Data were gathered for all factors for all shares that were listed on the JSE during the period under review, irrespective of whether a share has been delisted. In addition to survivorship bias, other statistical biases identified through prior research that may cause inaccuracies have been controlled for as well, including data snooping, infrequent trading, look-ahead bias and outliers.

A cross-sectional regression approach was applied first to determine which of the fifty factors contribute significantly in explaining the cross- section of returns on the JSE. The regressions were performed over three sample periods, namely January 1994 through December 2002 (Subsample_1), January 2003 through May 2011 (Subsample_2) and January 1994 through May 2011 (Total_sample). Additionally, the regressions were performed for samples based on different liquidity levels (by using market cap deciles as liquidity filters) over different payoff periods (1-month, 3-months, 6-months, 12-months, 24-months and 36-months).

Based on a one-month payoff period and including all shares in the sample (referred to as the All-share sample), significant value and momentum effects are observed on the JSE across all sample periods. The value effect is best captured by cash-flow to price (CFTP) and book-value to market (BVTMLOG), while the momentum effect is best captured by 12-month prior returns (MOM12). A size effect, best captured by the natural log of share price (LNP) and market cap value (MVLOG) is observed for the first sample period as well as the total sample period, but it disappeared during the second sample period. Hence, a value and momentum effect is observed on the JSE over a 1-month payoff period which is insensitive to time while the size effect is affected by time.

When the level of sample liquidity is increased (by selecting shares based on a filtering level set equal to the 5th market cap decile, referred to as the Large-cap sample), the value effect (captured by CFTP and BVTMLOG) remains significant across all sample periods while the momentum effect disappears during the period January 2003 through May 2011. The value effect therefore seems to be robust while the momentum effect becomes sensitive to time as a result of the change in the level of sample liquidity. Additionally, a short- term price-reversal effect, captured by prior 1-month returns (MOM1) is observed for Subsample_2. The size effect observed for the All-share sample is only observed once at least the top 68 shares in terms of market cap are included in the sample. Similar to the All-share sample results, the size effect disappears during 2003 through 2011. The size effect is therefore sensitive to liquidity and time. The CAPM beta is found to be significant for the Large-cap sample for two of the three sample periods. Its significance therefore depends on time as well as the level of sample liquidity, confirming that the use of the single factor CAPM model to explain returns for all shares on the JSE is inappropriate.

When the payoff period is increased to at least three-months, a significant value and size effect is observed across all sample periods for both the All-share and Large-cap samples. Value (best captured by CFTP) therefore appears not to be affected by time, liquidity or payoff period. Over payoff periods of at least three months the size effect (best captured by LNP) is not affected by time or liquidity. Momentum, price-reversal and growth effects appear to be sensitive to time, liquidity and/or payoff period. For Subsample_1 and Total_sample the significance associated with the momentum effect decreases while a longer term price-reversal effect becomes highly significant as the payoff period is increased. The longer term price reversal effect is captured by prior 36- (MOM36) and 60-month (MOM60) returns. The momentum effect remains significant across longer payoff periods for Subsample_2 with no evidence of a longer-term price-reversal effect. A growth effect appears across all longer term payoff periods (three-months and longer) for all sample periods, but the nature of its effect (positive or negative) on returns is not consistent.

In summary, the univariate cross- sectional regression results suggest that, although a number of technical and fundamental factors contribute significantly to explaining the cross- sectional variation in equity returns on the JSE, the value effect (as captured specifically by CFTP) appear to be the only robust effect as it is insensitive to time, liquidity or payoff period. The momentum effect (captured mainly by MOM6 and MOM12) is significant mainly over a one-month payoff period irrespective of level of liquidity or sample period, while the size effect (captured by especially LNP) is significant over payoff periods in excess of three months, irrespective of liquidity or sample period. The significance associated with all other factors is found to be a function of at least one or more of time, liquidity and payoff period.

The results obtained following a single-factor portfolio construction approach (Chapter 6) correlate strongly with the results obtained following a univariate cross-sectional regression approach. Value factor portfolios (using especially CFTP) offer significant outperformance across all sample periods and the two payoff periods tested (1-month and 3-months), irrespective of level of liquidity applied. Constructing portfolios based on size factors (specifically LNP) generally offer superior returns that are insensitive to the payoff periods and level of liquidity, but the significant outperformance is limited to Subsample_1 and Total_sample, implying sensitivity towards time. When the holding period is increased to three months however, the size factor portfolios offer significant outperformance during all sample periods across all levels of liquidity.

Momentum, growth and price reversal are dependent on sample period, level of liquidity and payoff period. Portfolios constructed on momentum factors work well for Subsample_1 and Total_sample, over a one-month payoff period, irrespective of level of liquidity applied, while such a strategy is only profitable over the three-month payoff period for the Large-cap sample during these two sample periods. With regard to Subsample_2, the momentum strategy works well only for the All-share sample and a one-month payoff period. A short- term price reversal portfolio construction strategy works well for Subsample_2, but only for a one-month payoff period, irrespective of the level of liquidity.

Although the results obtained for portfolios based on growth factors were similar across the one- and three-month payoff periods, they appear to be sensitive to time and liquidity, as significant superior returns are offered only during Subsample_2 and only for the All-share sample.

Longer term price reversal portfolios, based specifically on MOM60, appear to offer abnormal returns for Subsample_1 and Total_sample as long as it is constructed from the Large-cap sample and rebalanced every three months, making such a strategy dependent on time, liquidity and payoff period.

Risk-adjusted performance evaluation shows that neither the traditional CAPM nor the Van Rensburg (2002) two-factor APT models are able to explain the excess returns offered following a single-factor portfolio construction approach, implying either that market anomalies are present on the JSE or that the market models are incorrectly specified.

Multifactor analyses were performed (Chapter 7) using the factors identified through the cross-sectional regression and factor portfolio construction approaches. A multiple cross-sectional regression approach was followed to examine whether multifactor models could increase the explanatory power of the cross-section of returns on the JSE. Using the All-share sample, a ‘value, momentum and size’ (represented by CFTP, LNP and MOM12) three-factor model was derived for Sample_1 and Total_sample while a ‘value, momentum and short-term price-reversal’ model (represented by CFTP, MOM6 and MOM1) was derived for Sample_2. The fact that a size factor could not be included in a multifactor model for Subsample_2 is directly in line with the finding that the size effect is sensitive to time when using a 1-month payoff period. A fourth factor could not be added to any of the three factor models without some or all candidate factors losing their significance. For the Large-cap sample, a ‘value, momentum and short- term price reversal’ (captured by CFTP, MOM6 or MOM12 and MOM1) three-factor model was derived for all sample periods. It therefore appears that such a three-factor model is significant in explaining the monthly cross-section of returns of the larger shares on the JSE. As with the All-share sample, adding a fourth factor to the three-factor models resulted in some or all of the factors to become insignificant.

A third, rather unexplored approach to testing the EMH was identified during the literature review. This approach is referred to as the 'extreme performer' approach in this thesis. A 'first of its kind' -method was followed to apply the extreme performer approach (Chapter 8 and Chapter 9) to examine the impact of technical and fundamental factors on the cross-section of returns on the JSE. Specifically, a combination of cross-sectional regression and logistic regression techniques was applied. Shares that increased at least 6% in any month were categorised as winners while those that decreased at least 5% in a month were categorised as losers. The remaining shares were categorised into the 'REST' category. The All-share sample was split (in a cross-sectional fashion) into two subsamples, Sample_A and Sample_B. Each sample was similar in size and representative of the economic groups on the JSE. Using only Sample_A, a cross-sectional regression approach was applied to determine which technical and fundamental factors significantly differentiate between winner or loser shares, and the REST. Based on the results, a logistic regression approach was applied to create logit models for predicting potential winner and loser shares. Value (CFTP) and two volatility (Retvar12 and Beta) factors were found to be significant in the final winner and loser logit models. The positive relation between the value factor and potential winner shares together with the negative relation between the same value factor and potential loser shares, once again confirmed a strong value effect on the JSE. Although volatility factors were found to be positively related to potential winner and loser shares, the level of volatility was found to be relatively higher for potential loser shares, contradicting capital market theory. The value and volatility factors were the only factors found to be significant with regard to the winner logit model while momentum factors (represented by price relative to a 12-month high or Pricerel12, MOM12 and a 2-month moving average factor, MA2) also form part of the loser logit model. The negative relationship between the 'longer term' momentum factors (Pricerel12 and MOM12) and potential loser shares supports the momentum effect while the positive relationship between MA2 and potential loser shares confirms a short-term price reversal effect.

The logistic regression models were applied to filter potential winner and loser shares from Sample_B. Equally weighted winner and loser portfolios were constructed and rebalanced monthly, based on the filtered shares. In addition an equally weighted benchmark portfolio was created using all available shares. This portfolio-construction approach was followed for the period January 1994 through May 2011. The winner portfolio significantly outperformed while the loser portfolio significantly underperformed the benchmark portfolio by approximately 1% per month. The respective portfolios also had relatively higher levels of volatility compared to the benchmark portfolio, as can be expected. According to the Sharpe ratio however, the higher risk associated with the winner portfolio is compensated for by a significant increase in return.

A second cross-sectional regression approach was applied to refine the distinction between potential winner and loser shares. This was done by conducting the cross-sectional regression on the sample of extreme performing shares only, ignoring the REST. Subsequent ‘refined’ winner and loser logit models were developed. Value (CFTP), momentum (MOM12) and volatility (Beta, Retvar12) factors were included in both winner and loser logit models. In addition, the winner logit model includes a short-term price reversal (MOM1), a growth (C24MDPSP) and a size (LNP) factor while the loser logit model includes MA3, representing a short-term price reversal effect. The refined logit models were again applied to filter shares from Sample_B for portfolio construction purposes. Based on the portfolio performance evaluation it was seen that this refined process resulted in improved portfolio characteristics. The significant outperformance of the winner portfolio increased to a monthly average of 1.1% while the relative underperformance associated with the loser portfolio decreased to a monthly average of -1.3%. Together with the improvement in returns, the standard deviations of the respective portfolios remained similar, resulting in an even higher Sharpe ratio associated with the winner portfolio. A risk-adjusted performance evaluation further revealed that the excess return offered by the winner portfolio cannot be explained by either the CAPM or Van Rensburg (2002) two-factor APT model.

To examine the effect payoff period may have on the results obtained following an extreme performer approach, it was repeated for a 12-month payoff period (Chapter 9). Shares that experienced an increase of at least 100% over a 12-month period were classified as winners while those that experienced a decrease of at least 50% during a 12-month period were classified as losers. Due to earlier findings, namely that the refined cross- sectional regression approach (i.e. using the sample of extreme performers only, ignoring the REST) offers better results, a similar approach was followed using Sample_A to determine which factors differ significantly between winner and loser shares based on a 12-month holding period. Subsequent logistic regression models were developed to predict potential winner and loser shares respectively. Value (CFTP), size (LNP) and momentum (MOM6) factors were included in the final winner and loser logit models. The positive (negative) relation between the value and momentum factors and potential winners (losers) indicates that a value and momentum effect can be integrated into a logit model to discriminate between potential winner and loser shares over a 12-month holding period. The negative (positive) relationship between the size factor and winners (losers) indicates that a size effect further contributes to distinguish between potential winners and losers over the longer payoff period. The factors used in the final logit models are similar to those found to be amongst the most significant in explaining the cross-section of returns over a 12-month holding period (Chapter 5).

Once again the logistic regression models were applied to filter potential winner and loser shares from Sample_B for portfolio construction purposes. Equally weighted winner and loser portfolios were constructed monthly and rebalanced every 12 months. The returns were converted into monthly returns for performance evaluation purposes. A benchmark portfolio was constructed by weighting all available shares equally. The winner portfolio significantly outperformed the benchmark portfolio, with an average outperformance of 12% over a 12-month period. The loser portfolio significantly underperformed the benchmark portfolio by an average of -16% over a 12-month period. The risk-adjusted performance evaluation revealed that the excess return offered by the winner portfolio cannot be explained by either the CAPM or the Van Rensburg (2002) two-factor APT model.

Comparing the factors included in the final refined logit models for a 12-month payoff period with those for a 1-month payoff period, it is seen that the value (CFTP) and momentum factors (although not represented by the same momentum factors) are significant across both payoff periods for both winner and loser logit models. The size factor (LNP) is also significant over both periods, but is only included in the winner logit model over a 1-month payoff period. Volatility (Beta and Retvar12), growth (C24MDPSP) and short- term price reversal (MOM1 and MA3) factors are significant only over the 1-month payoff period.

In summary, the analyses conducted in this thesis suggest that anomalies are present on the JSE. Specifically, a strong value effect is present and robust on the JSE and best captured by CFTP, while a momentum (best captured by MOM6 or MOM12), size (best captured by LNP) and price reversal (best captured by MOM1 for short term and MOM60 for long term) effect are present but sensitive to time, liquidity and/or payoff period. Value and momentum factors are collectively significant in explaining the cross-section of returns across all time periods and level of liquidity, while three factor categories, namely value, size and momentum, can collectively be used to distinguish between potential winners and losers. In keeping with the sensitivities with respect to time, liquidity and/or payoff period, the identified firm-specific characteristics can be used to create portfolios that offer significant outperformance which cannot be explained by current market models.

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Appendix A

This appendix refers to Chapter 3: Literature Review.

Appendix A.1. Factors identified in past literature

The table shows potential technical and firm specific factors that may be related to share return as identified in prior empirical studies. Factors identified to be significantly related to share or company earnings performance are categorised as technical, fundamental, macroeconomic and other. Where applicable, the nature of the observed relationship between the specific factor and return or earnings performance is summarised in column 3.

*Unless stated otherwise, the relationship is of a **positive** nature with earnings or share performance.

Category	Factor	Relationship*	Author(s)
Technical	• Relative strength	Weighted ≥70	Reinganum (1988)
		≥ 70 based on: Top 2/3 companies ranked by annual earnings and sales growth, profit margins (pre- and post- tax), ROE, product quality.	O'Neil (2002)
		Higher 2-year return until 1 year ago→ lower expected 3-month return	Glickman et al. (2001)
	• Change in relative strength	Positive from previous quarter	Reinganum (1988)
	• Daily volatility	Higher over previous quarter	Glickman et al. (2001)
	• Momentum	Lower past 1-year return → lower expected 3-month return	
	• Age	Younger companies	
	• Market capitalisation	Smaller	
		Smaller to be avoided	O'Neil (2002)
	• Share price	Within 15% of 2-year high	Reinganum (1988)
		Within 15% of year's high Buy more securities if price > 2-3% above purchase price Stop buying after increase of 5% Sell if price < 7% below purchase price	O'Neil (2002)
	• Daily trading volume	Increase by at least 50% above average	
		Higher prior 6-month average	Glickman et al. (2001)
	• # Shares outstanding	< 25 million	O'Neil (2002)
		< 20 million	Reinganum (1988)
	• Standard deviation		Tunstall, Stein and Carris (2004)
	• P/B	< 1	Reinganum (1988)
	• Diluted earnings to price	Inconclusive	Glickman et al. (2001)
	• I/B/E/S Long term growth	Larger long term means	
	• Annual earnings growth	Top ranked (industry)	O'Neil (2002)
	• Annual sales growth	Top ranked (industry)	

Fundamental	• Post-tax profit margin	Top ranked (industry)	
	• Pre-tax profit margin	Top ranked (industry)	
		Positive	Reinganum (1988)
	• Quarterly earnings	Acceleration	
	• Quarterly sales	Acceleration	
	• 5-year quarterly earnings growth	Positive	
	• Accruals / Total Assets	Fewer income-increasing accruals	Glickman et al. (2001)
	• Receivables	Lower	
	• Operating cash flow	Higher Do not experience decrease over past year	
	• Quarterly EPS	18-20% higher; accelerated growth	O'Neil (2002)
	• Annual EPS	Annual growth of 25% over past 3 years	
	• Annual pre-tax profit margin	Increasing	
	• Expected earnings	Consensus reasonable increase	
	• ROE	≥17% Top ranked (industry)	
	• % Δ in current ratio • % Δ in quick ratio • % Δ in inventory turnover • Inventory/Total Assets • % Δ in Inventory/Total Assets • % Δ in inventory • % Δ in sales • % Δ in depreciation • Δ DPS • % Δ in (depreciation/plant assets) • Return on opening equity • % Δ in return on opening equity • % Δ in capital expenditure / total assets • % Δ in capital expenditure / total assets, lagged 1 year • Debt-equity • % Δ in Debt/Equity • % Δ in Sales/Total assets • Return on total assets • Return on closing equity • Gross margin ratio • % Δ in pre-tax income / sales • Sales/Total cash • % Δ in Total assets • Cash flow / Debt • Working capital / Total assets • Operating income/Total assets		Ou and Penman (1989)

	• Repayment of LT debt as % of total LT debt • Cash dividend / cash flow		
	• Δ Inventory – Δ Sales • Δ Accounts receivable – Δ Sales • Δ Industry capital expenditure – Δ Firm capital expenditure • Δ Sales – Δ Gross margin • Δ Selling and administrative expenses – Δ Sales • Effective tax rate • Δ Sales – Δ Order backlog • Labour Force • Audit qualification • LIFO vs. FIFO earnings		Lev and Thiagarajan (1993)
	• EBITDA		Liu, Nissim and Thomas (2002)
	• Dividend yield • Price/Cash flow		O'Shaughnessy (2005)
	• Sales/Price		Mukherji and Raines (1996)
	• Payout ratio		Tunstall, Stein and Carris (2004)
Macro Economic	• Inflation • GNP • Business Inventories		Lev and Thiagarajan (1993)
	• Resources index • Financial-Industrial index		Van Rensburg (2002)
Other	• Share buybacks • Management ownership	Yes Yes	O'Neil (2002)
	• Number of institutional owners	Major increase between quarters	Reinganum (1988)
		≥ 25 Must have increased during past few quarters	O'Neil (2002)
	•% Shares owned by institutions	5% - 35%	
		Major increase between quarters	Reinganum (1988)
	• Product quality	Top ranked (industry)	O'Neil (2002)

Appendix B

This appendix refers to Chapter 4: Data and Methodology.

Appendix B.1. Delisted shares and shares with incomplete data

The table shows those securities that have been delisted or restructured with a change in share code during the period January 1994 to May 2011. These securities were included in the dataset to eliminate the potential effect(s) of survivorship bias.

Share code	Name	Last date of available data	Share code	Name	Last date of available data
AHV	African Harvest	2003/03	GNK	Grintek	2005/05
AFI	African Life	2005/12	HCI	Hosken Consolidated Investments	2003/03
AOD	African Rainbow Minerals	2003/03	ISC	Iscor	2007/12
AFL	Aflease Gold and Uranium Resources	2005/12	JCD	JCI	1999/10
AGI	AG Industries	2005/12	JNC	Johnnic Holdings	2003/03
ABI	Amalgamated Beverage Industries	2004/12	KER	Kersaf Investments	2007/12
AMB	AMB Holdings	2003/03	MRT	Marriott Property	2007/12
AIN	Anglovaal Mining	2007/12	MPL	Metboard Properties	2006/08
ARP	Arnold Property Fund	2007/04	MTC	Metro Cash & Carry	2005/04
AVG	Avgold	2004/05	MEL	Mettle	2000/09
AVS	Avis Southern Africa	2004/03	APL	Net 1 Applied Tech Holdings	2004/06
BJM	Barnard Jacobs Mellot Holdings	2003/12	NAC	New African Capital	2007/12
BDS	Bridgestone Firestone Maxiprest	2003/12	NAI	New Africa Invest	2004/12
CPT	Capital Alliance	2005/04	NWL	Nu-World Holdings	2005/12
CXT	Caxton Publishers and Printers	2007/12	PEP	Pepkor	2004/02
CHE	Chemical Services	2003/12	RNG	Randgold & Exploration	2005/09
COM	Comair	2005/12	RBV	Rebserve Holdings	2007/12
CPX	Comparex holdings	2007/12	SGG	Sage Group	2005/09
CRH	Coronation Holdings	2003/03	SFT	Softline	2003/03
CRN	Coronation Holdings N	2003/03	SCE	SA Chrome & Alloys	2007/12
CPA	Corpcapital	2004/02	SIS	Sun International SA	2004/08
DLV	Dorbyl	2003/12	TDH	Tradehold	2003/12
DUR	Durban Roodepoort Deep	2007/12	USV	United Services Technologies	2004/12
ENR	Energy Africa	2003/12	VNF	Venfin	2006/02
GMB	Glenrand M.I.B.	2005/12	WET	Wetherlys Investment Holdings	2003/04
GNN	Grindrod	2004/02			

Appendix B.2. Variables undergoing logarithmic transformation

The table shows those variables to which a natural logarithmic transformation was applied. The transformation was applied to these variables as it would make statistically sense to do so, i.e. to remove the effect of significant positive skewness.

Code before transformation	Variable	Code after transformation
price	Share price	lnp
mv	Market value	mvlog
dps	Dividend per share	dpslog
sps	Sales per share	spslog
bvtm	Book value to market	bvtmlog

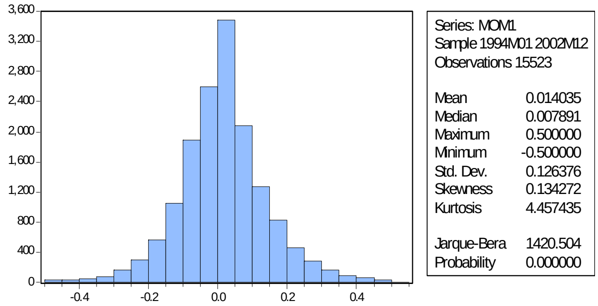
Appendix B.3. List of initial variables considered

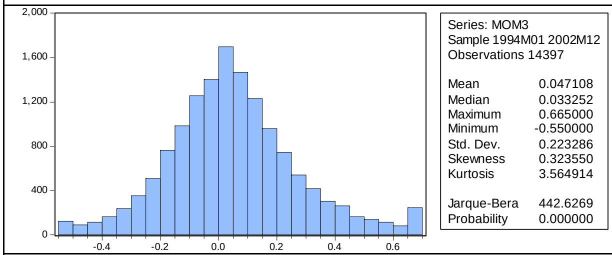
Category	Sub-category	Code	Description	Formula
Value		bvtmlog	Natural log of book value to market	ln[book value to market]
		cftp	Cash flow to price	Cash flow / price
		dy	Dividend yield	dividend / price
		ey	Earnings yield	earnings / price
		stp	Sales to price	sales / price
Growth		eg1	% 1-year earnings forecast revision	$[w_1(eps1 – eps) + w_2(eps2 – eps1)]/eps$ where w_1 = (#days from month t to financial year end)/365 $w_2 = 1 – w_1$ eps = earnings per share eps1 = 1-year forward-looking eps eps 2 = 2-year forward-looking eps
		roe	Return on equity	earnings / equity
		dpslog	Natural log of dividend per share	ln[dividend per share]
		de	Debt to equity	total debt / total equity
		icbtin	Inverse of Interest coverage before tax	1/[interest coverage before tax]
		poutrat	Payout ratio	dividend / earnings
		g	Sustainable growth rate	roe x [1 - poutrat]
		earnrev3m	3-month % change in eps1	$([eps1_t – eps1_{t-3}])/[eps1_{t-3}]$
		c24mdpsp	Change in 24-month dps to price	$([DPS_t – DPS_{t-24}])/[price_t]$
		c24mepsp	Change in 24-month eps to price	$([eps_t – eps_{t-24}])/[price_t]$
		c24mbvtm	Change in 24-month book value to market	$[bvtm_t – bvtm_{t-24}]/bvtm_{t-24}$
Technical	Momentum	mom1	Previous 1-month return	$([\text{Total return}_t – \text{Total return}_{t-1}])/[\text{Total return}_{t-1}]$ Where Total return refers to the capital appreciation and dividend yield of a share.
		mom3	Previous 3-month's return	$([\text{Total return}_t – \text{Total return}_{t-3}])/[\text{Total return}_{t-3}]$
		mom12	Previous 12-month's return	$([\text{Total return}_t – \text{Total return}_{t-12}])/[\text{Total return}_{t-12}]$
		mom36	Previous 36-month's return	$([\text{Total return}_t – \text{Total return}_{t-36}])/[\text{Total return}_{t-36}]$
		mom60	Previous 60-month's return	$([\text{Total return}_t – \text{Total return}_{t-60}])/[\text{Total return}_{t-60}]$
		ma_p	price relative to p-month moving average in price	$1/t(price_1 + ... + price_t)$
		$OBOS_pmMA$ where p = 2 to 12	Overbought – oversold with p-month moving average of price	equal to 1 if $price_t$ > p-month moving average in price, 0 otherwise. p = 2 to 12. $[price_t – ma_k]/ma_k$ for k = 2 to 12.
		pricerel12	Comparison of price to 12-month high	$price_t/max[price_{t-12\ to\ t}]$
	Size	mvlog	Log of market value	ln[market value]
		lnp	Natural log of price	ln[price]
		eps	Earnings per share	earnings / # shares in issue
		eps1	1-year forward-looking eps	$[eps]_{t+12}$
		eps2	2-year forward-looking eps	$[eps]_{t+24}$
		logassets	Natural log of total assets	ln[assets]
		equity	Total equity	assets – total liabilities
		spslog	Natural log of sales per share	ln[sales per share]
	Volatility	retvar12	Variance of monthly returns over previous12 months	Var[prior 12 monthly returns]
		beta	Beta	CAPM Beta, where beta is based on 3 year monthly returns.

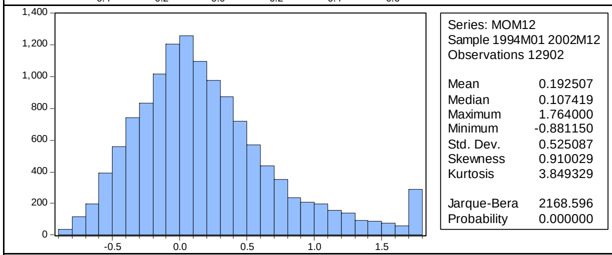
Appendix B.4. Histograms and descriptive statistics of variables

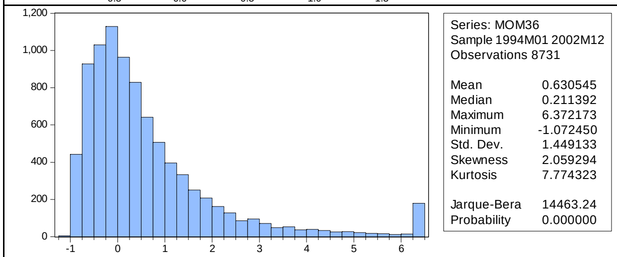
Histograms of all variables (for both subsamples) after the winzorising and transformation (where applicable) process are reported here. Visual inspection of the histograms shows that the winzorising process eliminated extreme outliers, while the natural logarithmic transformation process (where applicable) resulted in more normally distributed variables. Positively skew distributions are evident for those variables that were not transformed.

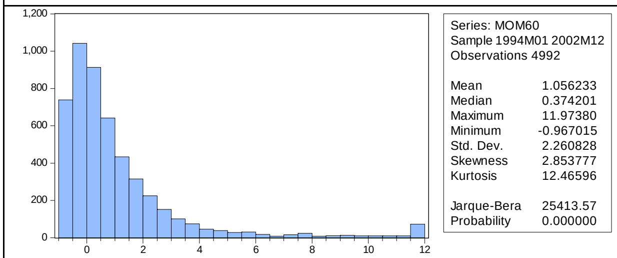
Subsample: 1994 - 2002



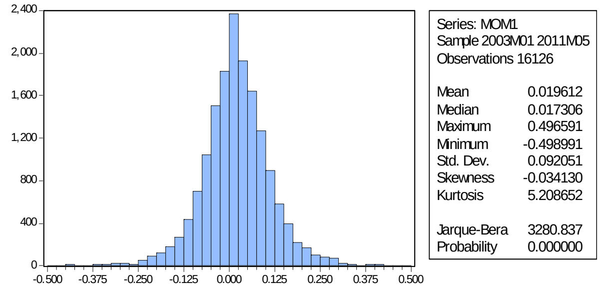


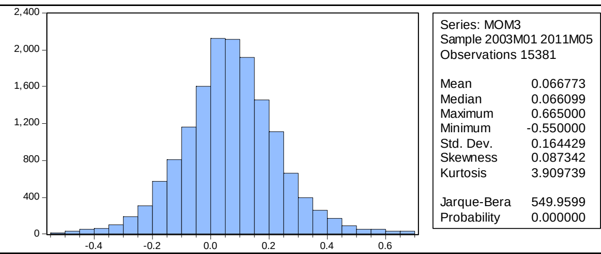


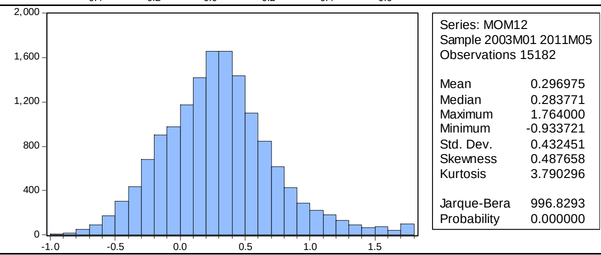


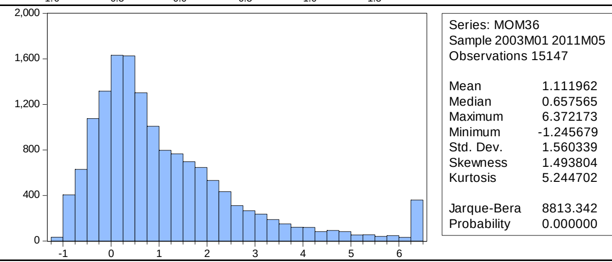


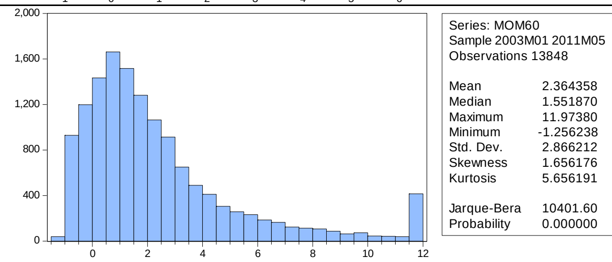
Subsample: 2003 – 2011

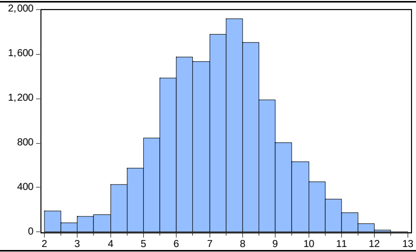




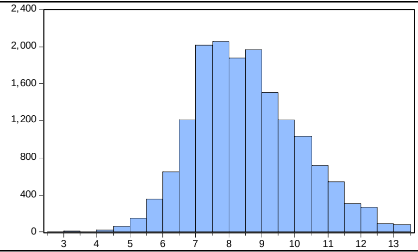




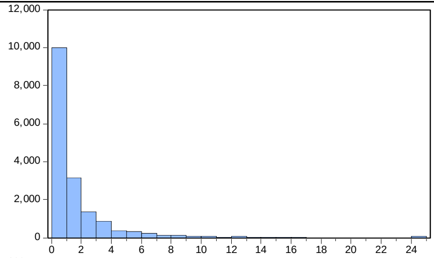




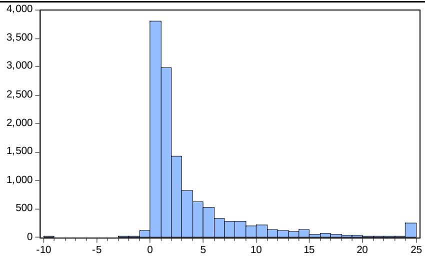
Series: MVLOG	
Sample 1994M01 2002M12	
Observations 15975	
Mean	7.245130
Median	7.304966
Maximum	12.57549
Minimum	2.414000
Std. Dev.	1.783429
Skewness	-0.118200
Kurtosis	3.053176
Jarque-Bera	39.08079
Probability	0.000000



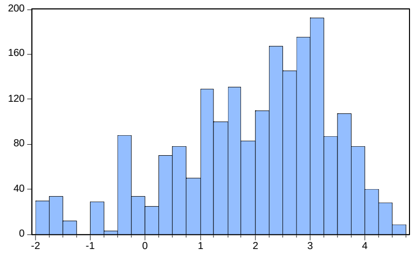
Series: MVLOG	
Sample 2003M01 2011M05	
Observations 16161	
Mean	8.553325
Median	8.423770
Maximum	13.38700
Minimum	2.985177
Std. Dev.	1.597584
Skewness	0.367901
Kurtosis	2.961362
Jarque-Bera	365.5742
Probability	0.000000



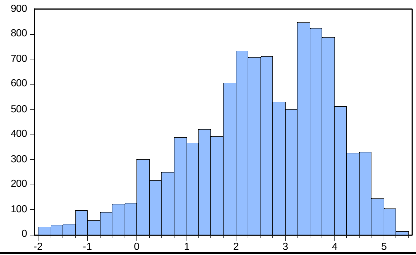
Series: EPS	
Sample 1994M01 2002M12	
Observations 17150	
Mean	1.756712
Median	0.760000
Maximum	24.03633
Minimum	0.000000
Std. Dev.	3.065694
Skewness	4.135060
Kurtosis	24.62671
Jarque-Bera	383094.8
Probability	0.000000



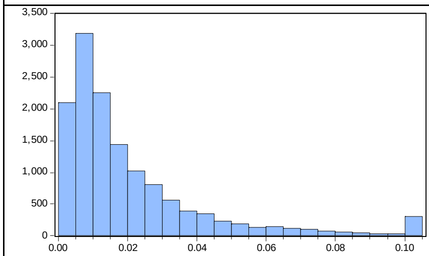
Series: EPS	
Sample 2003M01 2011M05	
Observations 12789	
Mean	3.700317
Median	1.700000
Maximum	24.03633
Minimum	-10.00000
Std. Dev.	5.020547
Skewness	2.232942
Kurtosis	8.304198
Jarque-Bera	25619.90
Probability	0.000000



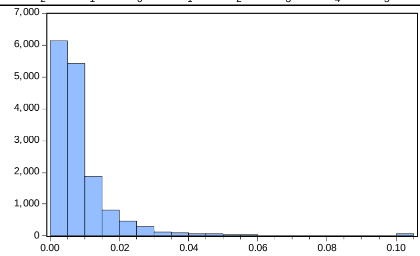
Series: SPSLOG	
Sample 1994M01 2002M12	
Observations 2034	
Mean	1.967678
Median	2.262700
Maximum	4.541348
Minimum	-2.000000
Std. Dev.	1.440448
Skewness	-0.681681
Kurtosis	2.977289
Jarque-Bera	157.5733
Probability	0.000000



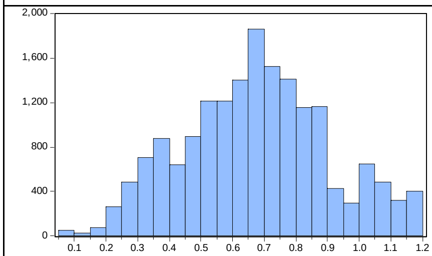
Series: SPSLOG	
Sample 2003M01 2011M05	
Observations 10637	
Mean	2.484470
Median	2.606062
Maximum	5.326797
Minimum	-2.000000
Std. Dev.	1.441201
Skewness	-0.556807
Kurtosis	2.852256
Jarque-Bera	559.3124
Probability	0.000000



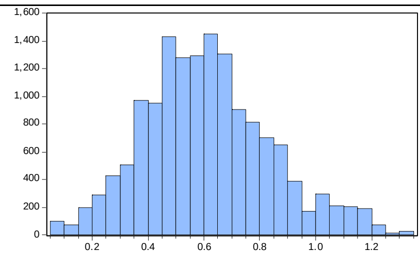
Series: RETVAR12	
Sample 1994M01 2002M12	
Observations 13589	
Mean	0.020718
Median	0.013133
Maximum	0.100000
Minimum	0.000000
Std. Dev.	0.021226
Skewness	2.043602
Kurtosis	7.153794
Jarque-Bera	19228.00
Probability	0.000000



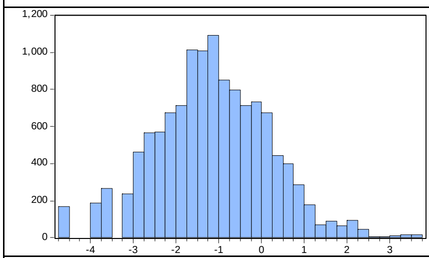
Series: RETVAR12	
Sample 2003M01 2011M05	
Observations 15578	
Mean	0.009243
Median	0.006167
Maximum	0.100000
Minimum	0.000114
Std. Dev.	0.011185
Skewness	4.593963
Kurtosis	31.38712
Jarque-Bera	577844.1
Probability	0.000000



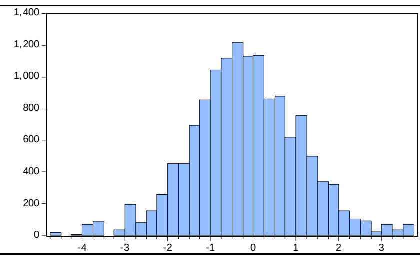
Series: BETA	
Sample 1994M01 2002M12	
Observations 17544	
Mean	0.672426
Median	0.682000
Maximum	1.183000
Minimum	0.080000
Std. Dev.	0.229881
Skewness	0.077119
Kurtosis	2.575640
Jarque-Bera	149.0293
Probability	0.000000



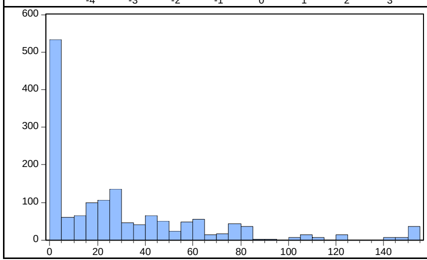
Series: BETA	
Sample 2003M01 2011M05	
Observations 14921	
Mean	0.611993
Median	0.594000
Maximum	1.300000
Minimum	0.067000
Std. Dev.	0.227879
Skewness	0.397177
Kurtosis	3.023571
Jarque-Bera	392.6421
Probability	0.000000



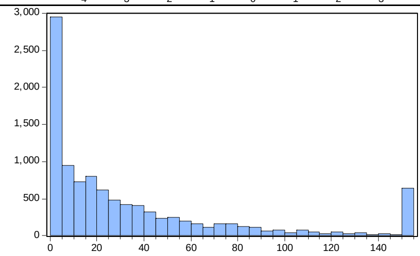
Series: DPSLOG	
Sample 1994M01 2002M12	
Observations 12458	
Mean	-1.141529
Median	-1.171183
Maximum	3.516000
Minimum	-4.605170
Std. Dev.	1.323916
Skewness	0.066745
Kurtosis	3.289114
Jarque-Bera	52.63853
Probability	0.000000



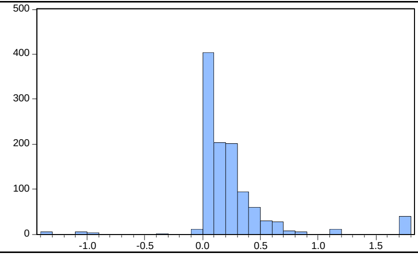
Series: DPSLOG	
Sample 2003M01 2011M05	
Observations 13839	
Mean	-0.181979
Median	-0.223144
Maximum	3.516000
Minimum	-4.605170
Std. Dev.	1.268990
Skewness	-0.020596
Kurtosis	3.421169
Jarque-Bera	103.2621
Probability	0.000000



Series: DE	
Sample 1994M01 2002M12	
Observations 1529	
Mean	29.81745
Median	20.54200
Maximum	150.0000
Minimum	0.000000
Std. Dev.	34.89211
Skewness	1.612064
Kurtosis	5.506116
Jarque-Bera	1062.376
Probability	0.000000

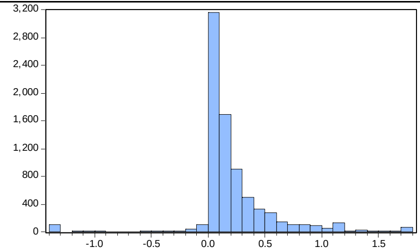


Series: DE	
Sample 2003M01 2011M05	
Observations 10354	
Mean	34.49011
Median	18.89790
Maximum	150.0000
Minimum	0.000000
Std. Dev.	42.08989
Skewness	1.569455
Kurtosis	4.569078
Jarque-Bera	5312.793
Probability	0.000000



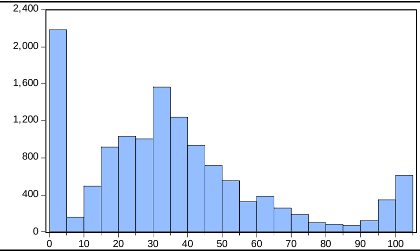
Series: ICBTIN
Sample 1994M01 2002M12
Observations 1116

Mean	0.241703
Median	0.159594
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.383285
Skewness	1.818009
Kurtosis	11.35555
Jarque-Bera	3861.168
Probability	0.000000



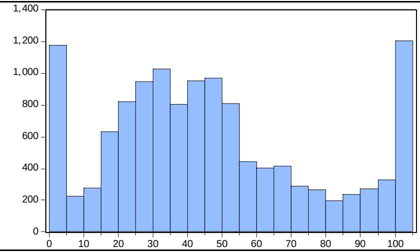
Series: ICBTIN
Sample 2003M01 2011M05
Observations 8080

Mean	0.205835
Median	0.125225
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.378244
Skewness	0.322786
Kurtosis	9.369533
Jarque-Bera	13799.20
Probability	0.000000



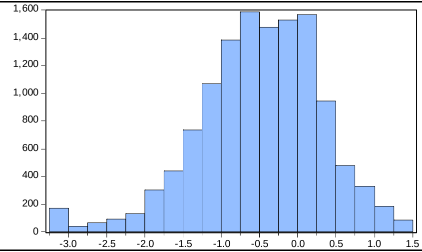
Series: POUTRAT
Sample 1994M01 2002M12
Observations 13303

Mean	35.83182
Median	32.79653
Maximum	100.0000
Minimum	0.000000
Std. Dev.	27.19952
Skewness	0.787824
Kurtosis	3.196797
Jarque-Bera	1397.587
Probability	0.000000



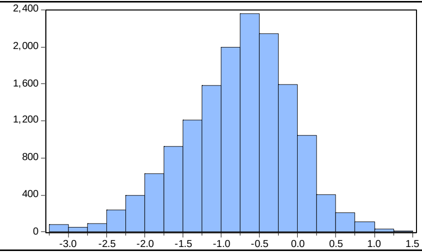
Series: POUTRAT
Sample 2003M01 2011M05
Observations 12689

Mean	46.36473
Median	42.12773
Maximum	100.0000
Minimum	0.000000
Std. Dev.	29.66921
Skewness	0.388365
Kurtosis	2.258359
Jarque-Bera	609.7808
Probability	0.000000



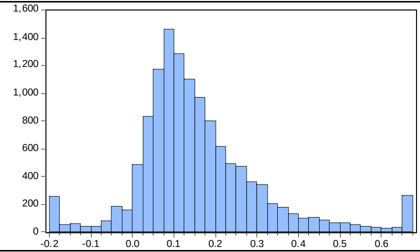
Series: BVTMLOG
Sample 1994M01 2002M12
Observations 12625

Mean	-0.502072
Median	-0.451076
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.812571
Skewness	-0.580879
Kurtosis	3.836306
Jarque-Bera	1077.908
Probability	0.000000



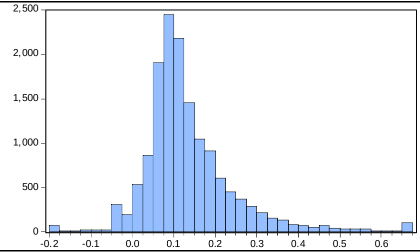
Series: BVTMLOG
Sample 2003M01 2011M05
Observations 15140

Mean	-0.785217
Median	-0.708036
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.712659
Skewness	-0.426552
Kurtosis	3.340462
Jarque-Bera	532.2348
Probability	0.000000



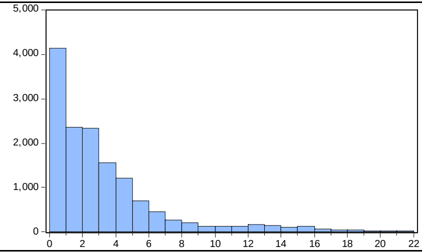
Series: CFTP
Sample 1994M01 2002M12
Observations 12673

Mean	0.157926
Median	0.130378
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.151889
Skewness	0.962911
Kurtosis	5.087217
Jarque-Bera	4258.796
Probability	0.000000



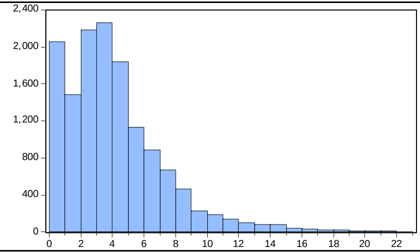
Series: CFTP
Sample 2003M01 2011M05
Observations 14849

Mean	0.134887
Median	0.110742
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.113259
Skewness	1.534422
Kurtosis	7.659079
Jarque-Bera	19257.19
Probability	0.000000



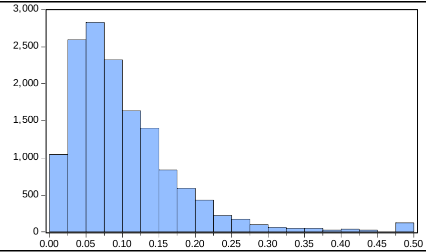
Series: DY
Sample 1994M01 2002M12
Observations 14375

Mean	3.270170
Median	2.240000
Maximum	21.98000
Minimum	0.000000
Std. Dev.	3.749957
Skewness	2.006750
Kurtosis	7.422244
Jarque-Bera	21361.50
Probability	0.000000



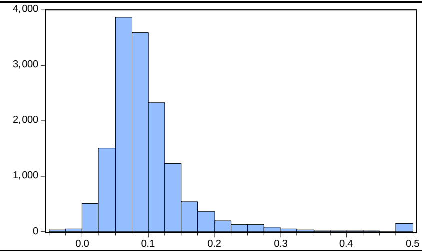
Series: DY
Sample 2003M01 2011M05
Observations 13957

Mean	4.081458
Median	3.512500
Maximum	22.00000
Minimum	0.000000
Std. Dev.	3.223999
Skewness	1.428708
Kurtosis	6.309396
Jarque-Bera	11117.29
Probability	0.000000



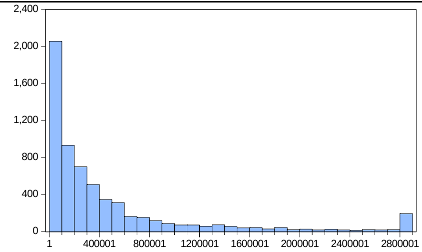
Series: EY
Sample 1994M01 2002M12
Observations 14622

Mean	0.102055
Median	0.083333
Maximum	0.479000
Minimum	4.42e-05
Std. Dev.	0.077100
Skewness	2.010522
Kurtosis	8.830822
Jarque-Bera	30564.41
Probability	0.000000



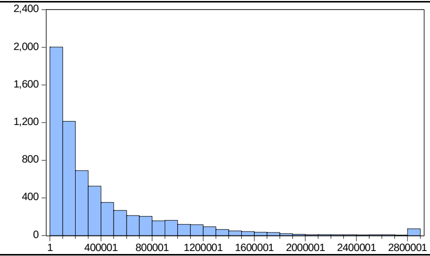
Series: EY
Sample 2003M01 2011M05
Observations 14907

Mean	0.098252
Median	0.084000
Maximum	0.479000
Minimum	-0.050000
Std. Dev.	0.067397
Skewness	2.764831
Kurtosis	14.31442
Jarque-Bera	98506.29
Probability	0.000000



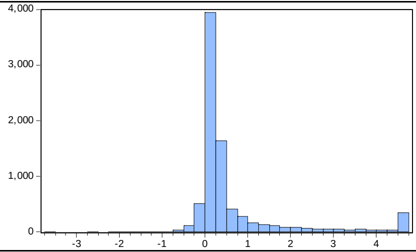
Series: PTSINV
Sample 1994M01 2002M12
Observations 6255

Mean	477121.5
Median	215761.7
Maximum	2860279.
Minimum	11668.61
Std. Dev.	667103.0
Skewness	2.239818
Kurtosis	7.540932
Jarque-Bera	10604.10
Probability	0.000000



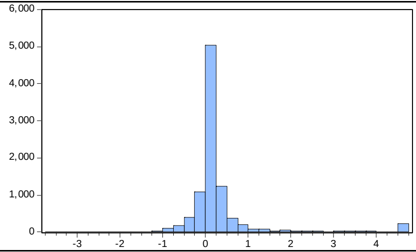
Series: PTSINV
Sample 2003M01 2011M05
Observations 6498

Mean	405509.8
Median	204521.9
Maximum	2860279.
Minimum	11668.61
Std. Dev.	507869.0
Skewness	2.384965
Kurtosis	9.837827
Jarque-Bera	18819.32
Probability	0.000000



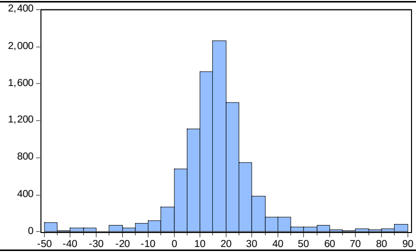
Series: EG1
Sample 1994M01 2002M12
Observations 8306

Mean	0.639229
Median	0.225210
Maximum	4.700000
Minimum	-3.610000
Std. Dev.	1.145509
Skewness	2.473662
Kurtosis	8.572714
Jarque-Bera	19218.41
Probability	0.000000



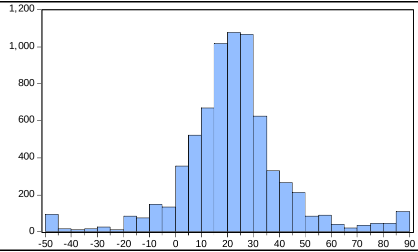
Series: EG1
Sample 2003M01 2011M05
Observations 9384

Mean	0.316696
Median	0.148696
Maximum	4.700000
Minimum	-3.610000
Std. Dev.	0.914744
Skewness	3.224795
Kurtosis	16.26597
Jarque-Bera	85075.07
Probability	0.000000



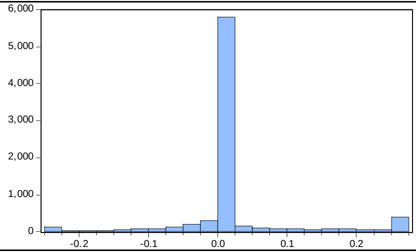
Series: ROE
Sample 1994M01 2002M12
Observations 9603

Mean	16.35199
Median	16.15000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	17.02662
Skewness	0.262656
Kurtosis	8.197389
Jarque-Bera	10918.93
Probability	0.000000



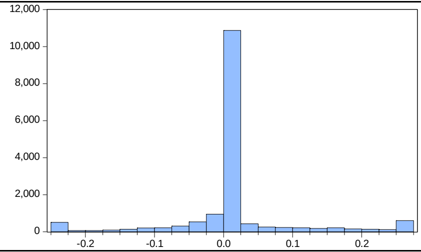
Series: ROE
Sample 2003M01 2011M05
Observations 7236

Mean	22.30562
Median	21.92000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	20.37933
Skewness	0.047064
Kurtosis	5.614994
Jarque-Bera	2064.387
Probability	0.000000



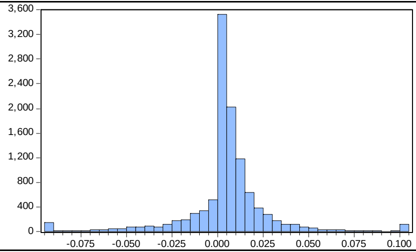
Series: EARNREV3M
Sample 1994M01 2002M12
Observations 8064

Mean	0.013671
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.082828
Skewness	1.048647
Kurtosis	7.145301
Jarque-Bera	7251.606
Probability	0.000000



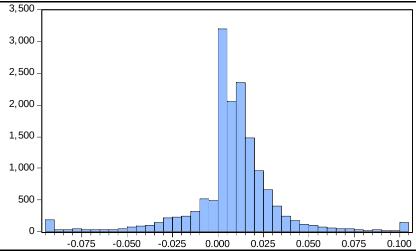
Series: EARNREV3M
Sample 2003M01 2011M05
Observations 16515

Mean	0.007159
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.085750
Skewness	0.418272
Kurtosis	6.715810
Jarque-Bera	9982.666
Probability	0.000000



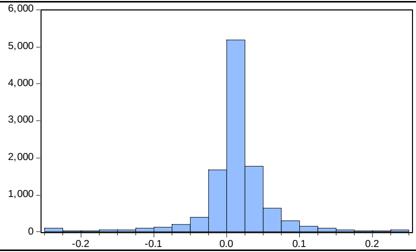
Series: C24MDPSP
Sample 1994M01 2002M12
Observations 11283

Mean	0.004606
Median	0.004453
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.024798
Skewness	-0.201874
Kurtosis	8.649070
Jarque-Bera	15079.26
Probability	0.000000



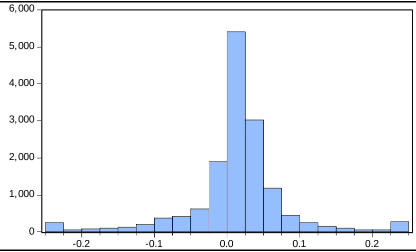
Series: C24MDPSP
Sample 2003M01 2011M05
Observations 15169

Mean	0.007819
Median	0.008589
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.025593
Skewness	-0.399867
Kurtosis	7.867140
Jarque-Bera	15376.70
Probability	0.000000



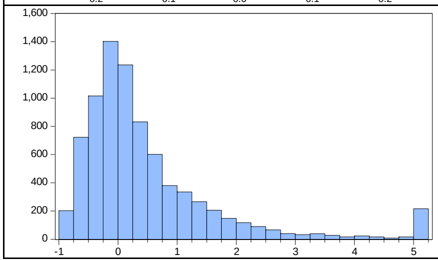
Series: C24MEPSP
Sample 1994M01 2002M12
Observations 11099

Mean	0.010846
Median	0.005340
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.052921
Skewness	-0.625474
Kurtosis	10.27932
Jarque-Bera	25228.67
Probability	0.000000



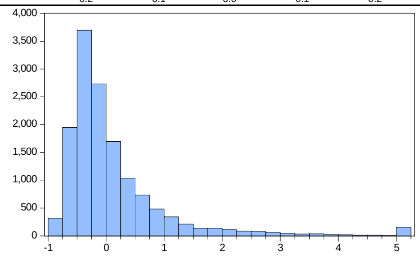
Series: C24MEPSP
Sample 2003M01 2011M05
Observations 15108

Mean	0.012495
Median	0.014408
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.068989
Skewness	-0.270962
Kurtosis	7.208097
Jarque-Bera	11332.11
Probability	0.000000



Series: C24MBVTM
Sample 1994M01 2002M12
Observations 8064

Mean	0.479394
Median	0.127602
Maximum	5.000000
Minimum	-0.955022
Std. Dev.	1.182873
Skewness	2.108544
Kurtosis	7.899152
Jarque-Bera	14039.93
Probability	0.000000



Series: C24MBVTM
Sample 2003M01 2011M05
Observations 14158

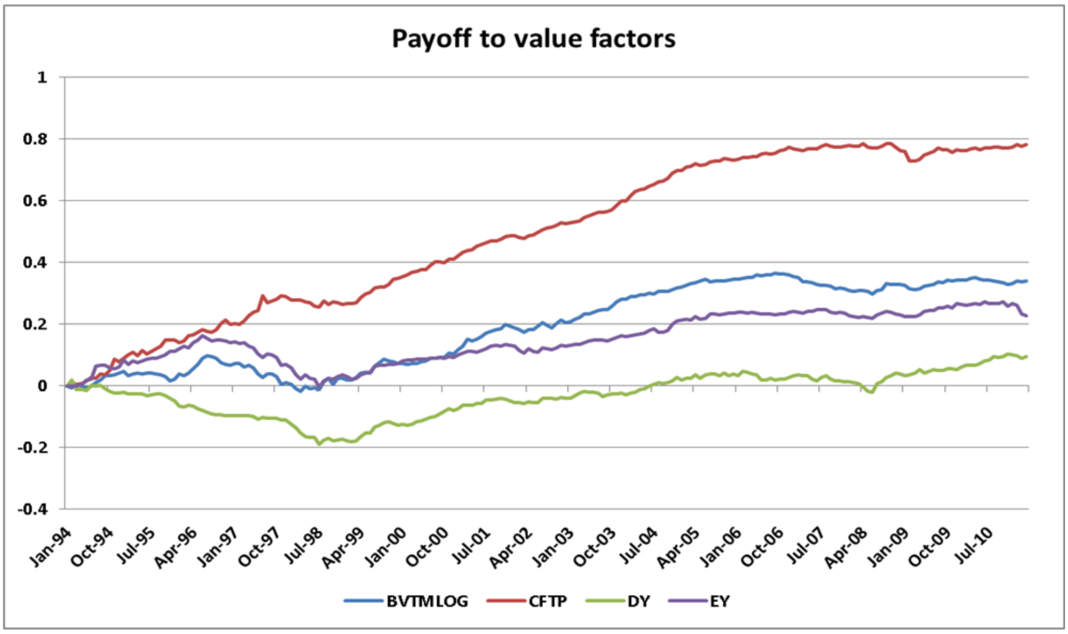
Mean	0.119712
Median	-0.165114
Maximum	5.000000
Minimum	-1.000000
Std. Dev.	0.935461
Skewness	2.788952
Kurtosis	12.68072
Jarque-Bera	73638.95
Probability	0.000000

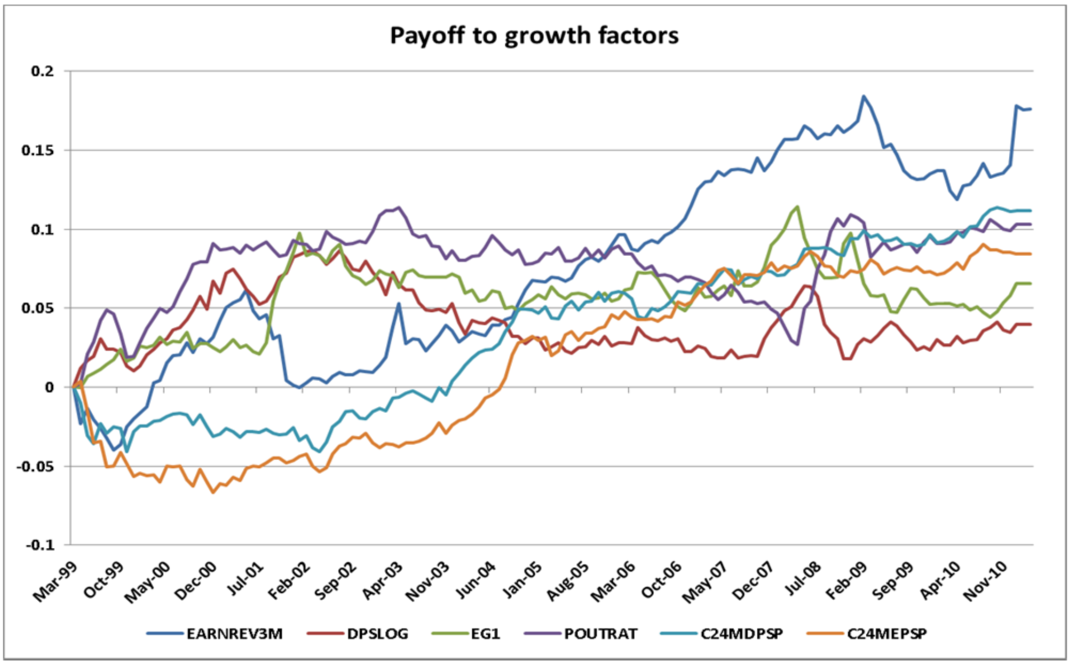
Appendix C

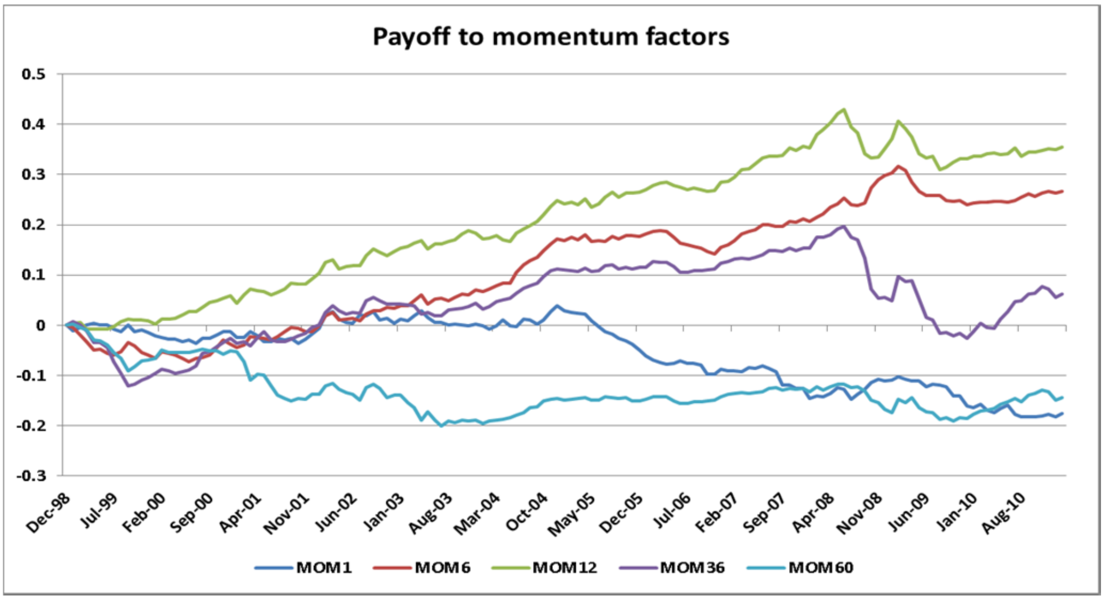
This appendix refers to Chapter 5: A univariate regression approach to identify firm-specific factors that explain the cross-section of returns on the JSE

Appendix C.1: Time series graphs of payoff to factors

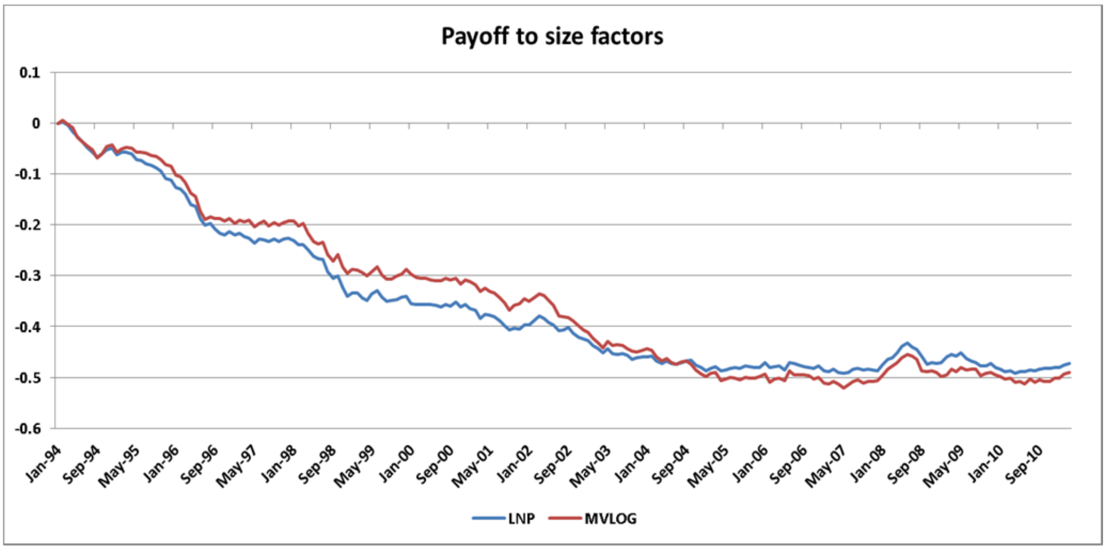
The payoff to the most significant factors as identified in Chapter 5 (Section 5.3.1) for each category is illustrated graphically below. Cumulative regression coefficients are used to illustrate the associated payoff over time. Payoffs are presented over the period January 1994 through May 2011 (or part thereof, depending on the common period available for all factors presented within a specific category). A logarithmic scale is used.







Payoff to momentum factors
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
Dec-98
Jul-99
Feb-00
Sep-00
Apr-01
Nov-01
Jun-02
Jan-03
Aug-03
Mar-04
Oct-04
May-05
Dec-05
Jul-06
Feb-07
Sep-07
Apr-08
Nov-08
Jun-09
Jan-10
Aug-10
MOM1
MOM6
MOM12
MOM36
MOM60



Payoff to size factors
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
Jan-94
Sep-94
May-95
Jan-96
Sep-96
May-97
Jan-98
Sep-98
May-99
Jan-00
Sep-00
May-01
Jan-02
Sep-02
May-03
Jan-04
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Jan-06
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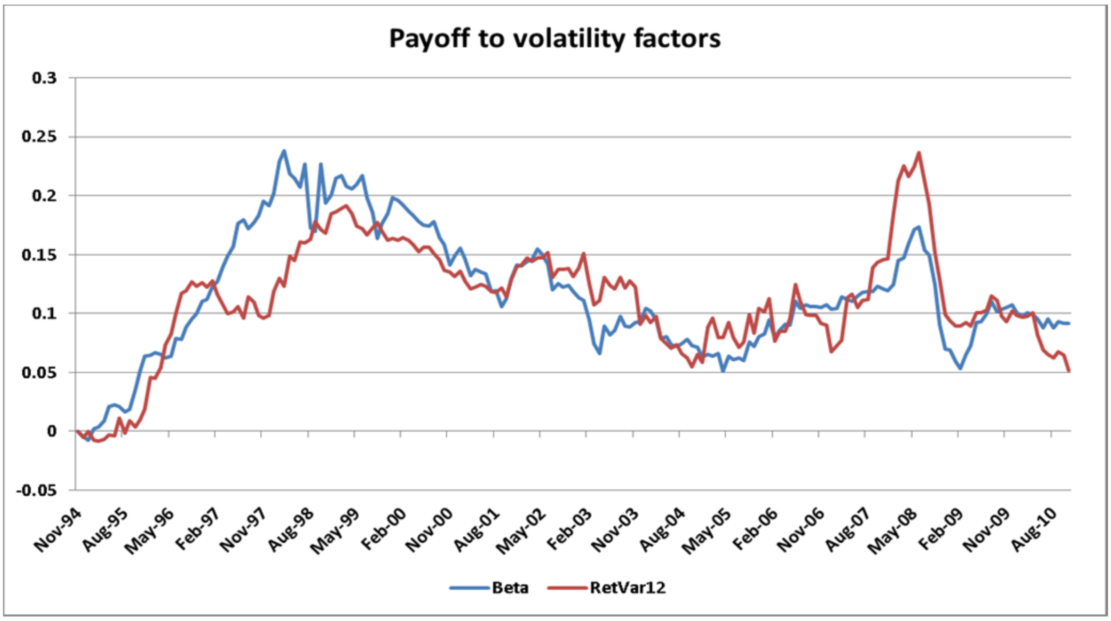
May-07
Jan-08
Sep-08
May-09
Jan-10
Sep-10
LNP
MVLOG



Payoff to volatility factors
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
Nov-94
Aug-95
May-96
Feb-97
Nov-97
Aug-98
May-99
Feb-00
Nov-00
Aug-01
May-02
Feb-03
Nov-03
Aug-04
May-05
Feb-06
Nov-06
Aug-07
May-08
Feb-09
Nov-09
Aug-10
Beta
RetVar12

Appendix C.2: Monthly cross-sectional regression results when liquidity filter is set to the 3rd decile based on market capitalisation value. Average number of shares included is 41 per month.

A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns and a liquidity filter set equal to the 3rd decile based on market cap. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional slope coefficients is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.017	**4.714**	OBOS3MMA	0.008	0.970
MOM12	0.012	**3.099**	EG1	0.001	0.905
OBOS12MMA	0.036	**2.885**	MA3	-0.006	-0.850
OBOS11MMA	0.034	**2.842**	MA8	0.005	0.794
OBOS10MMA	0.032	**2.763**	DPSLOG	0.002	0.758
OBOS9MMA	0.029	**2.628**	MA5	0.004	0.621
C24MEPSP	0.016	**2.507**	OBOS2MMA	0.005	0.610
OBOS8MMA	0.026	**2.424**	MA6	0.004	0.569
BETA	0.008	**2.288**	EY	0.004	0.562
OBOS7MMA	0.023	**2.224**	MOM3	0.002	0.507
MOM6	0.010	2.009	MA7	0.003	0.477
PRICEREL12	0.010	2.009	MA9	0.003	0.477
OBOS6MMA	0.020	1.937	LNP	-0.001	-0.473
MOM36	0.008	1.936	ROE	0.002	0.440
BVTMLOG	0.005	1.912	RETVAR12	-0.003	-0.439
C24MBVTM	-0.008	-1.875	SPSLOG	0.002	0.323
MA11	0.011	1.748	MVLOG	0.001	0.300
MA12	0.010	1.688	MOM60	-0.002	-0.272
OBOS5MMA	0.016	1.645	DE	-0.001	-0.229
MA2	-0.008	-1.577	MA4	0.001	0.218
EPS	0.004	1.534	C24MDPSP	0.001	0.208
EARNREV3M	-0.029	-1.499	MOM1	0.001	0.175
MA10	0.007	1.221	POUTRAT	0.000	0.053
OBOS4MMA	0.011	1.160	DY	0.000	-0.036

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.006	**2.765**	MA3	-0.004	-0.874
BVTMLOG	0.004	**2.604**	LNP	-0.003	-0.861
EY	0.008	**2.035**	ROE	0.002	0.839
EPS	0.002	1.930	ICBTIN	-0.008	-0.838
MA11	0.010	1.844	OBOS10MMA	0.009	0.828
OBOS2MMA	-0.011	-1.829	OBOS11MMA	0.008	0.794
C24MBVTM	0.012	1.786	OBOS12MMA	0.008	0.767
MA12	0.010	1.722	BETA	0.002	0.716
MOM1	-0.005	-1.718	OBOS9MMA	0.007	0.713
MA10	0.009	1.697	OBOS8MMA	0.007	0.676
DPSLOG	-0.003	-1.504	OBOS5MMA	-0.005	-0.595
OBOS3MMA	-0.011	-1.468	OBOS7MMA	0.004	0.473
MA8	0.007	1.412	MOM60	-0.001	-0.450
C24MEPSP	0.002	1.326	MVLOG	-0.001	-0.430
MA5	0.006	1.223	MOM3	0.001	0.405
OBOS4MMA	-0.009	-1.136	RETVAR12	-0.003	-0.376
MA6	0.006	1.121	MOM12	0.001	0.370
MOM36	-0.004	-1.090	MOM6	0.002	0.356
MA2	-0.004	-1.048	PRICEREL12	0.002	0.287
MA7	0.005	0.987	SPSLOG	0.000	0.226
MA9	0.005	0.987	MA4	0.001	0.131
POUTRAT	-0.001	-0.901	STP	0.000	-0.096
DY	0.002	0.900	OBOS6MMA	0.000	-0.055
EG1	0.001	0.894	DE	0.000	0.011
C24MDPSP	0.002	0.889	EARNREV3M	0.000	0.003

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.012	**5.401**	C24MBVTM	0.005	1.121
BVTMLOG	0.005	**2.933**	MA6	0.005	1.100
C24MEPSP	0.009	**2.748**	MA7	0.004	0.950
OBOS12MMA	0.021	**2.579**	MA9	0.004	0.950
OBOS11MMA	0.021	**2.569**	LNP	-0.002	-0.934
OBOS10MMA	0.020	**2.530**	MOM1	-0.002	-0.918
MA11	0.010	**2.527**	ICBTIN	-0.008	-0.838
MA12	0.010	**2.413**	OBOS5MMA	0.005	0.764
MOM12	0.007	**2.398**	ROE	0.002	0.726
OBOS9MMA	0.018	**2.355**	OBOS2MMA	-0.003	-0.693
BETA	0.005	**2.272**	MOM3	0.002	0.650
OBOS8MMA	0.016	**2.185**	RETVAR12	-0.003	-0.566
MA10	0.008	**2.030**	C24MDPSP	0.001	0.550
EPS	0.003	2.005	MOM60	-0.001	-0.517
OBOS7MMA	0.013	1.902	DPSLOG	-0.001	-0.415
MA2	-0.006	-1.896	MOM36	0.001	0.353
MOM6	0.006	1.628	SPSLOG	0.001	0.351
PRICEREL12	0.006	1.571	POUTRAT	-0.001	-0.312
EY	0.006	1.479	OBOS3MMA	-0.002	-0.307
MA8	0.006	1.471	MA4	0.001	0.255
EARNREV3M	-0.009	-1.433	DY	0.001	0.244
OBOS6MMA	0.009	1.334	DE	0.000	-0.108
EG1	0.001	1.271	STP	0.000	-0.096
MA3	-0.005	-1.188	OBOS4MMA	0.000	0.048
MA5	0.005	1.182	MVLOG	0.000	-0.005

Appendix C.3: Monthly cross-sectional regression results when liquidity filter is set to the 4th decile based on market capitalisation value. Average number of shares included is 53 per month.

A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns and a liquidity filter set equal to the 4th decile based on market cap. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional slope coefficients is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.018	**5.065**	OBOS5MMA	0.007	0.786
MOM12	0.011	**2.955**	MA3	-0.005	-0.774
OBOS12MMA	0.027	**2.395**	MOM60	-0.003	-0.708
BVTMLOG	0.006	**2.229**	SPSLOG	-0.003	-0.698
BETA	0.007	**2.224**	MA8	0.003	0.554
OBOS11MMA	0.024	**2.196**	MA6	0.003	0.502
MOM6	0.010	**2.144**	MA5	0.003	0.431
C24MEPSP	0.012	**2.044**	ROE	0.002	0.409
OBOS10MMA	0.021	**2.023**	MVLOG	-0.002	-0.400
OBOS9MMA	0.019	1.908	DPSLOG	-0.001	-0.380
C24MBVTM	-0.006	-1.835	MOM3	0.001	0.351
OBOS8MMA	0.017	1.731	MA7	0.002	0.332
PRICEREL12	0.008	1.672	MA9	0.002	0.332
LNP	-0.004	-1.665	EY	0.002	0.294
MA12	0.010	1.656	OBOS4MMA	0.002	0.235
MOM36	0.007	1.651	RETVAR12	-0.001	-0.217
EARNREV3M	-0.033	-1.567	C24MDPSP	0.001	0.213
MA11	0.009	1.563	MA4	-0.001	-0.191
OBOS7MMA	0.014	1.536	OBOS2MMA	-0.001	-0.139
EPS	0.003	1.366	DY	0.001	0.133
OBOS6MMA	0.010	1.160	POUTRAT	0.000	-0.121
EG1	0.002	1.024	ICBTIN	-0.003	-0.103
MA2	-0.005	-0.992	MOM1	0.000	0.090
MA10	0.005	0.939	OBOS3MMA	0.000	-0.025
DE	-0.004	-0.929	STP	0.000	0.003

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
MOM1	-0.007	**-2.768**	MOM60	-0.003	-0.914
OBOS2MMA	-0.013	**-2.553**	MA5	0.004	0.884
CFTP	0.005	**2.533**	OBOS12MMA	0.008	0.745
BVTMLOG	0.003	**2.333**	OBOS11MMA	0.007	0.729
OBOS3MMA	-0.014	**-2.136**	OBOS10MMA	0.007	0.720
EY	0.006	1.957	EARNREV3M	0.002	0.693
MA11	0.011	1.941	OBOS9MMA	0.005	0.569
EPS	0.002	1.904	STP	0.001	0.545
DPSLOG	-0.003	-1.849	ICBTIN	0.001	0.500
MA8	0.008	1.693	MVLOG	-0.001	-0.494
MA10	0.009	1.692	RETVAR12	-0.004	-0.487
MA12	0.010	1.627	OBOS8MMA	0.004	0.463
OBOS4MMA	-0.012	-1.582	C24MEPSP	0.001	0.405
MOM6	0.005	1.516	EG1	0.001	0.384
MOM36	-0.006	-1.411	PRICEREL12	0.002	0.377
C24MDPSP	0.003	1.408	OBOS6MMA	-0.003	-0.352
C24MBVTM	0.007	1.385	MOM3	-0.001	-0.314
MA3	-0.005	-1.210	MA4	-0.001	-0.248
MA2	-0.004	-1.170	MOM12	0.001	0.235
MA6	0.006	1.157	OBOS7MMA	0.002	0.216
MA7	0.005	1.072	BETA	0.001	0.200
MA9	0.005	1.072	SPSLOG	0.000	-0.136
LNP	-0.003	-1.063	DE	0.000	0.134
DY	0.002	0.986	ROE	0.000	-0.048
OBOS5MMA	-0.007	-0.935	POUTRAT	0.000	0.022

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.012	**5.546**	OBOS7MMA	0.008	1.268
BVTMLOG	0.005	**3.062**	MOM60	-0.003	-1.159
MOM6	0.007	**2.622**	EY	0.004	1.126
MA11	0.010	**2.461**	MA6	0.004	1.077
MA12	0.010	**2.328**	EG1	0.001	1.025
OBOS12MMA	0.017	**2.255**	OBOS4MMA	-0.005	-0.904
OBOS11MMA	0.016	**2.107**	MA7	0.004	0.888
MOM12	0.006	**2.101**	MA9	0.004	0.888
C24MEPSP	0.006	**2.060**	MA5	0.003	0.856
OBOS10MMA	0.014	1.972	C24MDPSP	0.002	0.797
LNP	-0.004	-1.938	OBOS6MMA	0.004	0.612
BETA	0.004	1.873	MVLOG	-0.001	-0.610
EPS	0.003	1.843	C24MBVTM	0.002	0.572
MA10	0.007	1.829	RETVAR12	-0.002	-0.524
OBOS9MMA	0.012	1.781	SPSLOG	-0.001	-0.470
OBOS2MMA	-0.007	-1.615	DE	-0.001	-0.460
MOM1	-0.003	-1.582	DY	0.001	0.431
OBOS8MMA	0.011	1.577	ROE	0.001	0.373
DPSLOG	-0.002	-1.514	STP	0.001	0.362
MA2	-0.004	-1.482	ICBTIN	0.001	0.340
MA8	0.006	1.468	MA4	-0.001	-0.297
OBOS3MMA	-0.007	-1.445	MOM36	0.000	-0.168
PRICEREL12	0.005	1.425	POUTRAT	0.000	-0.102
EARNREV3M	-0.010	-1.339	OBOS5MMA	0.000	-0.058
MA3	-0.005	-1.303	MOM3	0.000	0.049

Appendix C.4: Monthly cross-sectional regression results when liquidity filter is set to the 6th decile based on market capitalisation value. Average number of shares included is 79 per month.

A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns and a liquidity filter set equal to the 6th decile based on market cap. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional slope coefficients is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.013	**5.327**	DY	0.007	1.220
MOM12	0.011	**3.337**	EPS	0.003	1.160
OBOS12MMA	0.026	**2.499**	MA10	0.007	1.144
BETA	0.007	**2.371**	MOM3	0.003	1.079
OBOS11MMA	0.023	**2.286**	MA6	0.007	1.075
MOM6	0.009	**2.206**	OBOS4MMA	0.006	0.943
LNP	-0.005	**-2.156**	MA5	0.005	0.931
OBOS9MMA	0.020	**2.152**	RETVAR12	-0.004	-0.892
OBOS10MMA	0.021	**2.106**	OBOS3MMA	0.005	0.809
OBOS8MMA	0.018	**2.090**	MA8	0.005	0.809
OBOS7MMA	0.017	1.990	MA2	-0.003	-0.731
POUTRAT	0.006	1.847	MA7	0.004	0.675
EG1	0.004	1.834	MA9	0.004	0.675
MA12	0.010	1.829	MA4	0.003	0.517
C24MEPSP	0.009	1.794	C24MDPSP	-0.002	-0.502
MA11	0.011	1.789	OBOS2MMA	0.003	0.496
OBOS6MMA	0.013	1.681	MOM1	0.001	0.481
C24MBVTM	-0.005	-1.676	MVLOG	-0.001	-0.392
PRICEREL12	0.008	1.675	EY	-0.002	-0.344
DPSLOG	0.005	1.597	MOM60	-0.002	-0.199
EARNREV3M	-0.036	-1.594	ROE	0.001	0.153
OBOS5MMA	0.011	1.500	ROE	0.001	0.153
BVTMLOG	0.003	1.409	MA3	-0.001	-0.120
MOM36	0.007	1.375			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.007	**4.096**	DE	-0.001	-0.677
BVTMLOG	0.004	**3.294**	OBOS12MMA	0.007	0.677
MOM1	-0.007	**-2.932**	OBOS11MMA	0.006	0.660
EPS	0.002	**2.470**	OBOS10MMA	0.006	0.646
OBOS3MMA	-0.016	**-2.157**	MA7	0.003	0.608
EY	0.005	1.996	MA9	0.003	0.608
EARNREV3M	0.003	1.649	STP	-0.001	-0.603
C24MDPSP	0.002	1.611	MA5	0.002	0.584
OBOS2MMA	-0.034	-1.542	OBOS9MMA	0.005	0.557
C24MEPSP	0.002	1.495	C24MBVTM	0.002	0.536
DY	0.003	1.477	MOM12	0.002	0.529
MOM6	0.004	1.475	OBOS8MMA	0.004	0.460
OBOS4MMA	-0.010	-1.453	EG1	0.001	0.426
DPSLOG	-0.002	-1.394	MVLOG	-0.001	-0.337
MA11	0.006	1.334	RETVAR12	0.001	0.312
MA12	0.006	1.319	OBOS6MMA	-0.002	-0.303
LNP	-0.002	-1.240	MOM3	0.001	0.253
MA10	0.006	1.151	PRICEREL12	0.001	0.235
MOM36	-0.004	-0.950	SPSLOG	0.000	0.215
MA8	0.004	0.939	OBOS7MMA	0.002	0.191
MA3	-0.003	-0.807	ROE	0.000	-0.144
MA6	0.003	0.806	POUTRAT	0.000	-0.049
OBOS5MMA	-0.006	-0.794	MA4	0.000	-0.049
MA2	-0.003	-0.784	BETA	0.000	-0.001
MOM60	-0.002	-0.711			

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.010	**6.632**	MA8	0.005	1.203
BVTMLOG	0.004	**2.767**	MA5	0.004	1.101
MOM12	0.007	**2.656**	MA2	-0.003	-1.065
MOM6	0.007	**2.650**	OBOS3MMA	-0.005	-1.061
LNP	-0.004	**-2.467**	OBOS6MMA	0.006	1.025
OBOS12MMA	0.016	**2.273**	MOM3	0.002	0.972
MA12	0.008	**2.255**	MA7	0.003	0.902
MA11	0.009	**2.235**	MA9	0.003	0.902
C24MEPSP	0.005	**2.134**	MOM60	-0.002	-0.699
OBOS11MMA	0.015	**2.120**	DE	-0.001	-0.677
OBOS10MMA	0.013	1.984	STP	-0.001	-0.603
OBOS9MMA	0.012	1.962	MA3	-0.002	-0.547
BETA	0.004	1.878	OBOS5MMA	0.003	0.533
OBOS8MMA	0.011	1.847	MVLOG	-0.001	-0.514
DY	0.004	1.786	EY	0.001	0.488
EPS	0.002	1.757	MA4	0.001	0.398
EG1	0.002	1.619	RETVAR12	-0.001	-0.396
MA10	0.006	1.616	OBOS4MMA	-0.002	-0.335
OBOS7MMA	0.009	1.588	SPSLOG	0.000	0.215
POUTRAT	0.002	1.448	C24MDPSP	0.000	0.138
MOM1	-0.003	-1.431	MOM36	0.000	-0.124
PRICEREL12	0.004	1.406	ROE	0.000	0.110
OBOS2MMA	-0.015	-1.362	DPSLOG	0.000	-0.039
MA6	0.005	1.341	C24MBVTM	0.000	0.001
EARNREV3M	-0.010	-1.290			

Appendix C.5: Monthly cross-sectional regression results when liquidity filter is set to the 7th decile based on market capitalisation value. Average number of shares included is 95 per month.

A slope coefficient is estimated in each month for each factor for Subsample_1 (Panel A), Subsample_2 (Panel B) and Total_sample (Panel C) using univariate cross-sectional regressions of stock returns and a liquidity filter set equal to the 7th decile based on market cap. In each month each factor has been standardised to have a mean of zero and standard deviation of unity. This facilitates the comparison of the magnitude of slope values across factors. Results in bold indicate where the mean value of the time series of cross-sectional slope coefficients is significantly different from zero at the ninety-five percent level of confidence.

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.013	**5.509**	RETVAR12	-0.004	-0.997
MOM12	0.009	**3.050**	C24MEPSP	0.004	0.954
OBOS12MMA	0.022	**2.297**	MA10	0.005	0.946
LNP	-0.005	**-2.248**	MVLOG	-0.003	-0.914
OBOS11MMA	0.020	**2.070**	MOM3	0.003	0.885
EG1	0.003	1.916	STP	0.003	0.798
OBOS10MMA	0.017	1.846	C24MDPSP	-0.002	-0.778
OBOS9MMA	0.016	1.846	DY	0.003	0.679
MOM6	0.008	1.818	ROE	-0.002	-0.657
BETA	0.005	1.811	MA6	0.004	0.619
BVTMLOG	0.004	1.788	MA8	0.003	0.544
OBOS8MMA	0.015	1.781	POUTRAT	0.002	0.541
OBOS7MMA	0.013	1.680	OBOS4MMA	0.003	0.516
MA12	0.009	1.578	MA3	-0.002	-0.451
EARNREV3M	-0.036	-1.524	MA5	0.003	0.446
PRICEREL12	0.007	1.486	SPSLOG	0.002	0.318
MA11	0.009	1.483	MA7	0.002	0.298
C24MBVTM	-0.004	-1.442	MA9	0.002	0.298
OBOS6MMA	0.011	1.417	OBOS2MMA	-0.001	-0.258
DPSLOG	0.004	1.395	MOM1	-0.001	-0.250
EPS	0.003	1.376	EY	0.001	0.220
MA2	-0.005	-1.364	OBOS3MMA	0.001	0.206
DE	-0.004	-1.334	MOM36	0.001	0.144
OBOS5MMA	0.008	1.135	MA4	0.000	0.081
MOM60	-0.005	-1.035			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.008	**4.942**	MA5	0.004	0.899
BVTMLOG	0.005	**3.920**	OBOS8MMA	0.009	0.899
MOM1	-0.006	**-2.744**	OBOS10MMA	0.009	0.898
EPS	0.002	**2.420**	OBOS11MMA	0.009	0.887
EARNREV3M	0.003	**2.030**	OBOS12MMA	0.009	0.879
ICBTIN	-0.005	-1.870	OBOS7MMA	0.009	0.829
MOM6	0.004	1.717	OBOS6MMA	0.008	0.654
DY	0.003	1.686	MOM12	0.002	0.648
OBOS3MMA	-0.014	-1.668	OBOS5MMA	0.009	0.623
C24MDPSP	0.002	1.622	ROE	0.001	0.577
OBOS2MMA	-0.033	-1.489	OBOS4MMA	0.009	0.552
MA11	0.007	1.477	C24MBVTM	-0.002	-0.520
MA12	0.006	1.369	MA3	-0.002	-0.504
EY	0.003	1.362	EG1	0.001	0.461
MA8	0.005	1.172	MOM60	-0.001	-0.395
MA2	-0.004	-1.121	MVLOG	-0.001	-0.350
DPSLOG	-0.002	-1.099	RETVAR12	-0.001	-0.295
C24MEPSP	0.001	1.060	DE	0.000	-0.283
MA10	0.005	1.054	SPSLOG	0.000	-0.249
LNP	-0.002	-1.029	MA4	0.001	0.244
MA7	0.004	0.970	PRICEREL12	0.001	0.235
MA9	0.004	0.970	BETA	0.000	-0.106
MOM36	-0.003	-0.948	STP	0.000	0.072
MA6	0.004	0.936	POUTRAT	0.000	-0.032
OBOS9MMA	0.009	0.908	MOM3	0.000	0.019

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Factor	Average coefficient	t-statistic
CFTP	0.011	**7.206**	PRICEREL12	0.004	1.231
BVTMLOG	0.005	**3.450**	EARNREV3M	-0.010	-1.198
MOM12	0.006	**2.531**	MA8	0.004	1.117
MOM6	0.006	**2.437**	OBOS5MMA	0.027	1.068
LNP	-0.003	**-2.402**	MA6	0.004	1.028
OBOS12MMA	0.022	**2.227**	MOM60	-0.002	-0.974
MA12	0.008	**2.093**	MVLOG	-0.002	-0.955
MA11	0.008	**2.088**	C24MBVTM	-0.002	-0.951
OBOS11MMA	0.022	**2.079**	RETVAR12	-0.003	-0.907
EPS	0.003	**2.000**	MA5	0.003	0.866
MOM1	-0.003	-1.931	DE	-0.001	-0.807
OBOS10MMA	0.022	1.927	MA7	0.003	0.786
OBOS9MMA	0.024	1.918	MA9	0.003	0.786
ICBTIN	-0.005	-1.870	EY	0.002	0.769
OBOS8MMA	0.026	1.837	MOM36	-0.002	-0.729
MA2	-0.004	-1.770	OBOS4MMA	0.025	0.705
EG1	0.002	1.691	STP	0.001	0.663
OBOS7MMA	0.027	1.679	MA3	-0.002	-0.656
OBOS2MMA	-0.155	-1.505	MOM3	0.001	0.653
DY	0.003	1.459	ROE	-0.001	-0.455
MA10	0.005	1.402	POUTRAT	0.001	0.427
BETA	0.003	1.388	MA4	0.001	0.204
OBOS6MMA	0.026	1.318	DPSLOG	0.000	0.073
OBOS3MMA	-0.036	-1.256	C24MDPSP	0.000	0.055
C24MEPSP	0.002	1.234	SPSLOG	0.000	-0.036

Appendix D

This appendix refers to Chapter 7: Multifactor analyses of factors that explain the cross-section of returns on the JSE.

APPENDIX D.1: Significant paired permutations of candidate factors: All-share sample
Monthly two-factor cross-sectional regressions were done for all permutations of candidate factors. Those pairs that were found to be jointly significant in explaining the cross-section of returns on the JSE are reported here. A number of pairs capture the same effect and are categorised accordingly. Pairs are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average Coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.011	**5.439**	5.54%	3.17%	Vale and size
LNP	-0.005	**-2.586**			
CFTP	0.011	**5.227**	8.45%	6.34%	Value and momentum
MOM12	0.007	**2.471**			
CFTP	0.010	**4.246**	8.44%	6.35%	
OBOS11MMA	0.018	**2.144**			
CFTP	0.010	**4.208**	8.32%	6.02%	
OBOS12MMA	0.020	**2.289**			
BVTMLOG	0.009	**4.040**	7.91%	5.72%	
MOM12	0.010	**3.575**			
BVTMLOG	0.008	**3.515**	7.68%	5.54%	
OBOS11MMA	0.023	**2.798**			
BVTMLOG	0.008	**3.567**	7.63%	5.48%	
OBOS12MMA	0.025	**2.972**			
MOM1	-0.006	**-2.796**	6.20%	4.73%	Short-term price reversal and momentum
OBOS11mMA	0.034	**4.692**			
MOM1	-0.007	**-3.115**	6.28%	4.79%	
OBOS12mMA	0.036	**5.035**			
MOM12	0.009	**3.698**	6.14%	4.61%	Momentum and size
LNP	-0.011	**-6.234**			
OBOS12mMA	0.024	**3.350**	5.91%	4.44%	
LNP	-0.011	**-6.001**			
OBOS11mMA	0.021	**3.114**	5.85%	4.38%	
LNP	-0.010	**-5.869**			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average Coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.006	**3.575**	4.85%	3.51%	Value and momentum
MA11	0.009	**2.002**			
CFTP	0.006	**3.777**	4.96%	3.60%	
MOM6	0.005	**2.422**			
BVTMLOG	0.004	**3.041**	4.16%	2.84%	
MA11	0.010	**2.296**			
BVTMLOG	0.003	**3.014**	4.36%	3.04%	
MA12	0.010	**2.315**			
BVTMLOG	0.004	**4.139**	5.41%	4.06%	
MOM12	0.006	**2.054**			
BVTMLOG	0.004	**3.267**	4.66%	3.32%	
MOM6	0.005	**2.668**			
CFTP	0.006	**4.011**	4.80%	3.46%	Value and short-term price reversal
MOM1	-0.006	**-2.956**			
BVTMLOG	0.003	**2.284**	4.18%	2.85%	
MOM1	-0.005	**-2.594**			
MOM1	-0.006	**-3.125**	5.18%	3.95%	Short-term price reversal and momentum
MA11	0.013	**2.993**			
MOM1	-0.006	**-3.050**	5.32%	4.09%	
MA12	0.012	**2.782**			
MOM1	-0.009	**-4.618**	5.56%	4.29%	
MOM6	0.008	**4.205**			
MOM1	-0.008	**-3.972**	5.88%	4.65%	
OBOS11mMA	0.020	**2.862**			

Panel C: Total_sample (1994 - 2011)

Factor	Average Coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.009	**6.583**	4.76%	2.88%	Value and size
LNP	-0.003	**-2.735**			
CFTP	0.008	**6.277**	7.10%	5.37%	Value and momentum
MOM12	0.005	**2.807**			
CFTP	0.006	**4.530**	9.85%	5.54%	
MOM6	0.005	**2.849**			
CFTP	0.008	**5.523**	6.81%	5.09%	
OBOS11MMA	0.011	**2.216**			
CFTP	0.008	**5.512**	6.78%	4.95%	
OBOS12MMA	0.013	**2.413**			
BVTMLOG	0.004	**3.763**	4.99%	3.29%	
MA11	0.009	**2.601**			
BVTMLOG	0.004	**3.771**	5.07%	3.39%	
MA12	0.009	**2.674**			
BVTMLOG	0.007	**5.528**	6.65%	4.88%	
MOM12	0.008	**3.884**			
BVTMLOG	0.006	**4.792**	6.29%	4.56%	
OBOS11MMA	0.016	**3.107**			
BVTMLOG	0.006	**4.896**	6.29%	4.55%	
OBOS12MMA	0.018	**3.327**			
MOM1	-0.004	**-2.696**	4.81%	3.49%	Short-term price reversal and momentum
MA11	0.011	**3.523**			
MOM1	-0.004	**-2.816**	4.83%	3.52%	
MA12	0.010	**3.417**			
MOM1	-0.006	**-4.079**	6.61%	5.20%	
MOM12	0.008	**4.327**			
MOM1	-0.006	**-2.837**	8.42%	5.55%	
MOM6	0.007	**3.796**			
MOM1	-0.007	**-4.771**	6.04%	4.69%	
OBOS11mMA	0.027	**5.353**			
MOM1	-0.008	**-5.025**	6.15%	4.79%	
OBOS12mMA	0.028	**5.587**			
MOM6	0.005	**2.952**	7.34%	4.46%	Momentum and size
LNP	-0.007	**-3.974**			
MOM12	0.007	**3.950**	5.92%	4.52%	
LNP	-0.006	**-5.363**			
OBOS12mMA	0.016	**3.104**	5.38%	4.02%	
LNP	-0.006	**-4.829**			
OBOS11mMA	0.015	**3.237**	5.32%	3.96%	
LNP	-0.006	**-4.701**			

Appendix D.2: Significant three-factor permutations of candidate factors: All-share sample
Monthly three-factor cross-sectional regressions were done for all permutations of significant pairs of candidate factors (Table 5.6) together with an additional candidate factor. Those permutations that were found to be jointly significant in explaining the cross-section of returns on the JSE are reported here. Three-factor models are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-Statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.011	5.459	10.57%	7.45%	Value, size, momentum
LNP	-0.007	-3.846			
MOM12	0.007	2.817			
CFTP	0.011	5.121	10.58%	7.18%	
LNP	-0.007	-3.702			
OBOS11mMA	0.018	2.335			
CFTP	0.010	5.078	10.27%	7.48%	
LNP	-0.007	-3.551			
OBOS12mMA	0.021	2.662			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-Statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.006	3.779	7.44%	5.47%	Value, momentum, short-term price reversal
MA11	0.013	2.853			
MOM1	-0.008	-3.894			
CFTP	0.006	3.831	7.47%	5.47%	
MOM6	0.008	4.068			
MOM1	-0.009	-4.870			
BVTMLOG	0.003	2.783	6.83%	4.88%	
MA11	0.013	3.079			
MOM1	-0.007	-3.448			
BVTMLOG	0.003	2.734	7.02%	5.08%	
MA12	0.013	2.932			
MOM1	-0.007	-3.374			
BVTMLOG	0.004	3.671	8.20%	6.22%	
MOM1	-0.009	-4.565			
MOM12	0.007	2.192			
BVTMLOG	0.004	3.066	7.17%	5.20%	
MOM1	-0.009	-5.046			
MOM6	0.008	4.210			

Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-Statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.008	6.218	8.92%	6.35%	Value, size, momentum
LNP	-0.004	-3.714			
MOM12	0.006	3.189			
CFTP	0.008	5.937	8.47%	5.93%	
LNP	-0.004	-3.429			
OBOS12MMA	0.015	2.891			
CFTP	0.008	5.960	8.61%	6.06%	
LNP	-0.004	-3.523			
OBOS11MMA	0.013	2.539			

Appendix D.3: Significant paired permutations of candidate factors: Large-cap sample.
Monthly two-factor cross-sectional regressions were done for all permutations of candidate factors. Those pairs that were found to be jointly significant in explaining the cross-section of returns on the JSE are reported here. A number of pairs capture the same effect and are categorised accordingly. Pairs are reported for the three periods January 1994 through December 2002 (Panel A), January 2003 through May 2011 (Panel B) and January 1994 through May 2011 (Panel C).

Panel A: Subsample_1 (1994 - 2002)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.014	6.042	11.04%	7.80%	Value and momentum
MOM12	0.009	3.015			
CFTP	0.012	5.272	11.18%	7.99%	
OBOS12mMA	0.020	2.008			
BVTMLOG	0.011	3.753	11.00%	7.75%	
MOM12	0.011	3.085			
BVTMLOG	0.025	2.499	11.72%	8.53%	
OBOS12mMA	0.027	2.365			
BVTMLOG	0.021	2.219	11.70%	8.48%	
OBOS11MMA	0.024	2.129			
BVTMLOG	0.011	2.041	8.52%	5.32%	
MA12	0.013	2.137			
MOM1	-0.009	-3.376	11.91%	9.16%	Short-term price reversal and momentum
OBOS12MMA	0.041	3.903			
MOM1	-0.009	-3.157	11.86%	9.12%	
OBOS11MMA	0.039	3.622			
MOM12	0.010	3.588	10.34%	7.51%	Momentum and size
LNP	-0.006	-2.691			
OBOS12MMA	0.024	2.498	10.36%	7.58%	
LNP	-0.006	-2.533			
OBOS11MMA	0.022	2.312	9.54%	6.74%	
LNP	-0.006	-2.586			

Panel B: Subsample_2 (2003 - 2011)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.007	3.773	7.87%	5.09%	Value and short-term price reversal
MOM1	-0.008	-3.387			
BVTMLOG	0.004	2.795	6.74%	3.99%	
MOM1	-0.008	-3.099			
MOM1	-0.011	-4.590	9.03%	6.46%	Short-term price reversal and momentum
MOM6	0.007	2.576			
MOM1	-0.011	-4.979	10.01%	7.50%	
OBOS11MMA	0.021	2.043			
MOM1	-0.010	-4.510	8.25%	5.75%	
MA11	0.010	2.305			
MOM1	-0.010	-4.464	8.47%	5.97%	
MA12	0.010	2.264			

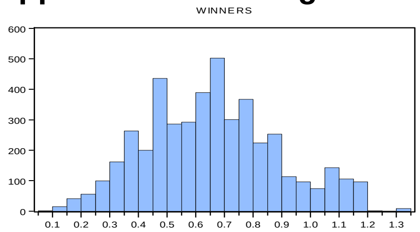
Panel C: Total_sample (1994 - 2011)

Factor	Average coefficient	t-statistic	Average r-squared	Average adjusted r-squared	Effect
CFTP	0.010	6.787	8.16%	5.02%	Value and short-term price reversal
MOM1	-0.004	-2.310			
BVTMLOG	0.004	3.156	8.28%	5.16%	
MOM1	-0.004	-2.128			
CFTP	0.006	3.189	14.06%	7.17%	Value and momentum
MOM6	0.005	1.983			
CFTP	0.009	6.563	10.23%	7.23%	
MOM12	0.005	2.335			
BVTMLOG	0.004	2.487	13.53%	6.63%	
MOM6	0.005	2.134			
BVTMLOG	0.007	2.807	9.94%	6.95%	
MOM12	0.007	2.641			
BVTMLOG	0.015	2.213	10.06%	7.10%	
OBOS12mMA	0.018	2.307			
BVTMLOG	0.014	2.021	9.97%	7.00%	
OBOS11MMA	0.016	2.124			
MOM1	-0.009	-3.985	14.42%	8.39%	Short-term price reversal and momentum
MOM6	0.009	3.507			
MOM1	-0.010	-5.778	11.03%	8.40%	
OBOS12MMA	0.031	4.145			
MOM1	-0.010	-5.612	10.93%	8.30%	
OBOS11MMA	0.030	4.022			
MOM1	-0.007	-4.300	11.24%	8.53%	
MOM12	0.007	3.068			
MOM1	-0.007	-4.096	8.36%	5.73%	
MA11	0.011	3.287			
MOM1	-0.007	-4.132	8.42%	5.80%	
MA12	0.012	3.553			
MOM1	-0.004	-2.319	7.66%	4.93%	Short-term price reversal and size
LNP	-0.004	-2.615			
MOM12	0.006	2.715	9.92%	7.22%	Momentum and size
LNP	-0.004	-2.815			
OBOS12MMA	0.014	2.152	9.55%	6.89%	
LNP	-0.004	-2.633			
OBOS11MMA	0.013	1.996	9.45%	6.15%	
LNP	-0.004	-2.660			

Appendix E

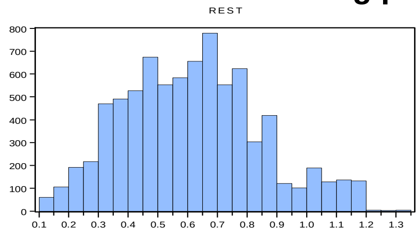
This appendix refers to Chapter 8: Extreme performance and filter rules on the JSE. To compare statistical properties of the factors across winners, losers and the rest, descriptive statistics were calculated and are presented together with histograms in Appendix E.1. The results of the forward stepwise logistic regression approach followed in Chapter 8 to derive the respective logit models are reported in Appendix E.2 through Appendix E.4.

Appendix E.1: Histograms and descriptive statistics: 1-month holding period



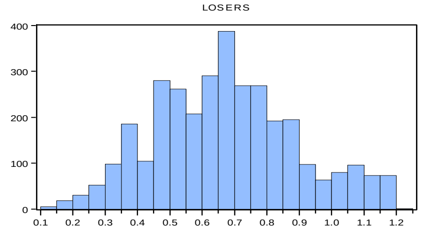
Series: BETA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4526

Mean	0.656603
Median	0.659000
Maximum	1.300000
Minimum	0.079935
Std. Dev.	0.230964
Skewness	0.269162
Kurtosis	2.617012
Jarque-Bera	82.31157
Probability	0.000000



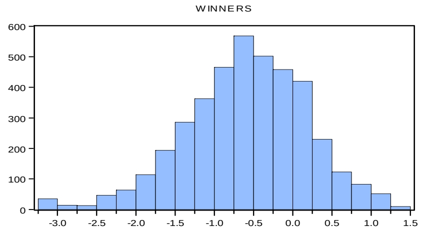
Series: BETA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 8026

Mean	0.614119
Median	0.609518
Maximum	1.300000
Minimum	0.137000
Std. Dev.	0.230529
Skewness	0.324461
Kurtosis	2.695587
Jarque-Bera	171.8123
Probability	0.000000



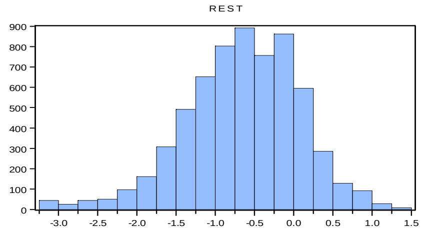
Series: BETA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3325

Mean	0.672833
Median	0.682000
Maximum	1.213923
Minimum	0.140000
Std. Dev.	0.220642
Skewness	0.232491
Kurtosis	2.622358
Jarque-Bera	49.71168
Probability	0.000000



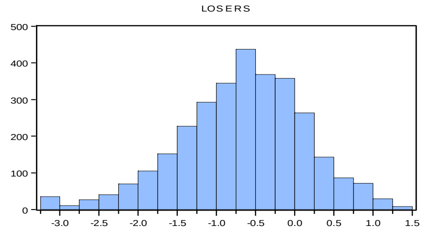
Series: BVTMLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4040

Mean	-0.595073
Median	-0.553885
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.778967
Skewness	-0.406305
Kurtosis	3.498348
Jarque-Bera	152.9618
Probability	0.000000



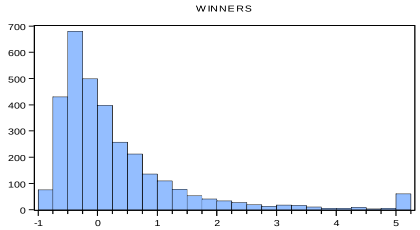
Series: BVTMLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6324

Mean	-0.652632
Median	-0.615186
Maximum	1.347074
Minimum	-3.210000
Std. Dev.	0.730972
Skewness	-0.471468
Kurtosis	3.626929
Jarque-Bera	337.8510
Probability	0.000000



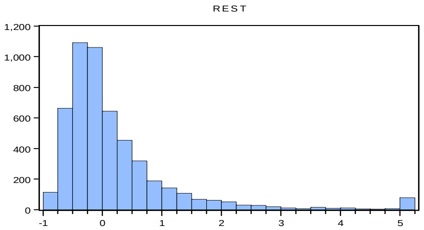
Series: BVTMLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3067

Mean	-0.669954
Median	-0.615186
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.808981
Skewness	-0.396978
Kurtosis	3.383830
Jarque-Bera	99.38249
Probability	0.000000



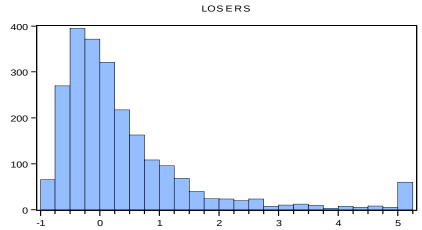
Series: C24MBVTM
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 3193

Mean	0.289142
Median	-0.057554
Maximum	5.000000
Minimum	-0.947257
Std. Dev.	1.105773
Skewness	2.350314
Kurtosis	9.317062
Jarque-Bera	8248.740
Probability	0.000000



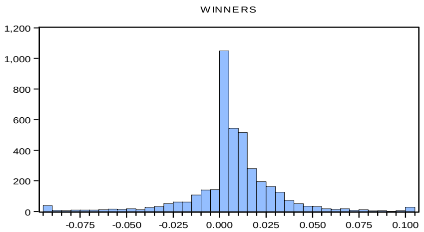
Series: C24MBVTM
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 5185

Mean	0.202774
Median	-0.090909
Maximum	5.000000
Minimum	-1.000000
Std. Dev.	0.998274
Skewness	2.676471
Kurtosis	11.77442
Jarque-Bera	22823.61
Probability	0.000000



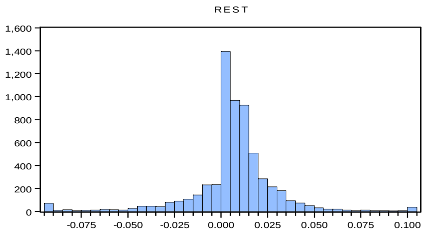
Series: C24MBVTM
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 2330

Mean	0.389856
Median	0.039408
Maximum	5.000000
Minimum	-0.955022
Std. Dev.	1.191092
Skewness	2.246481
Kurtosis	8.435052
Jarque-Bera	4827.614
Probability	0.000000



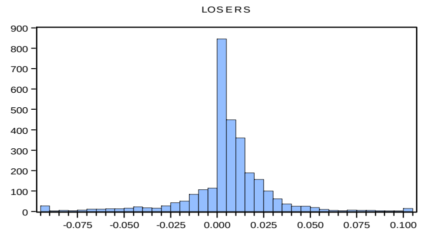
Series: C24MDPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 3944

Mean	0.006849
Median	0.006405
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.024626
Skewness	-0.396504
Kurtosis	7.826629
Jarque-Bera	3931.710
Probability	0.000000



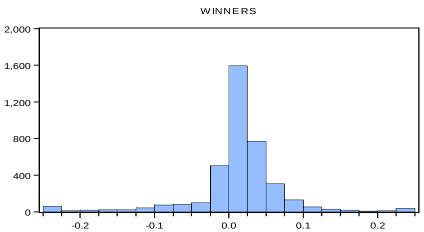
Series: C24MDPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6076

Mean	0.006419
Median	0.007172
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.023880
Skewness	-0.612496
Kurtosis	8.504446
Jarque-Bera	8050.582
Probability	0.000000



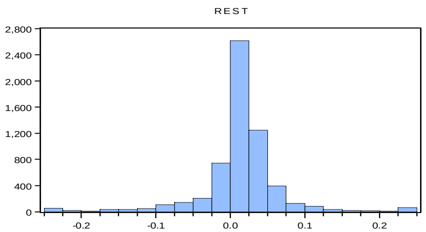
Series: C24MDPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 2921

Mean	0.005088
Median	0.005208
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.023356
Skewness	-0.520152
Kurtosis	8.411000
Jarque-Bera	3695.205
Probability	0.000000



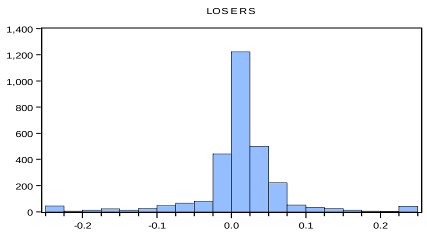
Series: C24MEPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 3904

Mean	0.012184
Median	0.011639
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.061565
Skewness	-0.654604
Kurtosis	8.740447
Jarque-Bera	5639.127
Probability	0.000000



Series: C24MEPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6030

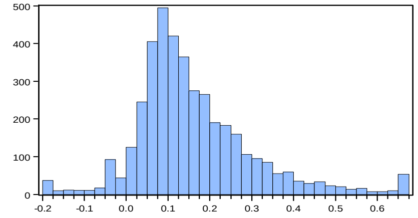
Mean	0.012374
Median	0.012335
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.056168
Skewness	-0.343644
Kurtosis	9.954868
Jarque-Bera	12271.69
Probability	0.000000



Series: C24MEPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 2881

Mean	0.010836
Median	0.008090
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.061255
Skewness	-0.354307
Kurtosis	9.302332
Jarque-Bera	4828.259
Probability	0.000000

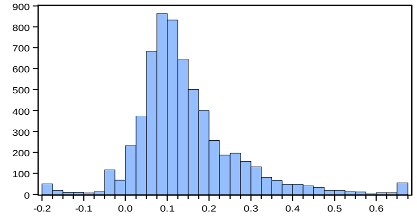
WINNERS



Series: CFTP
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 4007

Mean	0.159354
Median	0.130039
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.139967
Skewness	1.042756
Kurtosis	5.111470
Jarque-Bera	1470.513
Probability	0.000000

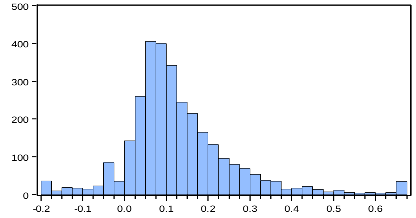
REST



Series: CFTP
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 6216

Mean	0.143534
Median	0.119474
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.122519
Skewness	1.233118
Kurtosis	6.515005
Jarque-Bera	4775.333
Probability	0.000000

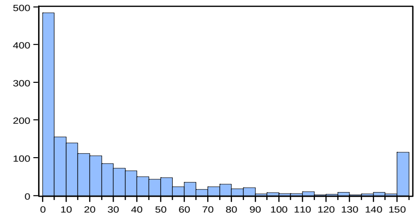
LOSERS



Series: CFTP
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 3052

Mean	0.129926
Median	0.105430
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.131872
Skewness	1.202976
Kurtosis	6.357650
Jarque-Bera	2169.771
Probability	0.000000

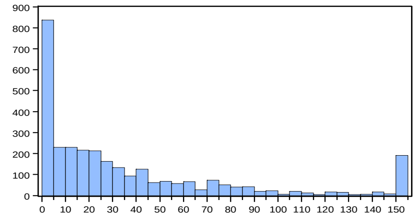
WINNERS



Series: DE
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 1695

Mean	34.02063
Median	18.37340
Maximum	150.0000
Minimum	0.000000
Std. Dev.	42.17416
Skewness	1.644785
Kurtosis	4.818680
Jarque-Bera	997.8511
Probability	0.000000

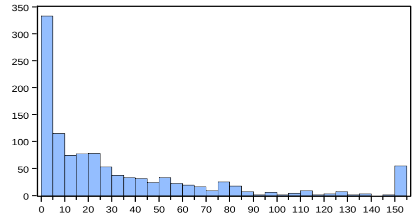
REST



Series: DE
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 3056

Mean	35.65901
Median	20.26110
Maximum	150.0000
Minimum	0.000000
Std. Dev.	42.07465
Skewness	1.526414
Kurtosis	4.465670
Jarque-Bera	1460.251
Probability	0.000000

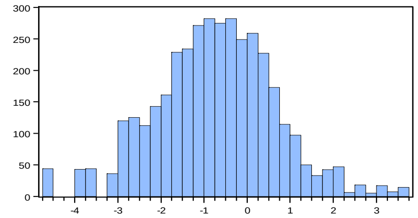
LOSERS



Series: DE
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 1095

Mean	31.08913
Median	16.52800
Maximum	150.0000
Minimum	0.000000
Std. Dev.	39.13673
Skewness	1.742245
Kurtosis	5.415636
Jarque-Bera	820.1994
Probability	0.000000

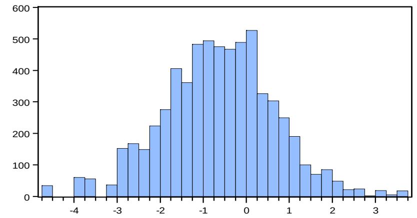
WINNERS



Series: DPSLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 3759

Mean	-0.751540
Median	-0.693147
Maximum	3.516000
Minimum	-4.605170
Std. Dev.	1.393635
Skewness	-0.015767
Kurtosis	3.375447
Jarque-Bera	22.23363
Probability	0.000015

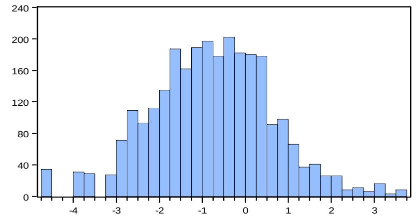
REST



Series: DPSLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 6308

Mean	-0.641027
Median	-0.616186
Maximum	3.516000
Minimum	-4.605170
Std. Dev.	1.293312
Skewness	-0.053725
Kurtosis	3.358952
Jarque-Bera	36.89975
Probability	0.000000

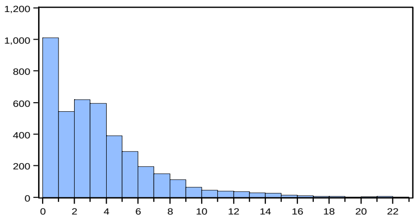
LOSERS



Series: DPSLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 2733

Mean	-0.774338
Median	-0.755023
Maximum	3.516000
Minimum	-4.605170
Std. Dev.	1.404669
Skewness	0.022947
Kurtosis	3.306156
Jarque-Bera	10.91353
Probability	0.004267

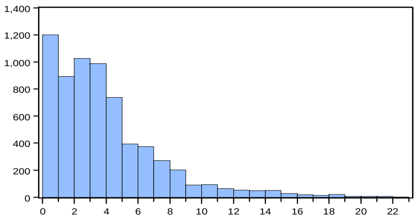
WINNERS



Series: DY
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 4182

Mean	3.516501
Median	2.860000
Maximum	22.00000
Minimum	0.000000
Std. Dev.	3.386599
Skewness	1.635657
Kurtosis	6.773858
Jarque-Bera	4346.406
Probability	0.000000

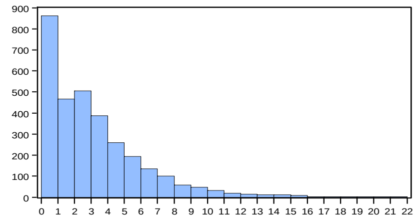
REST



Series: DY
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 6579

Mean	3.868941
Median	3.142900
Maximum	22.00000
Minimum	0.000000
Std. Dev.	3.451565
Skewness	1.600881
Kurtosis	6.411908
Jarque-Bera	6001.252
Probability	0.000000

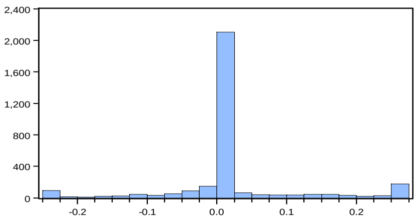
LOSERS



Series: DY
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 3130

Mean	3.104573
Median	2.500000
Maximum	21.97000
Minimum	0.000000
Std. Dev.	3.101577
Skewness	1.675479
Kurtosis	7.146437
Jarque-Bera	3706.684
Probability	0.000000

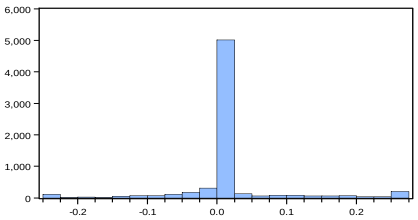
WINNERS



Series: EARNREV3M
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 3147

Mean	0.012931
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.092237
Skewness	0.610755
Kurtosis	5.956479
Jarque-Bera	1341.783
Probability	0.000000

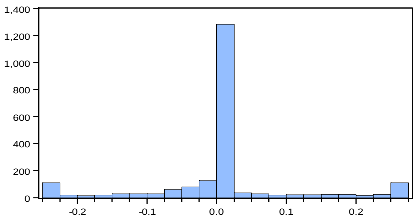
REST



Series: EARNREV3M
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 6744

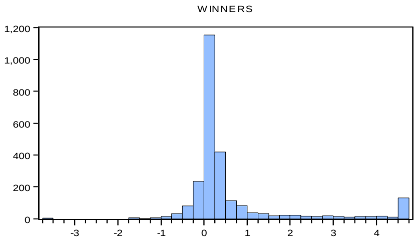
Mean	0.007445
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.072665
Skewness	0.872293
Kurtosis	9.118523
Jarque-Bera	11374.85
Probability	0.000000

LOSERS



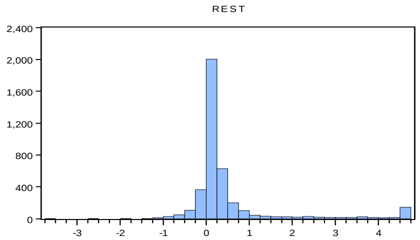
Series: EARNREV3M
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 2103

Mean	0.001492
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.101177
Skewness	0.278410
Kurtosis	5.188862
Jarque-Bera	446.9898
Probability	0.000000



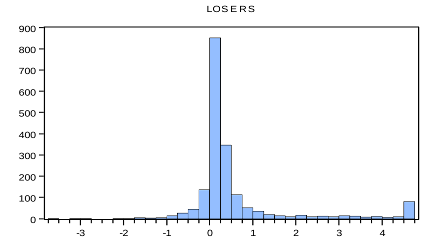
Series: EG1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 2524

Mean	0.607336
Median	0.192384
Maximum	4.700000
Minimum	-3.610000
Std. Dev.	1.248084
Skewness	2.249033
Kurtosis	7.677832
Jarque-Bera	4429.064
Probability	0.000000



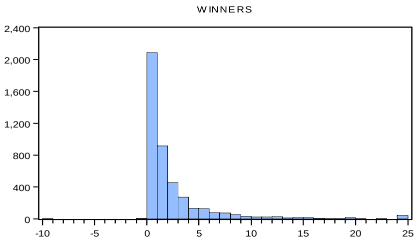
Series: EG1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 3923

Mean	0.480737
Median	0.181641
Maximum	4.700000
Minimum	-3.610000
Std. Dev.	1.084084
Skewness	2.766949
Kurtosis	10.90180
Jarque-Bera	15211.83
Probability	0.000000



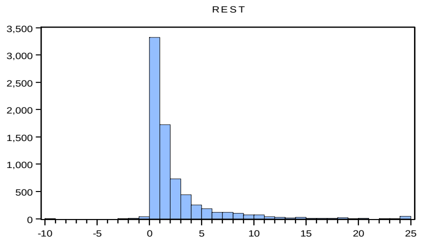
Series: EG1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 1854

Mean	0.570551
Median	0.206808
Maximum	4.700000
Minimum	-3.610000
Std. Dev.	1.176400
Skewness	2.402202
Kurtosis	8.679995
Jarque-Bera	4275.373
Probability	0.000000



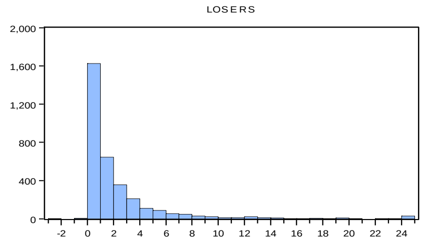
Series: EPS
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4413

Mean	2.315568
Median	1.050000
Maximum	24.03633
Minimum	-10.00000
Std. Dev.	3.684348
Skewness	3.377721
Kurtosis	17.12103
Jarque-Bera	45056.65
Probability	0.000000



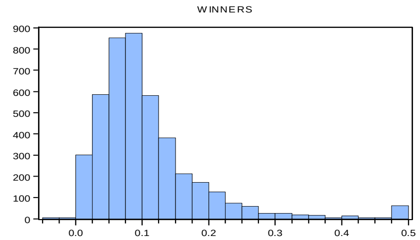
Series: EPS
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 7428

Mean	2.303038
Median	1.100000
Maximum	24.03633
Minimum	-10.00000
Std. Dev.	3.501837
Skewness	3.269061
Kurtosis	16.72085
Jarque-Bera	71497.22
Probability	0.000000



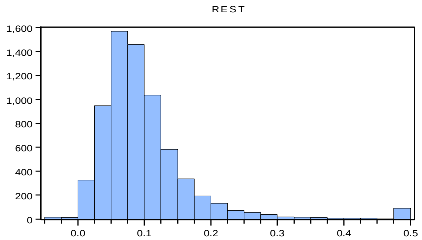
Series: EPS
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3303

Mean	2.144651
Median	1.020000
Maximum	24.03633
Minimum	-2.740000
Std. Dev.	3.437554
Skewness	3.698236
Kurtosis	20.09463
Jarque-Bera	47746.79
Probability	0.000000



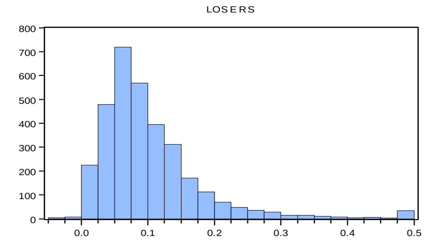
Series: EY
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4405

Mean	0.105965
Median	0.086207
Maximum	0.479000
Minimum	-0.047400
Std. Dev.	0.081142
Skewness	2.170134
Kurtosis	9.424489
Jarque-Bera	11033.05
Probability	0.000000



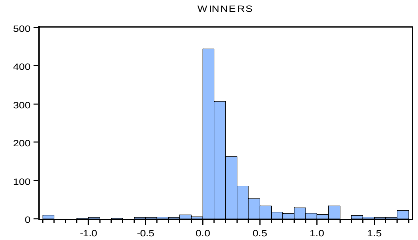
Series: EY
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6923

Mean	0.099408
Median	0.083333
Maximum	0.479000
Minimum	-0.050000
Std. Dev.	0.071837
Skewness	2.625638
Kurtosis	13.11862
Jarque-Bera	37488.72
Probability	0.000000



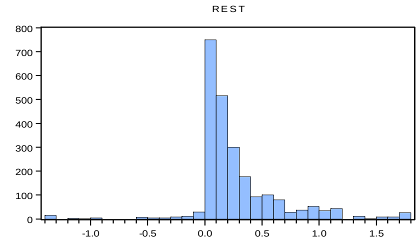
Series: EY
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3270

Mean	0.101579
Median	0.082645
Maximum	0.479000
Minimum	-0.046500
Std. Dev.	0.077791
Skewness	2.160139
Kurtosis	9.599225
Jarque-Bera	8476.735
Probability	0.000000



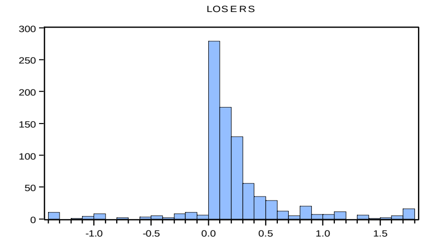
Series: ICBTIN
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 1280

Mean	0.252369
Median	0.150821
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.390788
Skewness	1.206840
Kurtosis	8.339483
Jarque-Bera	1831.250
Probability	0.000000



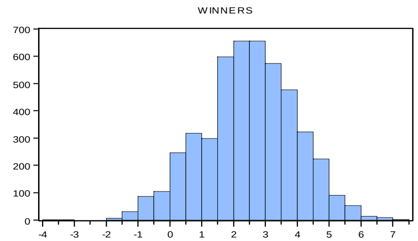
Series: ICBTIN
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 2334

Mean	0.265238
Median	0.159116
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.370854
Skewness	1.012099
Kurtosis	8.132675
Jarque-Bera	2960.459
Probability	0.000000



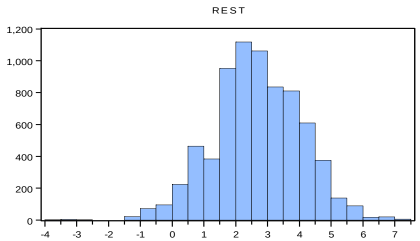
Series: ICBTIN
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 854

Mean	0.221932
Median	0.155738
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.432545
Skewness	0.575432
Kurtosis	7.909337
Jarque-Bera	904.7445
Probability	0.000000



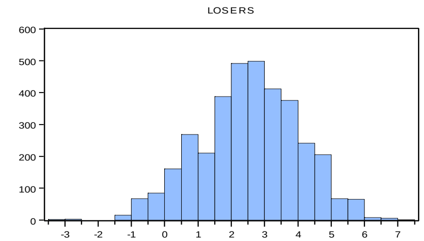
Series: LNP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4768

Mean	2.486756
Median	2.532903
Maximum	7.225409
Minimum	-3.506558
Std. Dev.	1.463304
Skewness	-0.135767
Kurtosis	2.907371
Jarque-Bera	16.35246
Probability	0.000281



Series: LNP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 7296

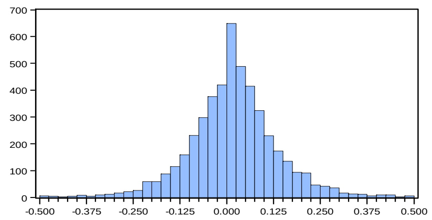
Mean	2.669236
Median	2.639057
Maximum	7.189175
Minimum	-3.506558
Std. Dev.	1.379452
Skewness	-0.105585
Kurtosis	3.178340
Jarque-Bera	23.22504
Probability	0.000009



Series: LNP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3569

Mean	2.550890
Median	2.595255
Maximum	7.059626
Minimum	-3.218876
Std. Dev.	1.490514
Skewness	-0.141841
Kurtosis	2.855571
Jarque-Bera	15.06945
Probability	0.000534

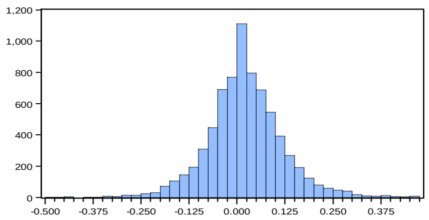
WINNERS



Series: MOM1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4708

Mean	0.017336
Median	0.016269
Maximum	0.491200
Minimum	-0.494237
Std. Dev.	0.117441
Skewness	-0.007890
Kurtosis	4.869435
Jarque-Bera	685.6099
Probability	0.000000

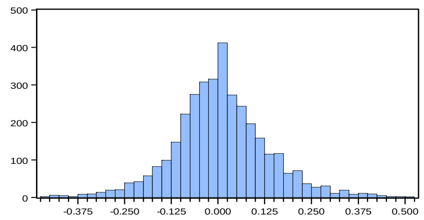
REST



Series: MOM1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 7231

Mean	0.021226
Median	0.016470
Maximum	0.474772
Minimum	-0.482426
Std. Dev.	0.098281
Skewness	0.146530
Kurtosis	5.082553
Jarque-Bera	1332.586
Probability	0.000000

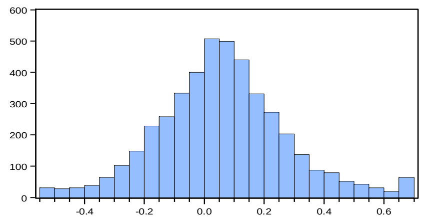
LOSERS



Series: MOM1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3480

Mean	0.007029
Median	0.000000
Maximum	0.500000
Minimum	-0.462903
Std. Dev.	0.126479
Skewness	0.160192
Kurtosis	4.247997
Jarque-Bera	240.7205
Probability	0.000000

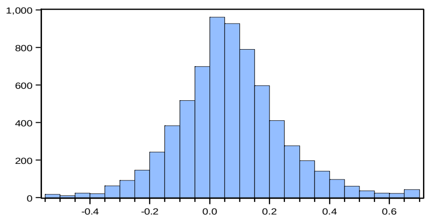
WINNERS



Series: MOM3
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4425

Mean	0.059213
Median	0.054052
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.214879
Skewness	0.204925
Kurtosis	3.593007
Jarque-Bera	95.80759
Probability	0.000000

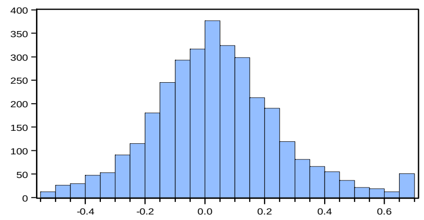
REST



Series: MOM3
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6779

Mean	0.068747
Median	0.061595
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.177111
Skewness	0.266354
Kurtosis	4.111108
Jarque-Bera	428.8672
Probability	0.000000

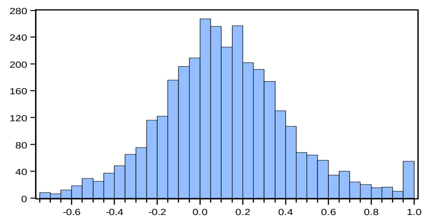
LOSERS



Series: MOM3
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3268

Mean	0.038860
Median	0.028910
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.215245
Skewness	0.335135
Kurtosis	3.588127
Jarque-Bera	108.2734
Probability	0.000000

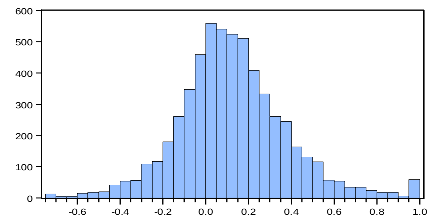
WINNERS



Series: MOM6
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 3354

Mean	0.118213
Median	0.102389
Maximum	0.969094
Minimum	-0.743870
Std. Dev.	0.302606
Skewness	0.303413
Kurtosis	3.492032
Jarque-Bera	85.29417
Probability	0.000000

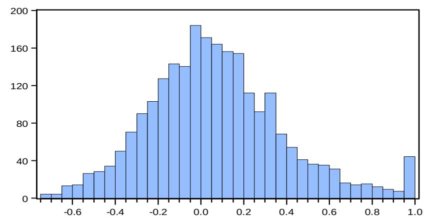
REST



Series: MOM6
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 5778

Mean	0.126443
Median	0.110974
Maximum	0.969094
Minimum	-0.743870
Std. Dev.	0.254394
Skewness	0.368817
Kurtosis	4.214932
Jarque-Bera	486.3544
Probability	0.000000

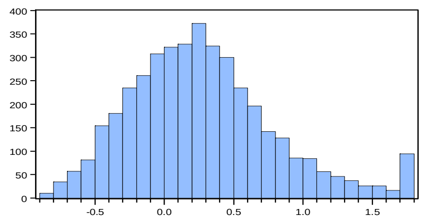
LOSERS



Series: MOM6
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 2373

Mean	0.070672
Median	0.047318
Maximum	0.969094
Minimum	-0.743870
Std. Dev.	0.314768
Skewness	0.501349
Kurtosis	3.464873
Jarque-Bera	120.7770
Probability	0.000000

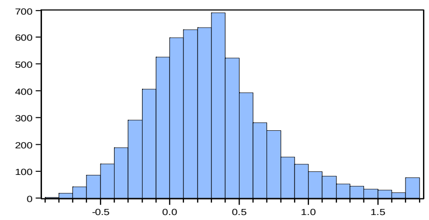
WINNERS



Series: MOM12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4136

Mean	0.273376
Median	0.223668
Maximum	1.764000
Minimum	-0.878071
Std. Dev.	0.522687
Skewness	0.659130
Kurtosis	3.436848
Jarque-Bera	332.3698
Probability	0.000000

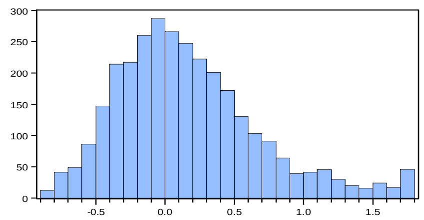
REST



Series: MOM12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6396

Mean	0.281578
Median	0.249236
Maximum	1.764000
Minimum	-0.879415
Std. Dev.	0.445547
Skewness	0.730730
Kurtosis	4.009216
Jarque-Bera	840.6432
Probability	0.000000

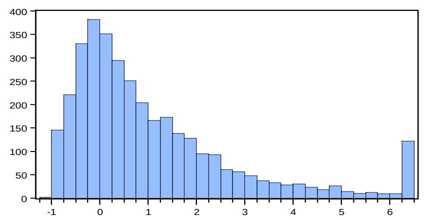
LOSERS



Series: MOM12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3087

Mean	0.165111
Median	0.089165
Maximum	1.764000
Minimum	-0.881150
Std. Dev.	0.519269
Skewness	0.857519
Kurtosis	3.735422
Jarque-Bera	447.8985
Probability	0.000000

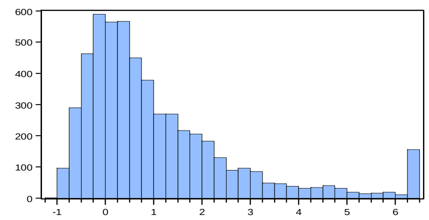
WINNERS



Series: MOM36
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 3509

Mean	1.053414
Median	0.522782
Maximum	6.372173
Minimum	-1.072450
Std. Dev.	1.702444
Skewness	1.528822
Kurtosis	5.021955
Jarque-Bera	1964.674
Probability	0.000000

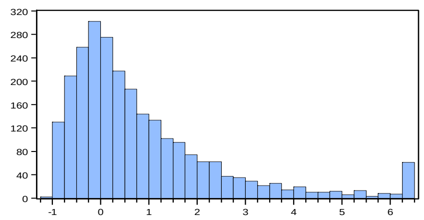
REST



Series: MOM36
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 5445

Mean	1.063612
Median	0.571875
Maximum	6.372173
Minimum	-1.066673
Std. Dev.	1.598437
Skewness	1.615535
Kurtosis	5.492558
Jarque-Bera	3778.071
Probability	0.000000

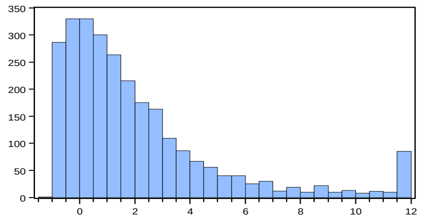
LOSERS



Series: MOM36
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 2561

Mean	0.844454
Median	0.375543
Maximum	6.372173
Minimum	-1.059031
Std. Dev.	1.576823
Skewness	1.712948
Kurtosis	5.963961
Jarque-Bera	2189.850
Probability	0.000000

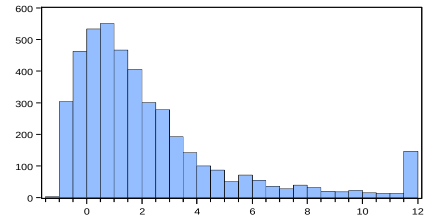
WINNERS



Series: MOM60
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 2716

Mean	2.073904
Median	1.196897
Maximum	11.97380
Minimum	-1.151435
Std. Dev.	2.922065
Skewness	1.795223
Kurtosis	6.091387
Jarque-Bera	2540.363
Probability	0.000000

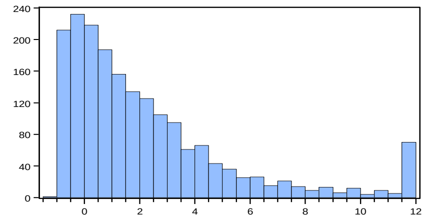
REST



Series: MOM60
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 4381

Mean	2.210208
Median	1.362103
Maximum	11.97380
Minimum	-1.256238
Std. Dev.	2.888916
Skewness	1.821708
Kurtosis	6.177133
Jarque-Bera	4265.753
Probability	0.000000

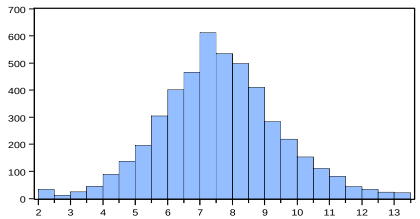
LOSERS



Series: MOM60
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 1900

Mean	2.229284
Median	1.298816
Maximum	11.97380
Minimum	-1.212551
Std. Dev.	3.050563
Skewness	1.639664
Kurtosis	5.423296
Jarque-Bera	1316.254
Probability	0.000000

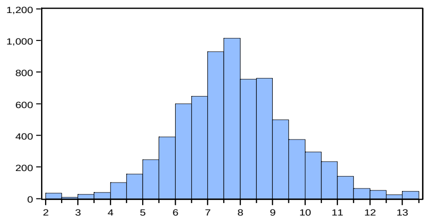
WINNERS



Series: MVLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 4736

Mean	7.613219
Median	7.533472
Maximum	13.38700
Minimum	2.414000
Std. Dev.	1.852419
Skewness	0.150964
Kurtosis	3.369051
Jarque-Bera	44.86555
Probability	0.000000

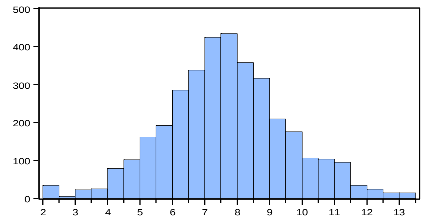
REST



Series: MVLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 7423

Mean	7.840262
Median	7.739255
Maximum	13.38700
Minimum	2.414000
Std. Dev.	1.768566
Skewness	0.139765
Kurtosis	3.407166
Jarque-Bera	75.44276
Probability	0.000000

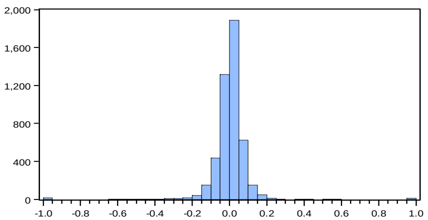
LOSERS



Series: MVLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 3548

Mean	7.664210
Median	7.593623
Maximum	13.38700
Minimum	2.414000
Std. Dev.	1.893435
Skewness	0.066226
Kurtosis	3.241704
Jarque-Bera	11.23004
Probability	0.003643

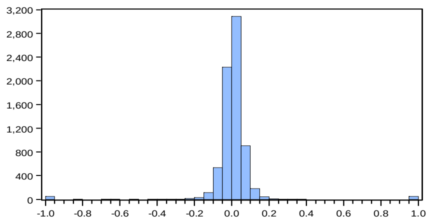
WINNERS



Series: OBOS2MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 4730

Mean	0.003358
Median	0.006363
Maximum	0.982309
Minimum	-0.981266
Std. Dev.	0.099752
Skewness	-1.042010
Kurtosis	57.78510
Jarque-Bera	592383.2
Probability	0.000000

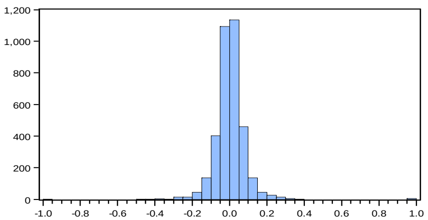
REST



Series: OBOS2MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 7251

Mean	0.006579
Median	0.006211
Maximum	0.983178
Minimum	-0.981714
Std. Dev.	0.122214
Skewness	-0.301305
Kurtosis	52.79999
Jarque-Bera	749391.6
Probability	0.000000

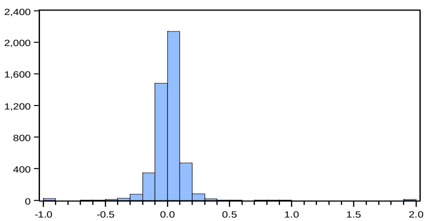
LOSERS



Series: OBOS2MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 3534

Mean	0.002624
Median	0.000000
Maximum	0.982816
Minimum	-0.978729
Std. Dev.	0.084029
Skewness	2.172868
Kurtosis	40.28552
Jarque-Bera	207489.3
Probability	0.000000

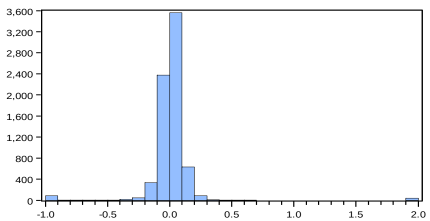
WINNERS



Series: OBOS3MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 4691

Mean	0.009367
Median	0.012959
Maximum	1.949700
Minimum	-0.972975
Std. Dev.	0.153425
Skewness	3.939552
Kurtosis	73.93499
Jarque-Bera	995635.9
Probability	0.000000

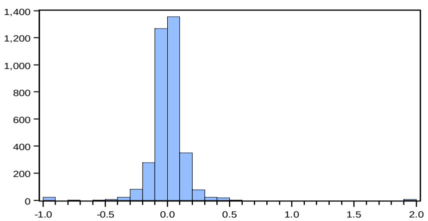
REST



Series: OBOS3MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 7198

Mean	0.014627
Median	0.014184
Maximum	1.949700
Minimum	-0.972837
Std. Dev.	0.198516
Skewness	4.077912
Kurtosis	60.44721
Jarque-Bera	1009729.
Probability	0.000000

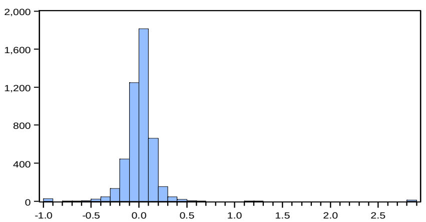
LOSERS



Series: OBOS3MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 3510

Mean	0.001005
Median	0.002328
Maximum	1.952110
Minimum	-0.972077
Std. Dev.	0.154912
Skewness	1.820390
Kurtosis	54.00733
Jarque-Bera	382444.2
Probability	0.000000

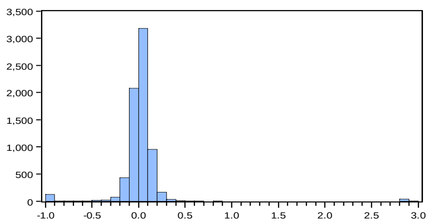
WINNERS



Series: OBOS4MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MWIN=1
AND CROSSID<>NA
Observations 4647

Mean	0.016627
Median	0.021066
Maximum	2.899909
Minimum	-0.964265
Std. Dev.	0.207003
Skewness	6.343768
Kurtosis	100.3259
Jarque-Bera	1865249.
Probability	0.000000

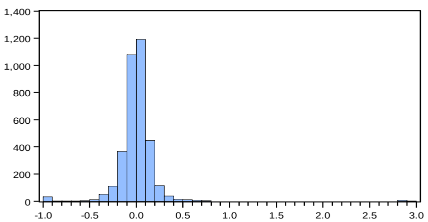
REST



Series: OBOS4MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=0 AND DUM1MWIN=0 AND
CROSSID<>NA
Observations 7151

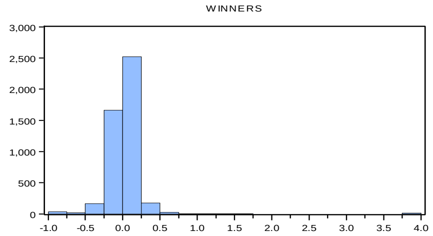
Mean	0.021622
Median	0.021611
Maximum	2.902920
Minimum	-0.967261
Std. Dev.	0.275645
Skewness	5.952326
Kurtosis	73.33717
Jarque-Bera	1516321.
Probability	0.000000

LOSERS



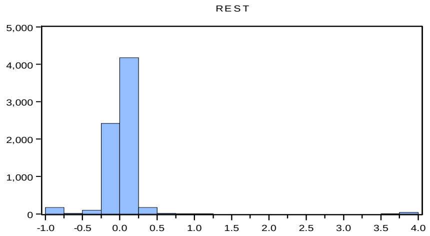
Series: OBOS4MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM1MLOSE
=1 AND CROSSID<>NA
Observations 3485

Mean	0.002303
Median	0.005071
Maximum	2.904979
Minimum	-0.968363
Std. Dev.	0.200669
Skewness	4.205881
Kurtosis	80.20151
Jarque-Bera	875726.9
Probability	0.000000



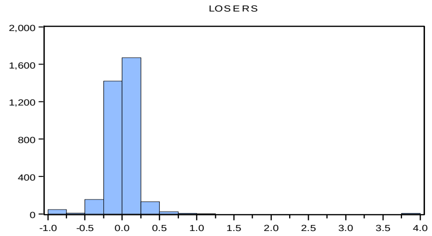
Series: OBOS5MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4611

Mean	0.024016
Median	0.025870
Maximum	3.838178
Minimum	-0.956924
Std. Dev.	0.258942
Skewness	7.867831
Kurtosis	123.0090
Jarque-Bera	2814589.
Probability	0.000000



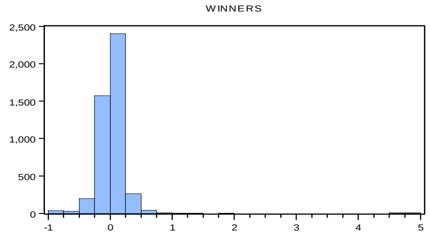
Series: OBOS5MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 7094

Mean	0.029286
Median	0.027096
Maximum	3.846689
Minimum	-0.964431
Std. Dev.	0.350073
Skewness	7.160459
Kurtosis	84.57529
Jarque-Bera	2027588.
Probability	0.000000



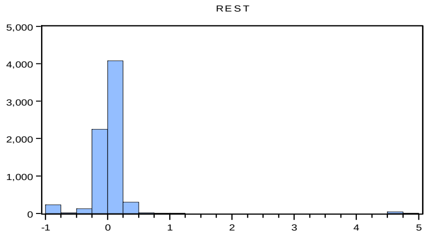
Series: OBOS5MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3462

Mean	0.002478
Median	0.008724
Maximum	3.841823
Minimum	-0.960809
Std. Dev.	0.246882
Skewness	5.789233
Kurtosis	103.5927
Jarque-Bera	1478990.
Probability	0.000000



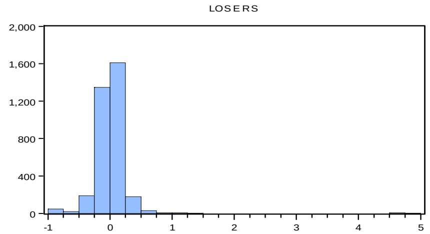
Series: OBOS6MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4559

Mean	0.032598
Median	0.029851
Maximum	4.767523
Minimum	-0.948791
Std. Dev.	0.307751
Skewness	9.222182
Kurtosis	145.3279
Jarque-Bera	3912650.
Probability	0.000000



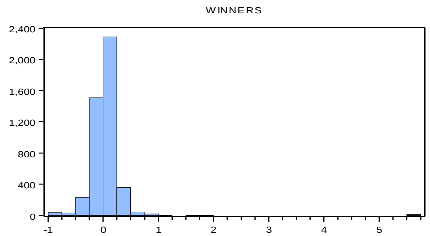
Series: OBOS6MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 7053

Mean	0.034013
Median	0.033197
Maximum	4.776125
Minimum	-0.959455
Std. Dev.	0.426385
Skewness	7.749898
Kurtosis	90.44233
Jarque-Bera	2317617.
Probability	0.000000



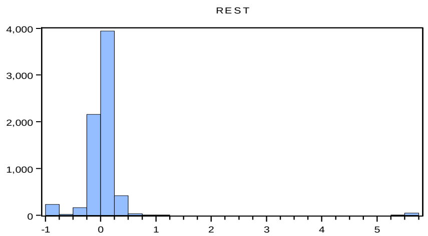
Series: OBOS6MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3439

Mean	0.007517
Median	0.011149
Maximum	4.766446
Minimum	-0.953360
Std. Dev.	0.285469
Skewness	7.600163
Kurtosis	134.2920
Jarque-Bera	2503111.
Probability	0.000000



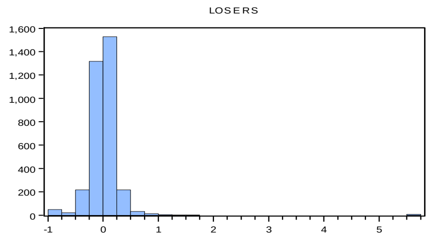
Series: OBOS7MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4523

Mean	0.042017
Median	0.036325
Maximum	5.680592
Minimum	-0.940778
Std. Dev.	0.355020
Skewness	10.28109
Kurtosis	164.4385
Jarque-Bera	4991354.
Probability	0.000000



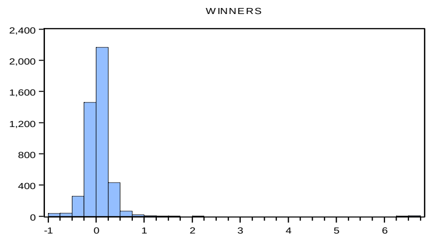
Series: OBOS7MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 7007

Mean	0.046500
Median	0.039283
Maximum	5.695471
Minimum	-0.953116
Std. Dev.	0.492648
Skewness	8.629509
Kurtosis	101.0104
Jarque-Bera	2891529.
Probability	0.000000



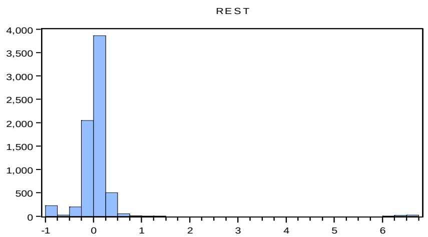
Series: OBOS7MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3405

Mean	0.011746
Median	0.011317
Maximum	5.674987
Minimum	-0.946047
Std. Dev.	0.323907
Skewness	9.060886
Kurtosis	162.0875
Jarque-Bera	3637283.
Probability	0.000000



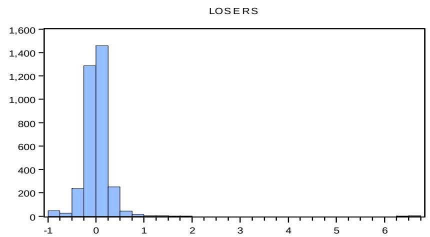
Series: OBOS8MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4487

Mean	0.050910
Median	0.042455
Maximum	6.588925
Minimum	-0.932904
Std. Dev.	0.402274
Skewness	11.07314
Kurtosis	179.5920
Jarque-Bera	5921938.
Probability	0.000000



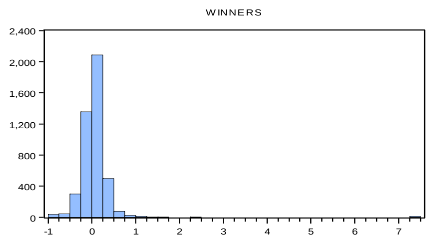
Series: OBOS8MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6952

Mean	0.059347
Median	0.045874
Maximum	6.608470
Minimum	-0.946855
Std. Dev.	0.559410
Skewness	9.243500
Kurtosis	108.6941
Jarque-Bera	3334938.
Probability	0.000000



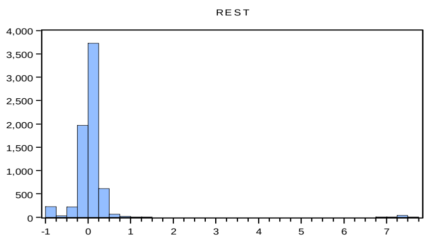
Series: OBOS8MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3380

Mean	0.016239
Median	0.010510
Maximum	6.569219
Minimum	-0.938863
Std. Dev.	0.363111
Skewness	10.13226
Kurtosis	183.9784
Jarque-Bera	4670573.
Probability	0.000000



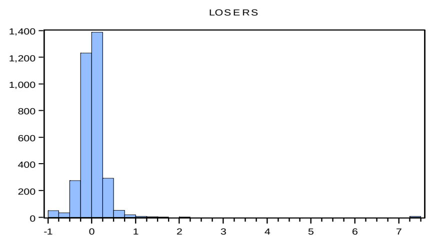
Series: OBOS9MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4441

Mean	0.060294
Median	0.048829
Maximum	7.490828
Minimum	-0.925133
Std. Dev.	0.450284
Skewness	11.65366
Kurtosis	190.6993
Jarque-Bera	6619730.
Probability	0.000000



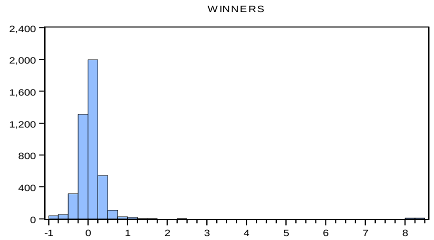
Series: OBOS9MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6909

Mean	0.071753
Median	0.049755
Maximum	7.511887
Minimum	-0.940887
Std. Dev.	0.626322
Skewness	9.675243
Kurtosis	114.2831
Jarque-Bera	3672818.
Probability	0.000000



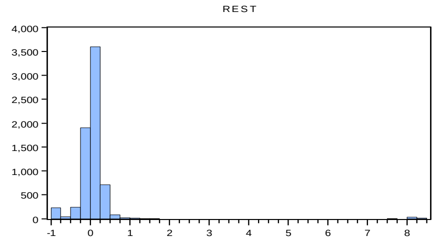
Series: OBOS9MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE =1 AND CROSSID<>NA
Observations 3355

Mean	0.019889
Median	0.010862
Maximum	7.451392
Minimum	-0.931803
Std. Dev.	0.401230
Skewness	11.07727
Kurtosis	204.7485
Jarque-Bera	5758476.
Probability	0.000000



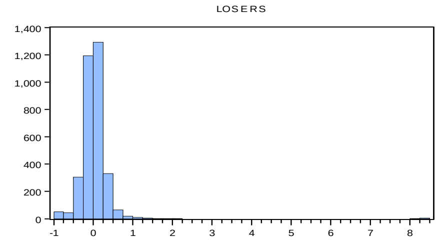
Series: OBOS10MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4414

Mean	0.069861
Median	0.052632
Maximum	8.382628
Minimum	-0.922686
Std. Dev.	0.497299
Skewness	12.12575
Kurtosis	200.1063
Jarque-Bera	7253497.
Probability	0.000000



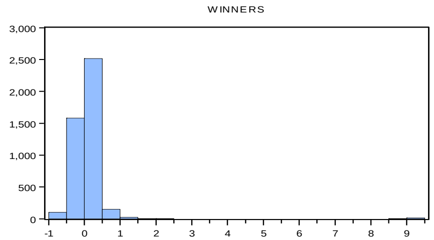
Series: OBOS10MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6860

Mean	0.084078
Median	0.056932
Maximum	8.407846
Minimum	-0.944403
Std. Dev.	0.693588
Skewness	9.982756
Kurtosis	118.2352
Jarque-Bera	3909564.
Probability	0.000000



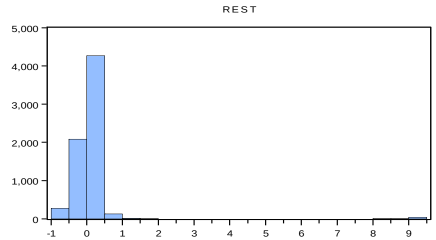
Series: OBOS10MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3317

Mean	0.022969
Median	0.010244
Maximum	8.319452
Minimum	-0.935254
Std. Dev.	0.439763
Skewness	11.85663
Kurtosis	222.1405
Jarque-Bera	6714836.
Probability	0.000000



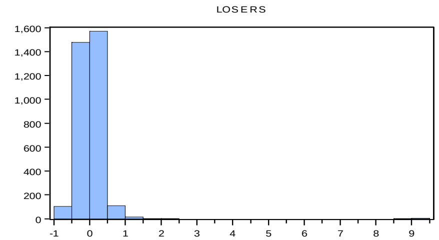
Series: OBOS11MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4383

Mean	0.079403
Median	0.057157
Maximum	9.265662
Minimum	-0.930426
Std. Dev.	0.543964
Skewness	12.50321
Kurtosis	207.5947
Jarque-Bera	7758701.
Probability	0.000000



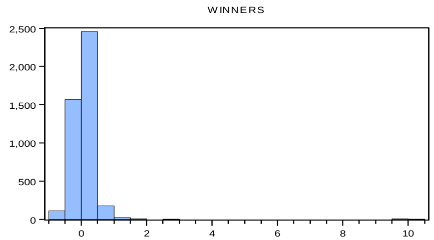
Series: OBOS11MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6809

Mean	0.096302
Median	0.062973
Maximum	9.297187
Minimum	-0.946388
Std. Dev.	0.760716
Skewness	10.20652
Kurtosis	121.0639
Jarque-Bera	4072851.
Probability	0.000000



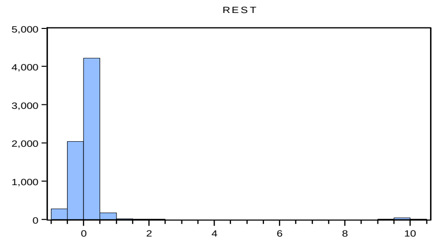
Series: OBOS11MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3285

Mean	0.027255
Median	0.008855
Maximum	9.172396
Minimum	-0.939654
Std. Dev.	0.478701
Skewness	12.43110
Kurtosis	235.0141
Jarque-Bera	7452663.
Probability	0.000000



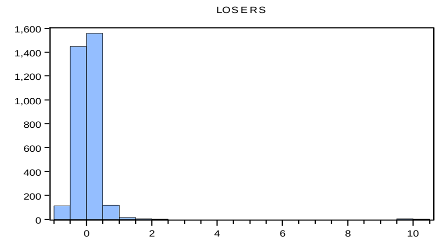
Series: OBOS12MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4343

Mean	0.088570
Median	0.065637
Maximum	10.14235
Minimum	-0.936463
Std. Dev.	0.591148
Skewness	12.79177
Kurtosis	213.1010
Jarque-Bera	8106378.
Probability	0.000000



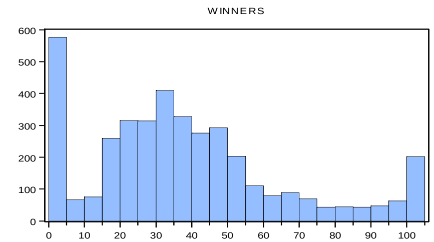
Series: OBOS12MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6761

Mean	0.107670
Median	0.068063
Maximum	10.18396
Minimum	-0.948565
Std. Dev.	0.819153
Skewness	10.45574
Kurtosis	125.4335
Jarque-Bera	4345989.
Probability	0.000000



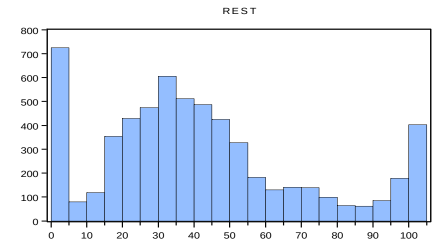
Series: OBOS12MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3260

Mean	0.031236
Median	0.011719
Maximum	10.01791
Minimum	-0.942737
Std. Dev.	0.516687
Skewness	12.95236
Kurtosis	247.0817
Jarque-Bera	8183542.
Probability	0.000000



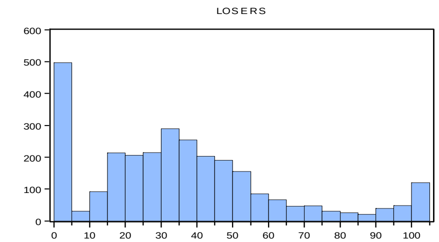
Series: POUTRAT
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 3905

Mean	37.76804
Median	34.06436
Maximum	100.0000
Minimum	0.000000
Std. Dev.	27.25277
Skewness	0.674841
Kurtosis	2.974956
Jarque-Bera	296.4984
Probability	0.000000



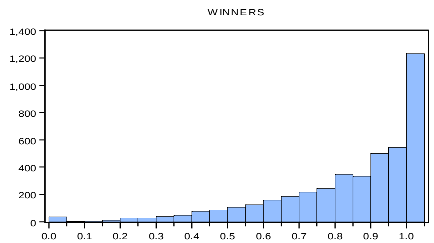
Series: POUTRAT
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6012

Mean	41.61388
Median	37.26000
Maximum	100.0000
Minimum	0.000000
Std. Dev.	28.45111
Skewness	0.587498
Kurtosis	2.672015
Jarque-Bera	372.7918
Probability	0.000000



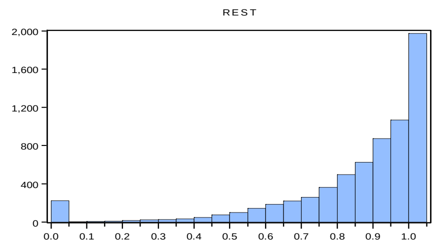
Series: POUTRAT
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 2871

Mean	35.71124
Median	33.01200
Maximum	100.0000
Minimum	0.000000
Std. Dev.	26.91943
Skewness	0.715391
Kurtosis	3.099762
Jarque-Bera	246.0796
Probability	0.000000



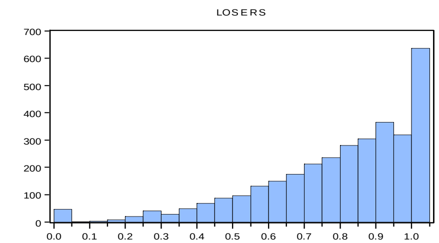
Series: PRICEREL12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4343

Mean	0.832914
Median	0.912000
Maximum	1.000000
Minimum	0.008938
Std. Dev.	0.201969
Skewness	-1.511835
Kurtosis	5.147111
Jarque-Bera	2488.660
Probability	0.000000



Series: PRICEREL12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6761

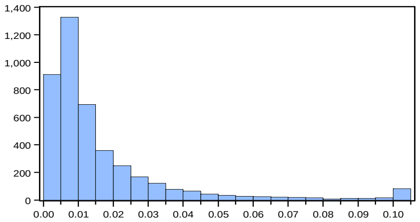
Mean	0.848377
Median	0.931940
Maximum	1.000000
Minimum	0.007037
Std. Dev.	0.218752
Skewness	-2.271323
Kurtosis	8.384005
Jarque-Bera	13979.25
Probability	0.000000



Series: PRICEREL12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3260

Mean	0.789789
Median	0.849315
Maximum	1.000000
Minimum	0.008122
Std. Dev.	0.215660
Skewness	-1.283716
Kurtosis	4.501905
Jarque-Bera	1201.775
Probability	0.000000

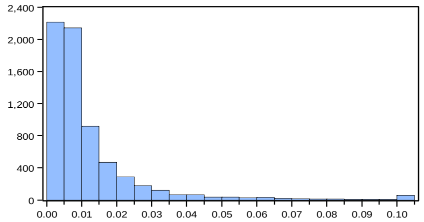
WINNERS



Series: RETVAR12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 4275

Mean	0.016359
Median	0.009543
Maximum	0.100000
Minimum	0.000286
Std. Dev.	0.019290
Skewness	2.695019
Kurtosis	10.72031
Jarque-Bera	15791.79
Probability	0.000000

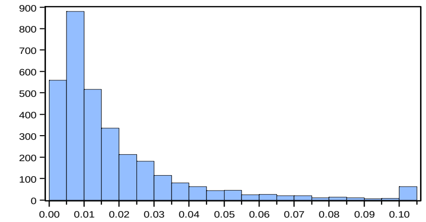
REST



Series: RETVAR12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 6718

Mean	0.012055
Median	0.007268
Maximum	0.100000
Minimum	0.000632
Std. Dev.	0.014886
Skewness	3.427615
Kurtosis	17.23826
Jarque-Bera	69901.45
Probability	0.000000

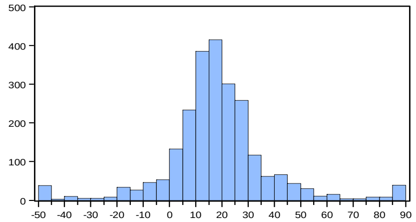
LOSERS



Series: RETVAR12
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 3227

Mean	0.018598
Median	0.011436
Maximum	0.100000
Minimum	0.000432
Std. Dev.	0.019906
Skewness	2.317444
Kurtosis	8.688981
Jarque-Bera	7240.135
Probability	0.000000

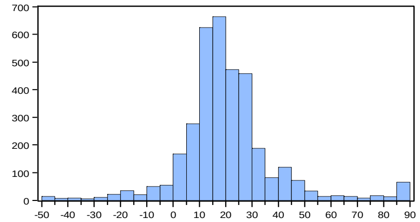
WINNERS



Series: ROE
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 2361

Mean	18.17848
Median	17.00000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	19.79856
Skewness	0.176203
Kurtosis	6.384440
Jarque-Bera	1139.047
Probability	0.000000

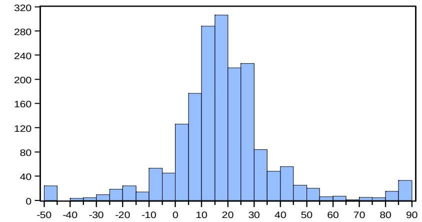
REST



Series: ROE
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 3531

Mean	20.34576
Median	18.47000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	18.32264
Skewness	0.699021
Kurtosis	6.729177
Jarque-Bera	2333.592
Probability	0.000000

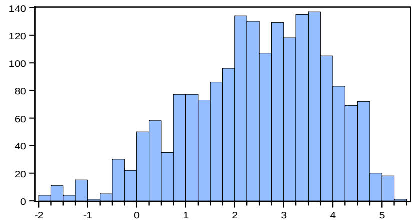
LOSERS



Series: ROE
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 1840

Mean	17.98388
Median	16.35500
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	19.94433
Skewness	0.434767
Kurtosis	6.282063
Jarque-Bera	883.8153
Probability	0.000000

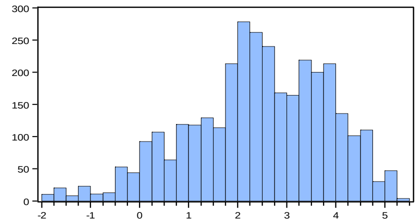
WINNERS



Series: SPSLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MWIN=1 AND CROSSID<>NA
Observations 1902

Mean	2.473583
Median	2.585947
Maximum	5.286503
Minimum	-2.000000
Std. Dev.	1.411900
Skewness	-0.472014
Kurtosis	2.770369
Jarque-Bera	74.80569
Probability	0.000000

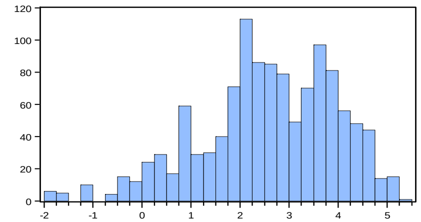
REST



Series: SPSLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=0 AND DUM1MWIN=0 AND CROSSID<>NA
Observations 3310

Mean	2.420697
Median	2.487113
Maximum	5.286503
Minimum	-2.000000
Std. Dev.	1.421983
Skewness	-0.441078
Kurtosis	2.840713
Jarque-Bera	110.8262
Probability	0.000000

LOSERS



Series: SPSLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM1MLOSE=1 AND CROSSID<>NA
Observations 1189

Mean	2.570331
Median	2.634913
Maximum	5.286503
Minimum	-2.000000
Std. Dev.	1.391775
Skewness	-0.573875
Kurtosis	3.103675
Jarque-Bera	65.79513
Probability	0.000000

Appendix E.2: Forward stepwise regression results for 1-month period: Loser shares

The tables below present the results of the forward stepwise regression approach followed to derive the logit model for the loser shares. The interpretation of each table is similar to that discussed in Chapter 8 (Section 8.4.2).

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	RETVAR12	18.419	1.674	121.068	1	.000	99863840.80
	Constant	-1.503	.034	1923.627	1	.000	.222
Step 2[b]	RETVAR12	16.325	1.703	91.922	1	.000	12293757.04
	MOM12	-.497	.057	75.510	1	.000	.608
	Constant	-1.369	.037	1349.902	1	.000	.254
Step 3[c]	RETVAR12	13.488	1.757	58.952	1	.000	720389.477
	MOM12	-.453	.057	62.641	1	.000	.636
	BETA	.882	.114	60.096	1	.000	2.417
	Constant	-1.910	.080	564.207	1	.000	.148
Step 4[d]	RETVAR12	13.311	1.760	57.195	1	.000	603588.214
	MOM12	-.481	.058	69.640	1	.000	.618
	BETA	.935	.114	67.153	1	.000	2.547
	CFTP	-1.516	.212	51.346	1	.000	.220
	Constant	-1.720	.084	417.424	1	.000	.179
Step 5[e]	MAD1(1)	.197	.053	14.073	1	.000	1.218
	RETVAR12	13.343	1.760	57.498	1	.000	623371.132
	MOM12	-.434	.059	54.331	1	.000	.648
	BETA	.935	.114	67.034	1	.000	2.546
	CFTP	-1.516	.212	51.386	1	.000	.219
	Constant	-1.824	.089	420.326	1	.000	.161
Step 6[f]	MAD1(1)	.171	.054	10.096	1	.001	1.187
	RETVAR12	12.150	1.837	43.764	1	.000	189136.830
	PRICEREL12	-.373	.166	5.022	1	.025	.689
	MOM12	-.345	.071	23.764	1	.000	.708
	BETA	.913	.115	63.488	1	.000	2.492
	CFTP	-1.535	.212	52.602	1	.000	.215
	Constant	-1.488	.174	72.978	1	.000	.226

a. Variable(s) entered on step 1: RETVAR12.

b. Variable(s) entered on step 2: MOM12.

c. Variable(s) entered on step 3: BETA.

d. Variable(s) entered on step 4: CFTP.

e. Variable(s) entered on step 5: MAD1.

f. Variable(s) entered on step 6: PRICEREL12.

Note that MAD1 is the code used when the logit models were developed. This is equivalent to MA2 used in the remainder of the thesis.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	9559.947[a]	.013	.019
2	9481.053[a]	.021	.032
3	9421.284[a]	.027	.042
4	9367.269[a]	.033	.051
5	9353.207[a]	.035	.053
6	9348.297[a]	.035	.054

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUM1MLOSE 0	Predicted DUM1MLOSE 1	Percentage Correct
Step 1	DUM1MLOSE	0	5136	2009	71.9
		1	1172	851	42.1
	Overall Percentage				65.3
Step 2	DUM1MLOSE	0	4467	2678	62.5
		1	870	1153	57.0
	Overall Percentage				61.3
Step 3	DUM1MLOSE	0	4411	2734	61.7
		1	876	1147	56.7
	Overall Percentage				60.6
Step 4	DUM1MLOSE	0	4498	2647	63.0
		1	863	1160	57.3
	Overall Percentage				61.7
Step 5	DUM1MLOSE	0	4445	2700	62.2
		1	842	1181	58.4
	Overall Percentage				61.4
Step 6	DUM1MLOSE	0	4490	2655	62.8
		1	849	1174	58.0
	Overall Percentage				61.8

a. The cut value is .217

Appendix E.3: Forward stepwise regression results for refined logit model for 1-month period: Winner shares

The tables below present the results of the forward stepwise regression approach followed to derive the refined logit model for the winner shares. The interpretation of each table is similar to that discussed in Chapter 8 (Section 8.4.2).

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CFTP	1.412	.198	50.734	1	.000	4.102
	Constant	-1.043	.040	684.579	1	.000	.352
Step 2[b]	CFTP	1.373	.199	47.817	1	.000	3.948
	BETA	.326	.108	9.093	1	.003	1.385
	Constant	-1.246	.079	250.446	1	.000	.288
Step 3[c]	CFTP	1.199	.207	33.554	1	.000	3.315
	BETA	.452	.117	14.952	1	.000	1.571
	LNP	-.062	.021	8.357	1	.004	.940
	Constant	-1.117	.090	152.290	1	.000	.327
Step 4[d]	CFTP	1.169	.208	31.684	1	.000	3.220
	BETA	.459	.117	15.446	1	.000	1.583
	C24MDPSP	3.423	1.237	7.659	1	.006	30.659
	LNP	-.062	.021	8.344	1	.004	.940
	Constant	-1.143	.091	156.922	1	.000	.319
Step 5[e]	CFTP	1.208	.209	33.501	1	.000	3.346
	MOM12	.137	.055	6.233	1	.013	1.147
	BETA	.495	.118	17.626	1	.000	1.640
	C24MDPSP	3.311	1.241	7.116	1	.008	27.410
	LNP	-.066	.022	9.471	1	.002	.936
	Constant	-1.193	.094	162.580	1	.000	.303
Step 6[f]	CFTP	1.216	.209	33.903	1	.000	3.373
	MOM12	.177	.057	9.626	1	.002	1.194
	MOM1	-.640	.251	6.520	1	.011	.527
	BETA	.496	.118	17.683	1	.000	1.642
	C24MDPSP	3.280	1.241	6.986	1	.008	26.571
	LNP	-.066	.022	9.385	1	.002	.936
	Constant	-1.195	.094	162.981	1	.000	.303
Step 7[g]	CFTP	1.207	.209	33.466	1	.000	3.343
	MOM12	.190	.057	11.013	1	.001	1.209
	RETVAR12	4.212	2.088	4.067	1	.044	67.471
	MOM1	-.654	.249	6.888	1	.009	.520
	BETA	.424	.123	11.825	1	.001	1.528
	C24MDPSP	3.516	1.248	7.936	1	.005	33.661
	LNP	-.056	.022	6.499	1	.011	.945
	Constant	-1.232	.095	166.695	1	.000	.292

a. Variable(s) entered on step 1: CFTP.

b. Variable(s) entered on step 2: BETA.

c. Variable(s) entered on step 3: LNP.

d. Variable(s) entered on step 4: C24MDPSP.

e. Variable(s) entered on step 5: MOM12.

f. Variable(s) entered on step 6: MOM1.

g. Variable(s) entered on step 7: RETVAR12.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	9509.667[a]	.006	.009
2	9500.596[a]	.008	.011
3	9492.260[a]	.009	.012
4	9484.539[a]	.010	.014
5	9478.332[a]	.010	.015
6	9471.787[a]	.011	.016
7	9467.781[a]	.012	.017

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted DUM1MWIN 0	Predicted DUM1MWIN 1	Predicted Percentage Correct
Step 1	DUM1MWIN	0	3137	2269	58.0
		1	1199	1170	49.4
	Overall Percentage				55.4
Step 2	DUM1MWIN	0	2953	2453	54.6
		1	1097	1272	53.7
	Overall Percentage				54.3
Step 3	DUM1MWIN	0	3087	2319	57.1
		1	1150	1219	51.5
	Overall Percentage				55.4
Step 4	DUM1MWIN	0	3111	2295	57.5
		1	1157	1212	51.2
	Overall Percentage				55.6
Step 5	DUM1MWIN	0	3075	2331	56.9
		1	1151	1218	51.4
	Overall Percentage				55.2
Step 6	DUM1MWIN	0	3047	2359	56.4
		1	1105	1264	53.4
	Overall Percentage				55.4
Step 7	DUM1MWIN	0	3042	2364	56.3
		1	1112	1257	53.1
	Overall Percentage				55.3

a. The cut value is .300

Appendix E.4: Forward stepwise regression results for refined logit model for 1-month period: Loser shares

The tables below present the results of the forward stepwise regression approach followed to derive the refined logit model for the loser shares. The interpretation of each table is similar to that discussed in Chapter 8 (Section 8.4.2).

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	PRICEREL12	-1.316	.120	120.988	1	.000	.268
	Constant	-.171	.102	2.833	1	.092	.843
Step 2[b]	PRICEREL12	-1.122	.122	84.200	1	.000	.326
	BETA	.984	.112	76.728	1	.000	2.676
	Constant	-.966	.137	49.605	1	.000	.381
Step 3[c]	CFTP	-1.569	.216	52.921	1	.000	.208
	PRICEREL12	-1.178	.123	91.610	1	.000	.308
	BETA	1.028	.113	83.381	1	.000	2.796
	Constant	-.725	.141	26.478	1	.000	.484
Step 4[d]	CFTP	-1.537	.214	51.786	1	.000	.215
	PRICEREL12	-.983	.129	58.097	1	.000	.374
	RETVAR12	10.129	1.869	29.374	1	.000	25055.339
	BETA	.915	.115	63.579	1	.000	2.496
	Constant	-.951	.148	41.287	1	.000	.386
Step 5[e]	CFTP	-1.573	.214	53.869	1	.000	.208
	PRICEREL12	-.503	.162	9.580	1	.002	.605
	MOM12	-.360	.071	25.715	1	.000	.698
	RETVAR12	10.785	1.889	32.582	1	.000	48301.913
	BETA	.901	.115	61.354	1	.000	2.462
	Constant	-1.269	.163	60.282	1	.000	.281
Step 6[f]	CFTP	-1.562	.214	53.180	1	.000	.210
	PRICEREL12	-.361	.172	4.375	1	.036	.697
	MOM12	-.349	.071	24.030	1	.000	.705
	MAD2(1)	.149	.057	6.828	1	.009	1.160
	RETVAR12	11.310	1.901	35.405	1	.000	81630.467
	BETA	.903	.115	61.580	1	.000	2.467
	Constant	-1.465	.181	65.585	1	.000	.231

a. Variable(s) entered on step 1: PRICEREL12.

b. Variable(s) entered on step 2: BETA.

c. Variable(s) entered on step 3: CFTP.

d. Variable(s) entered on step 4: RETVAR12.

e. Variable(s) entered on step 5: MOM12.

f. Variable(s) entered on step 6: MAD2.

Note that MAD2 is the code used when the logit models were developed. This is equivalent to MA3 used in the remainder of the thesis.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	9474.389[a]	.013	.019
2	9397.999[a]	.021	.032
3	9342.178[a]	.027	.041
4	9313.699[a]	.030	.046
5	9286.967[a]	.033	.050
6	9280.157[a]	.033	.051

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

			Predicted		
			DUM1MLOSE		Percentage Correct
Observed			0	1	
Step 1	DUM1MLOSE	0	4902	2216	68.9
		1	1082	917	45.9
	Overall Percentage				63.8
Step 2	DUM1MLOSE	0	4534	2584	63.7
		1	928	1071	53.6
	Overall Percentage				61.5
Step 3	DUM1MLOSE	0	4587	2531	64.4
		1	896	1103	55.2
	Overall Percentage				62.4
Step 4	DUM1MLOSE	0	4675	2443	65.7
		1	912	1087	54.4
	Overall Percentage				63.2
Step 5	DUM1MLOSE	0	4579	2539	64.3
		1	867	1132	56.6
	Overall Percentage				62.6
Step 6	DUM1MLOSE	0	4539	2579	63.8
		1	855	1144	57.2
	Overall Percentage				62.3

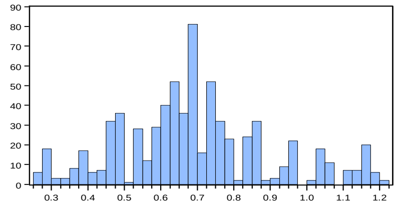
a. The cut value is .218

Appendix F

This appendix refers to Chapter 9: Extreme performance and filter rules for a 12-month payoff period. To compare statistical properties of the characteristics across winners, losers and the rest (REST), descriptive statistics were calculated and are presented together with histograms in Appendix F.1. The results of the forward stepwise logistic regression approach followed in Chapter 9 to derive the respective logit models are reported in Appendix F.2 and Appendix F.3.

Appendix F.1: Histograms and descriptive statistics: 12-month holding period

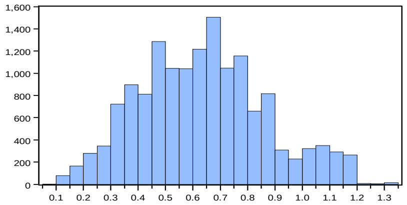
WINNERS



Series: BETA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 705

Mean	0.692485
Median	0.682000
Maximum	1.222000
Minimum	0.252000
Std. Dev.	0.209432
Skewness	0.381398
Kurtosis	2.972964
Jarque-Bera	17.11357
Probability	0.000192

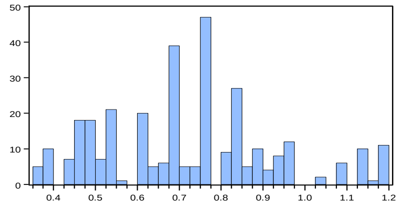
REST



Series: BETA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14853

Mean	0.634182
Median	0.627000
Maximum	1.300000
Minimum	0.079935
Std. Dev.	0.230787
Skewness	0.284224
Kurtosis	2.634741
Jarque-Bera	282.5461
Probability	0.000000

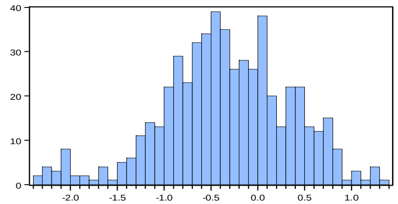
LOSERS



Series: BETA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 319

Mean	0.721536
Median	0.706000
Maximum	1.181000
Minimum	0.373000
Std. Dev.	0.205211
Skewness	0.399391
Kurtosis	2.606508
Jarque-Bera	10.53882
Probability	0.005147

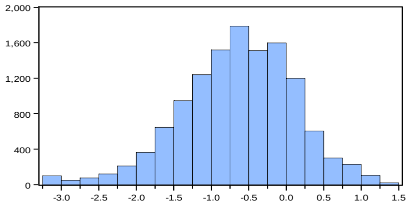
WINNERS



Series: BVTMLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 543

Mean	-0.345429
Median	-0.343590
Maximum	1.386294
Minimum	-2.391511
Std. Dev.	0.686054
Skewness	-0.328835
Kurtosis	3.307076
Jarque-Bera	11.91941
Probability	0.002581

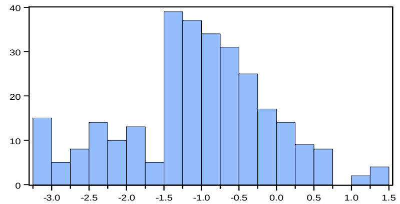
REST



Series: BVTMLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 12598

Mean	-0.642199
Median	-0.603559
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.756695
Skewness	-0.412998
Kurtosis	3.519255
Jarque-Bera	499.6653
Probability	0.000000

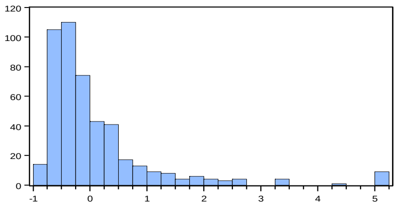
LOSERS



Series: BVTMLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 290

Mean	-1.062417
Median	-1.000632
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.985860
Skewness	-0.232489
Kurtosis	2.913410
Jarque-Bera	2.703071
Probability	0.258843

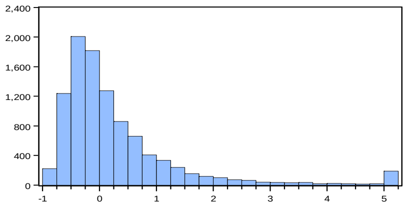
WINNERS



Series: C24MBVTM
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 469

Mean	0.086647
Median	-0.234899
Maximum	5.000000
Minimum	-0.862222
Std. Dev.	1.027367
Skewness	2.843530
Kurtosis	12.51894
Jarque-Bera	2402.705
Probability	0.000000

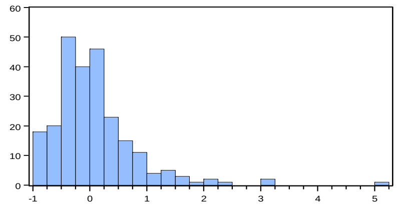
REST



Series: C24MBVTM
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 9997

Mean	0.282558
Median	-0.051020
Maximum	5.000000
Minimum	-1.000000
Std. Dev.	1.085634
Skewness	2.455244
Kurtosis	9.969247
Jarque-Bera	30275.62
Probability	0.000000

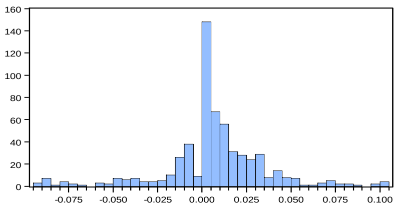
LOSERS



Series: C24MBVTM
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 242

Mean	0.072772
Median	-0.038176
Maximum	5.000000
Minimum	-0.923850
Std. Dev.	0.732445
Skewness	2.347161
Kurtosis	13.06939
Jarque-Bera	1244.579
Probability	0.000000

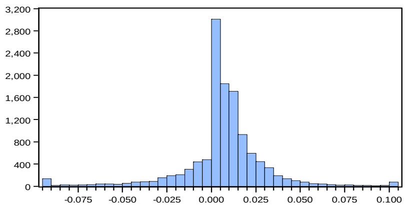
WINNERS



Series: C24MDPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 580

Mean	0.006237
Median	0.005298
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.028603
Skewness	-0.348523
Kurtosis	5.934533
Jarque-Bera	219.8528
Probability	0.000000

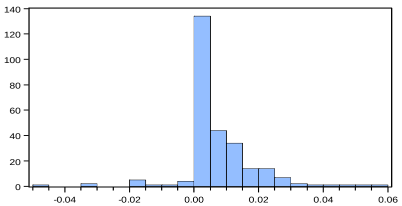
REST



Series: C24MDPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 12093

Mean	0.006253
Median	0.006667
Maximum	0.102453
Minimum	-0.090250
Std. Dev.	0.023971
Skewness	-0.530671
Kurtosis	8.301788
Jarque-Bera	14730.99
Probability	0.000000

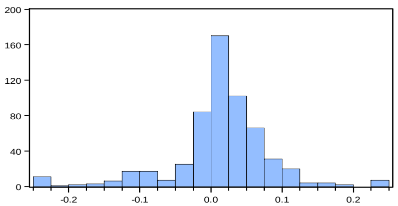
LOSERS



Series: C24MDPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 268

Mean	0.006145
Median	0.004354
Maximum	0.058140
Minimum	-0.046316
Std. Dev.	0.010975
Skewness	0.595524
Kurtosis	8.585717
Jarque-Bera	364.2436
Probability	0.000000

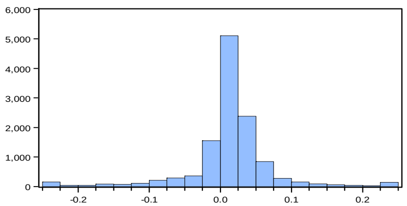
WINNERS



Series: C24MEPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 579

Mean	0.012645
Median	0.009800
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.069301
Skewness	-0.567357
Kurtosis	6.292435
Jarque-Bera	292.5809
Probability	0.000000

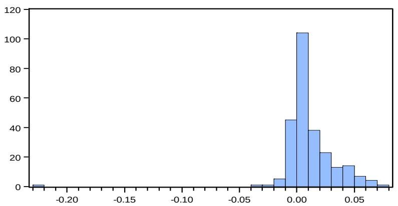
REST



Series: C24MEPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 11979

Mean	0.011974
Median	0.011592
Maximum	0.247800
Minimum	-0.225720
Std. Dev.	0.059012
Skewness	-0.441713
Kurtosis	9.484410
Jarque-Bera	21376.53
Probability	0.000000

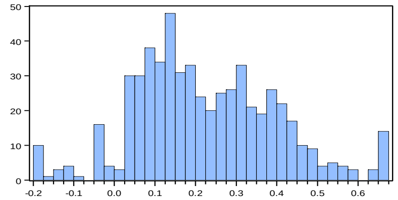
LOSERS



Series: C24MEPSP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 257

Mean	0.010259
Median	0.002765
Maximum	0.076733
Minimum	-0.225720
Std. Dev.	0.023007
Skewness	-3.564493
Kurtosis	45.00712
Jarque-Bera	19440.13
Probability	0.000000

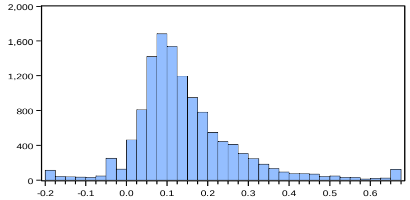
WINNERS



Series: CFTP
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 571

Mean	0.224089
Median	0.199203
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.173331
Skewness	0.237962
Kurtosis	3.028547
Jarque-Bera	5.408284
Probability	0.066928

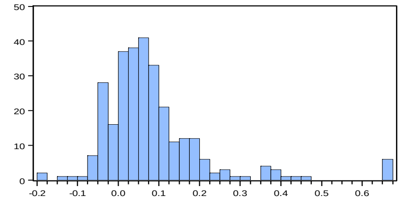
REST



Series: CFTP
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 12414

Mean	0.143035
Median	0.118343
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.126811
Skewness	1.196305
Kurtosis	6.325093
Jarque-Bera	8679.883
Probability	0.000000

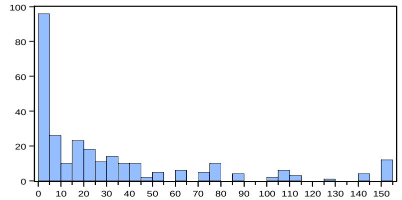
LOSERS



Series: CFTP
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 290

Mean	0.081633
Median	0.058445
Maximum	0.655300
Minimum	-0.200000
Std. Dev.	0.129412
Skewness	2.192626
Kurtosis	9.847092
Jarque-Bera	798.8668
Probability	0.000000

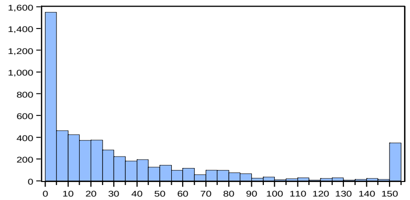
WINNERS



Series: DE
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 278

Mean	31.40569
Median	17.77890
Maximum	150.0000
Minimum	0.000000
Std. Dev.	40.62520
Skewness	1.631442
Kurtosis	4.801740
Jarque-Bera	160.9235
Probability	0.000000

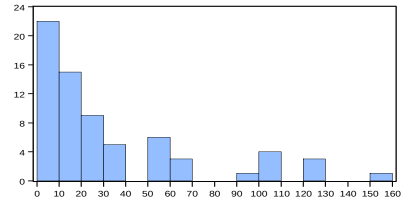
REST



Series: DE
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 5499

Mean	34.48306
Median	19.56600
Maximum	150.0000
Minimum	0.000000
Std. Dev.	41.69521
Skewness	1.598750
Kurtosis	4.724279
Jarque-Bera	3023.794
Probability	0.000000

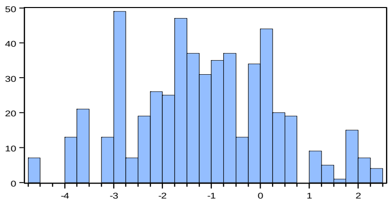
LOSERS



Series: DE
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 69

Mean	33.74477
Median	17.61740
Maximum	150.0000
Minimum	0.000000
Std. Dev.	37.58405
Skewness	1.486374
Kurtosis	4.195342
Jarque-Bera	29.51495
Probability	0.000000

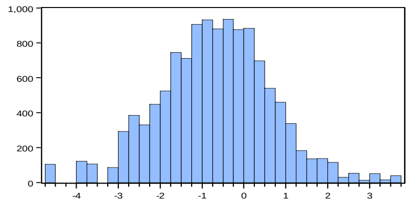
WINNERS



Series: DPSLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 538

Mean	-1.172894
Median	-1.203973
Maximum	2.468100
Minimum	-4.605170
Std. Dev.	1.485919
Skewness	0.107840
Kurtosis	2.695241
Jarque-Bera	3.124792
Probability	0.209633

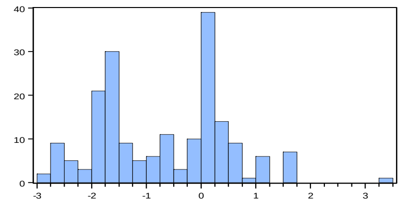
REST



Series: DPSLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 12071

Mean	-0.681404
Median	-0.653926
Maximum	3.516000
Minimum	-4.605170
Std. Dev.	1.341416
Skewness	-0.031945
Kurtosis	3.413983
Jarque-Bera	88.25110
Probability	0.000000

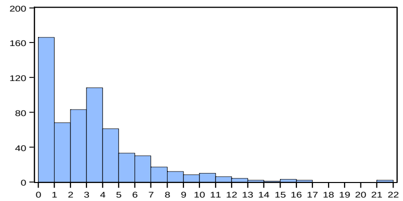
LOSERS



Series: DPSLOG
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 191

Mean	-0.673595
Median	-0.510826
Maximum	3.295837
Minimum	-2.995732
Std. Dev.	1.162583
Skewness	0.213301
Kurtosis	2.546639
Jarque-Bera	3.084056
Probability	0.213947

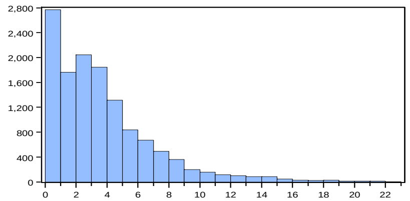
WINNERS



Series: DY
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 616

Mean	3.291844
Median	2.905000
Maximum	21.75570
Minimum	0.000000
Std. Dev.	3.246933
Skewness	1.742700
Kurtosis	7.669007
Jarque-Bera	871.3229
Probability	0.000000

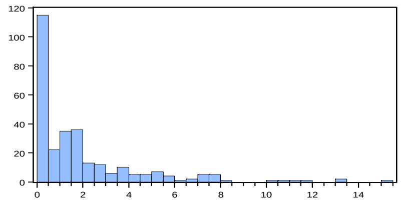
REST



Series: DY
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 12984

Mean	3.644270
Median	2.957800
Maximum	22.00000
Minimum	0.000000
Std. Dev.	3.379963
Skewness	1.619069
Kurtosis	6.625368
Jarque-Bera	12783.20
Probability	0.000000

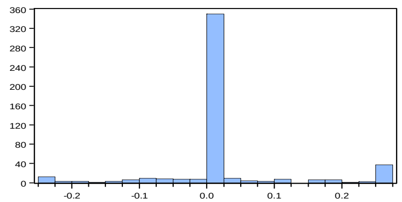
LOSERS



Series: DY
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 291

Mean	1.828533
Median	1.103700
Maximum	15.45000
Minimum	0.000000
Std. Dev.	2.553433
Skewness	2.256561
Kurtosis	9.115079
Jarque-Bera	700.3699
Probability	0.000000

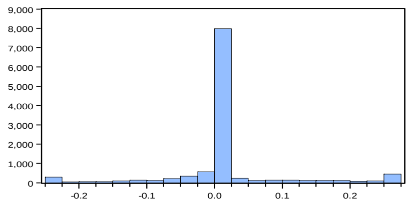
WINNERS



Series: EARNREV3M
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 484

Mean	0.015168
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.094515
Skewness	0.812453
Kurtosis	5.835069
Jarque-Bera	215.3383
Probability	0.000000

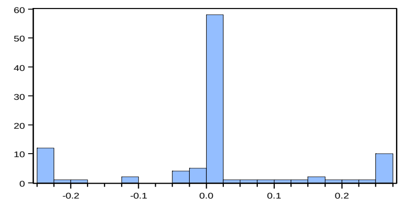
REST



Series: EARNREV3M
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 11407

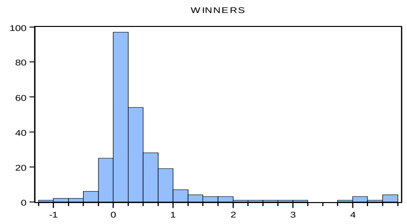
Mean	0.007576
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.082673
Skewness	0.616650
Kurtosis	7.320713
Jarque-Bera	9595.944
Probability	0.000000

LOSERS



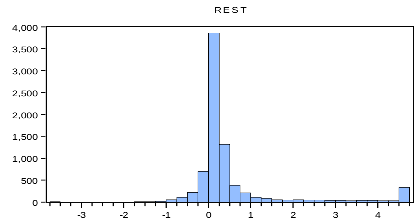
Series: EARNREV3M
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 103

Mean	0.002687
Median	0.000000
Maximum	0.262000
Minimum	-0.246000
Std. Dev.	0.131078
Skewness	0.067612
Kurtosis	3.414940
Jarque-Bera	0.817393
Probability	0.664516



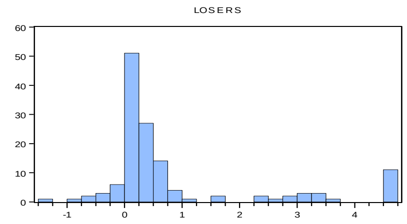
Series: EG1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 265

Mean	0.504965
Median	0.248487
Maximum	4.700000
Minimum	-1.137197
Std. Dev.	0.906366
Skewness	2.984850
Kurtosis	13.02160
Jarque-Bera	1502.437
Probability	0.000000



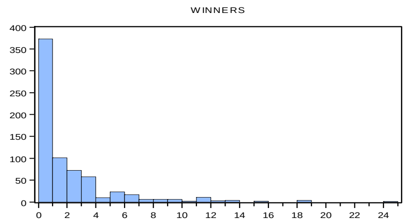
Series: EG1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 7901

Mean	0.535163
Median	0.186322
Maximum	4.700000
Minimum	-3.610000
Std. Dev.	1.159385
Skewness	2.512168
Kurtosis	9.257654
Jarque-Bera	21201.74
Probability	0.000000



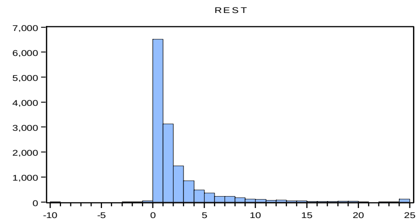
Series: EG1
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 135

Mean	0.848211
Median	0.265335
Maximum	4.700000
Minimum	-1.259278
Std. Dev.	1.449571
Skewness	1.742731
Kurtosis	4.796311
Jarque-Bera	86.48540
Probability	0.000000



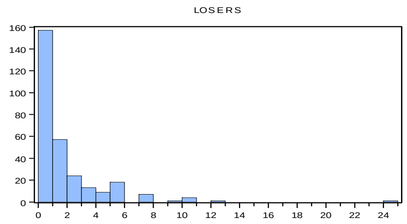
Series: EPS
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 699

Mean	2.069437
Median	0.860000
Maximum	24.03633
Minimum	0.000000
Std. Dev.	3.064010
Skewness	2.927623
Kurtosis	13.63481
Jarque-Bera	4292.535
Probability	0.000000



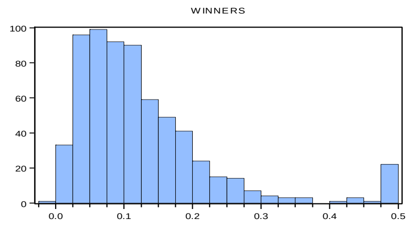
Series: EPS
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14153

Mean	2.293972
Median	1.090000
Maximum	24.03633
Minimum	-10.00000
Std. Dev.	3.580129
Skewness	3.394029
Kurtosis	17.46710
Jarque-Bera	150596.7
Probability	0.000000



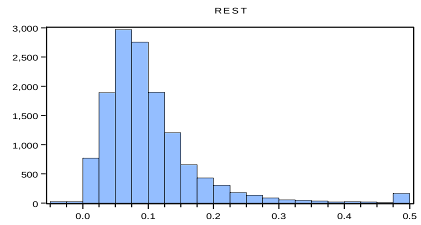
Series: EPS
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 292

Mean	1.699406
Median	0.730000
Maximum	24.03633
Minimum	0.000000
Std. Dev.	2.608326
Skewness	3.467854
Kurtosis	22.80900
Jarque-Bera	5359.422
Probability	0.000000



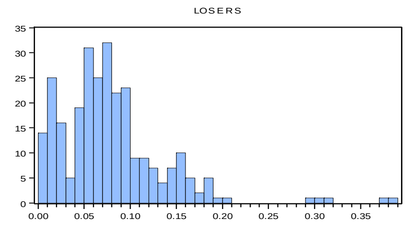
Series: EY
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 657

Mean	0.125045
Median	0.101010
Maximum	0.479000
Minimum	-0.008667
Std. Dev.	0.098988
Skewness	1.873213
Kurtosis	7.018060
Jarque-Bera	826.1916
Probability	0.000000



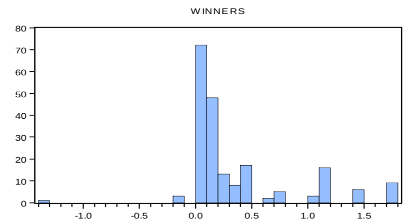
Series: EY
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 13664

Mean	0.101234
Median	0.084034
Maximum	0.479000
Minimum	-0.050000
Std. Dev.	0.074972
Skewness	2.381775
Kurtosis	11.17724
Jarque-Bera	50988.69
Probability	0.000000



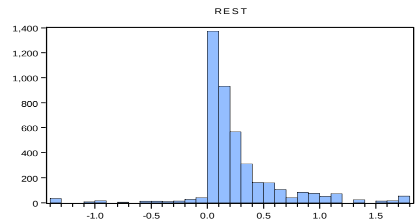
Series: EY
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 277

Mean	0.078410
Median	0.070423
Maximum	0.384615
Minimum	0.002000
Std. Dev.	0.056491
Skewness	1.908475
Kurtosis	9.571922
Jarque-Bera	666.6382
Probability	0.000000



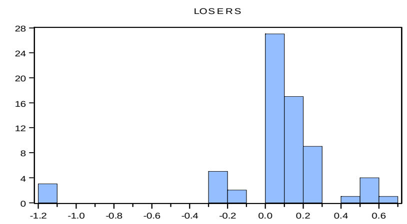
Series: ICBTIN
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 203

Mean	0.368483
Median	0.162652
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.496673
Skewness	1.321596
Kurtosis	4.672444
Jarque-Bera	82.75236
Probability	0.000000



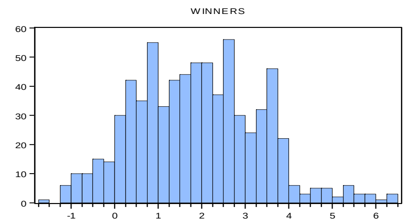
Series: ICBTIN
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 4196

Mean	0.250759
Median	0.156485
Maximum	1.742600
Minimum	-1.332660
Std. Dev.	0.382842
Skewness	0.901769
Kurtosis	8.410146
Jarque-Bera	5686.005
Probability	0.000000



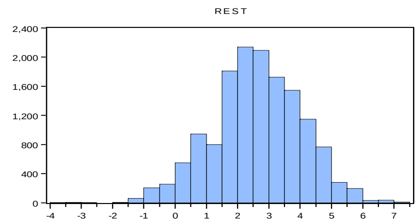
Series: ICBTIN
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 69

Mean	0.067249
Median	0.094838
Maximum	0.688800
Minimum	-1.175779
Std. Dev.	0.324511
Skewness	-2.244689
Kurtosis	10.26458
Jarque-Bera	209.6697
Probability	0.000000



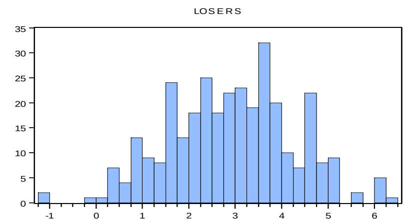
Series: LNP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 717

Mean	1.895020
Median	1.837370
Maximum	6.371612
Minimum	-1.514128
Std. Dev.	1.436035
Skewness	0.303675
Kurtosis	2.948818
Jarque-Bera	11.09835
Probability	0.003891



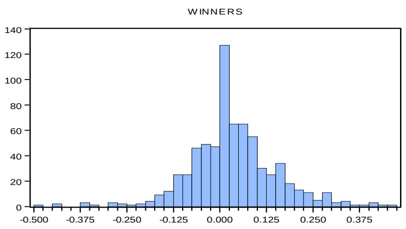
Series: LNP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14593

Mean	2.613089
Median	2.621039
Maximum	7.225409
Minimum	-3.506558
Std. Dev.	1.425694
Skewness	-0.152578
Kurtosis	3.067379
Jarque-Bera	59.38135
Probability	0.000000



Series: LNP
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 323

Mean	2.923183
Median	2.952303
Maximum	6.269437
Minimum	-1.237874
Std. Dev.	1.355438
Skewness	-0.061443
Kurtosis	2.855534
Jarque-Bera	0.484114
Probability	0.785012

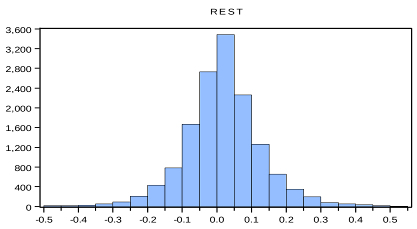


Series: MOM1

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA

Observations 705

Mean	0.034100
Median	0.023359
Maximum	0.473174
Minimum	-0.480815
Std. Dev.	0.117233
Skewness	0.001009
Kurtosis	5.245276
Jarque-Bera	148.0872
Probability	0.000000

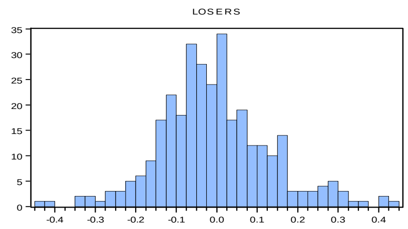


Series: MOM1

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA

Observations 14396

Mean	0.016489
Median	0.012920
Maximum	0.500000
Minimum	-0.494237
Std. Dev.	0.110233
Skewness	0.065548
Kurtosis	4.914798
Jarque-Bera	2209.569
Probability	0.000000

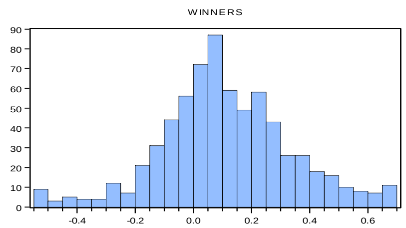


Series: MOM1

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA

Observations 318

Mean	-0.005791
Median	-0.018781
Maximum	0.442481
Minimum	-0.442100
Std. Dev.	0.136615
Skewness	0.332152
Kurtosis	3.903821
Jarque-Bera	16.67105
Probability	0.000240

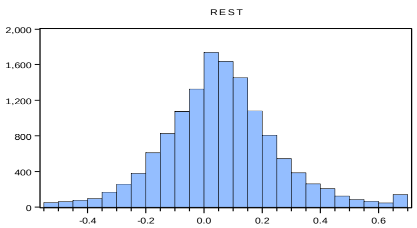


Series: MOM3

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA

Observations 686

Mean	0.109495
Median	0.091007
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.225095
Skewness	-0.022210
Kurtosis	3.567355
Jarque-Bera	9.257133
Probability	0.009769

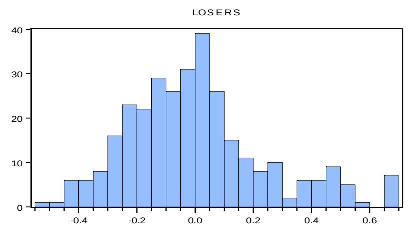


Series: MOM3

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA

Observations 13472

Mean	0.057885
Median	0.052644
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.195516
Skewness	0.237571
Kurtosis	3.895576
Jarque-Bera	576.9473
Probability	0.000000

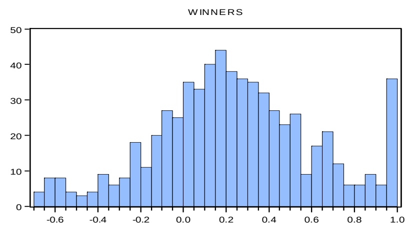


Series: MOM3

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA

Observations 314

Mean	0.000336
Median	-0.025710
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.237885
Skewness	0.697507
Kurtosis	3.441767
Jarque-Bera	28.01431
Probability	0.000001

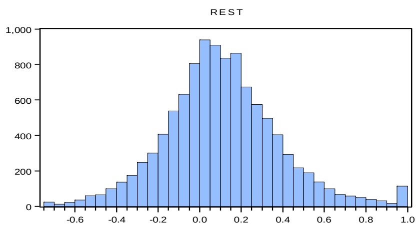


Series: MOM6

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA

Observations 646

Mean	0.237944
Median	0.211634
Maximum	0.969094
Minimum	-0.691814
Std. Dev.	0.370721
Skewness	-0.000110
Kurtosis	2.844027
Jarque-Bera	0.654821
Probability	0.720788

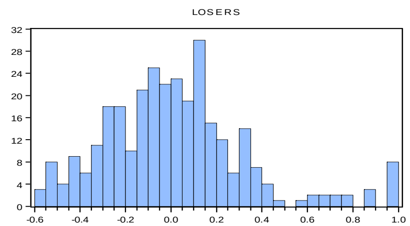


Series: MOM6

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA

Observations 10553

Mean	0.107603
Median	0.092199
Maximum	0.969094
Minimum	-0.743870
Std. Dev.	0.273487
Skewness	0.320844
Kurtosis	3.845279
Jarque-Bera	495.2255
Probability	0.000000

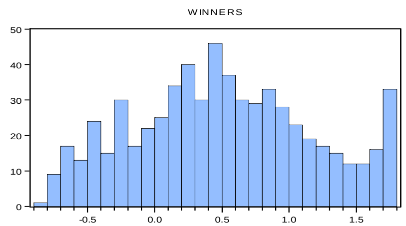


Series: MOM6

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA

Observations 306

Mean	0.018095
Median	-0.003522
Maximum	0.969094
Minimum	-0.597389
Std. Dev.	0.315069
Skewness	0.854936
Kurtosis	4.243326
Jarque-Bera	56.98641
Probability	0.000000

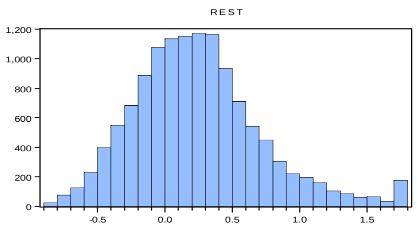


Series: MOM12

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA

Observations 627

Mean	0.506312
Median	0.486863
Maximum	1.764000
Minimum	-0.802563
Std. Dev.	0.661255
Skewness	0.112291
Kurtosis	2.243469
Jarque-Bera	16.27003
Probability	0.000293

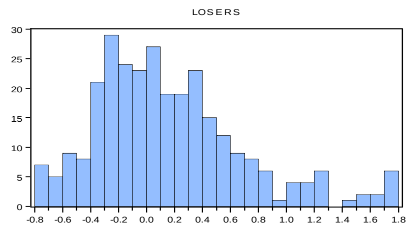


Series: MOM12

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA

Observations 12702

Mean	0.242314
Median	0.202139
Maximum	1.764000
Minimum	-0.881150
Std. Dev.	0.474656
Skewness	0.710420
Kurtosis	3.827046
Jarque-Bera	1430.454
Probability	0.000000

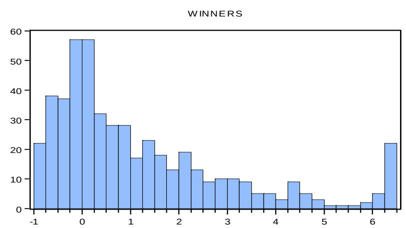


Series: MOM12

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA

Observations 290

Mean	0.158673
Median	0.082410
Maximum	1.764000
Minimum	-0.784766
Std. Dev.	0.534508
Skewness	0.940556
Kurtosis	3.904658
Jarque-Bera	52.64695
Probability	0.000000

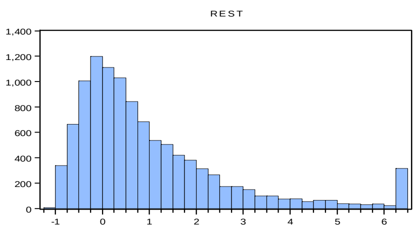


Series: MOM36

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA

Observations 502

Mean	1.218699
Median	0.559533
Maximum	6.372173
Minimum	-0.986294
Std. Dev.	1.880417
Skewness	1.304082
Kurtosis	3.993792
Jarque-Bera	162.9438
Probability	0.000000

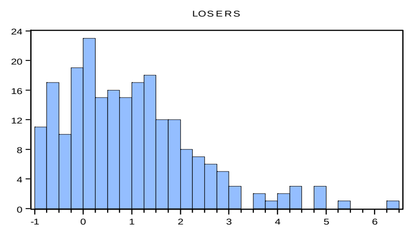


Series: MOM36

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA

Observations 10786

Mean	1.002682
Median	0.509236
Maximum	6.372173
Minimum	-1.072450
Std. Dev.	1.620799
Skewness	1.623750
Kurtosis	5.505305
Jarque-Bera	7560.451
Probability	0.000000



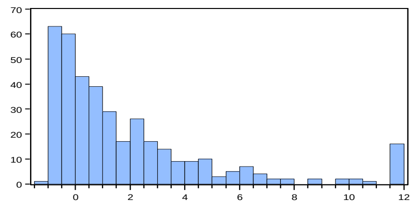
Series: MOM36

Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA

Observations 227

Mean	0.985611
Median	0.783373
Maximum	6.372173
Minimum	-0.850996
Std. Dev.	1.343772
Skewness	1.080552
Kurtosis	4.413491
Jarque-Bera	63.07128
Probability	0.000000

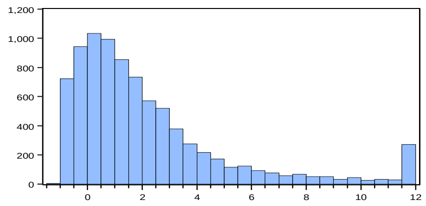
WINNERS



Series: MOM60
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 383

Mean	1.870967
Median	0.753980
Maximum	11.97380
Minimum	-1.159770
Std. Dev.	3.085921
Skewness	1.831901
Kurtosis	6.087465
Jarque-Bera	366.3376
Probability	0.000000

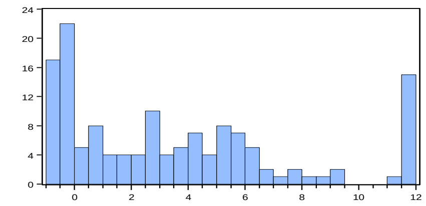
REST



Series: MOM60
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 8475

Mean	2.163943
Median	1.315530
Maximum	11.97380
Minimum	-1.256238
Std. Dev.	2.900959
Skewness	1.789194
Kurtosis	6.076257
Jarque-Bera	7863.464
Probability	0.000000

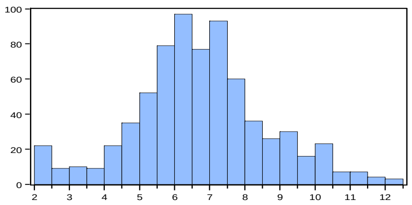
LOSERS



Series: MOM60
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 139

Mean	3.563213
Median	2.850892
Maximum	11.97380
Minimum	-0.753332
Std. Dev.	3.985409
Skewness	0.867581
Kurtosis	2.744165
Jarque-Bera	17.81654
Probability	0.000135

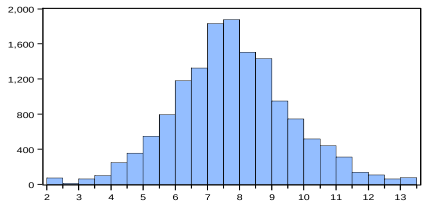
WINNERS



Series: MVLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 717

Mean	6.730081
Median	6.673253
Maximum	12.39671
Minimum	2.414000
Std. Dev.	1.890177
Skewness	0.100592
Kurtosis	3.315867
Jarque-Bera	4.189884
Probability	0.123077

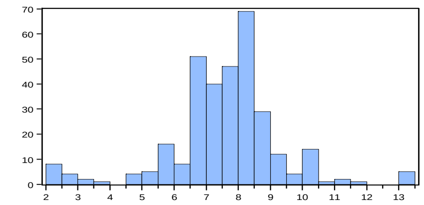
REST



Series: MVLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14667

Mean	7.783739
Median	7.693422
Maximum	13.38700
Minimum	2.414000
Std. Dev.	1.810174
Skewness	0.142420
Kurtosis	3.310358
Jarque-Bera	108.4476
Probability	0.000000

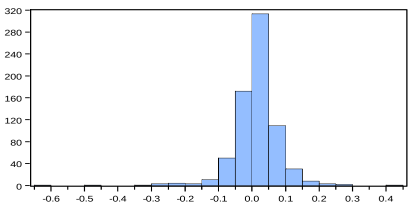
LOSERS



Series: MVLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 323

Mean	7.608411
Median	7.810268
Maximum	13.38700
Minimum	2.414000
Std. Dev.	1.736119
Skewness	-0.312509
Kurtosis	5.758744
Jarque-Bera	107.6844
Probability	0.000000

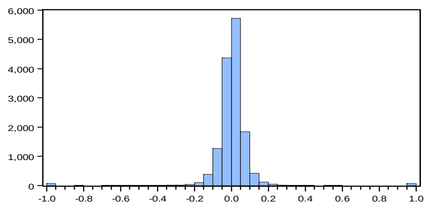
WINNERS



Series: OBOS2MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 712

Mean	0.011366
Median	0.009740
Maximum	0.402439
Minimum	-0.608000
Std. Dev.	0.070252
Skewness	-1.455502
Kurtosis	17.45307
Jarque-Bera	6448.498
Probability	0.000000

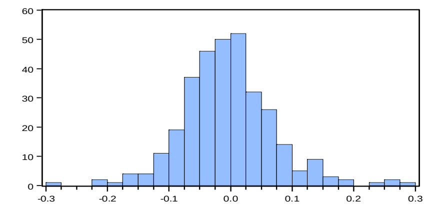
REST



Series: OBOS2MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14481

Mean	0.004562
Median	0.004975
Maximum	0.983178
Minimum	-0.981714
Std. Dev.	0.109937
Skewness	-0.192587
Kurtosis	56.33559
Jarque-Bera	1716501.
Probability	0.000000

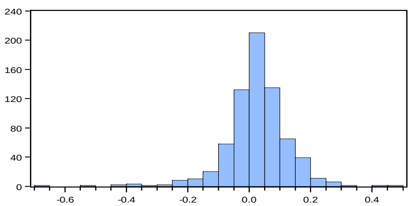
LOSERS



Series: OBOS2MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 322

Mean	-0.003995
Median	-0.009439
Maximum	0.280070
Minimum	-0.283761
Std. Dev.	0.074160
Skewness	0.414801
Kurtosis	4.967766
Jarque-Bera	61.18462
Probability	0.000000

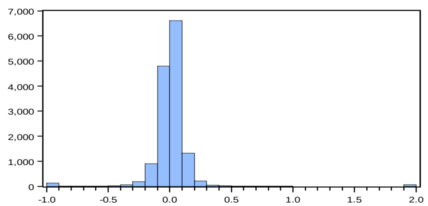
WINNERS



Series: OBOS3MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 707

Mean	0.024622
Median	0.025000
Maximum	0.465116
Minimum	-0.695652
Std. Dev.	0.101149
Skewness	-1.062926
Kurtosis	10.05838
Jarque-Bera	1600.763
Probability	0.000000

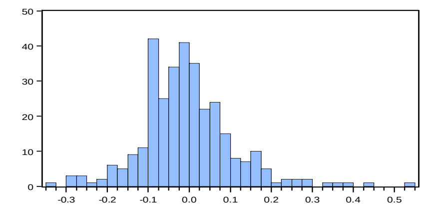
REST



Series: OBOS3MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14371

Mean	0.009544
Median	0.011375
Maximum	1.952110
Minimum	-0.972975
Std. Dev.	0.180297
Skewness	3.828473
Kurtosis	64.51828
Jarque-Bera	2301233.
Probability	0.000000

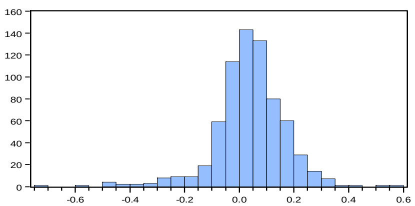
LOSERS



Series: OBOS3MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 321

Mean	-0.005651
Median	-0.016399
Maximum	0.545455
Minimum	-0.340298
Std. Dev.	0.113042
Skewness	0.790333
Kurtosis	5.924857
Jarque-Bera	147.8378
Probability	0.000000

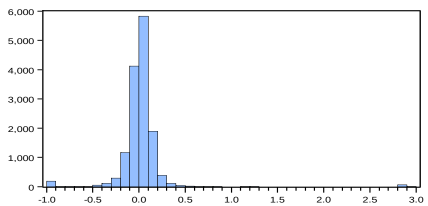
WINNERS



Series: OBOS4MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 701

Mean	0.038791
Median	0.041270
Maximum	0.584906
Minimum	-0.700306
Std. Dev.	0.128679
Skewness	-0.819308
Kurtosis	7.194291
Jarque-Bera	592.2615
Probability	0.000000

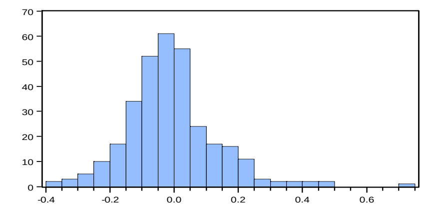
REST



Series: OBOS4MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 14263

Mean	0.015123
Median	0.018036
Maximum	2.904979
Minimum	-0.968363
Std. Dev.	0.246286
Skewness	5.994927
Kurtosis	82.94878
Jarque-Bera	3884032.
Probability	0.000000

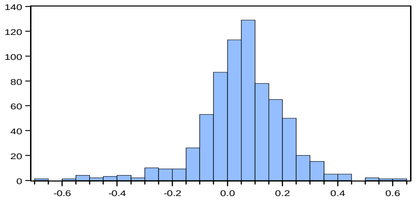
LOSERS



Series: OBOS4MMA
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 319

Mean	-0.009333
Median	-0.020459
Maximum	0.716350
Minimum	-0.360983
Std. Dev.	0.140275
Skewness	0.892565
Kurtosis	5.895617
Jarque-Bera	153.8017
Probability	0.000000

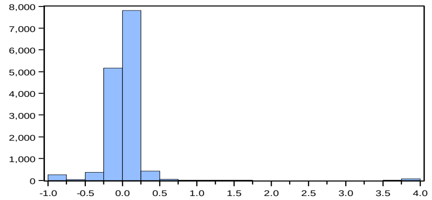
WINNERS



Series: OBOS5MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 695

Mean	0.053749
Median	0.056851
Maximum	0.615385
Minimum	-0.699755
Std. Dev.	0.152623
Skewness	-0.665509
Kurtosis	5.914467
Jarque-Bera	297.2783
Probability	0.000000

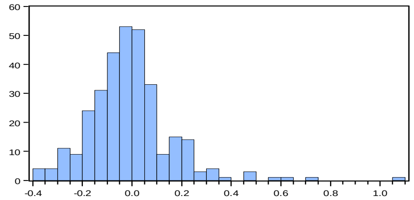
REST



Series: OBOS5MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 14154

Mean	0.020685
Median	0.022589
Maximum	3.846689
Minimum	-0.964431
Std. Dev.	0.310536
Skewness	7.367860
Kurtosis	98.37789
Jarque-Bera	5492981.
Probability	0.000000

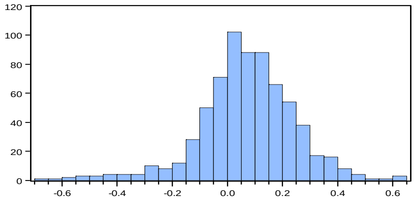
LOSERS



Series: OBOS5MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 318

Mean	-0.009599
Median	-0.024070
Maximum	1.054498
Minimum	-0.396051
Std. Dev.	0.168544
Skewness	1.444221
Kurtosis	9.195415
Jarque-Bera	619.1231
Probability	0.000000

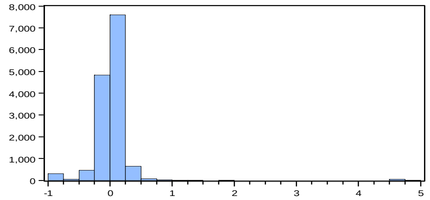
WINNERS



Series: OBOS6MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 687

Mean	0.070593
Median	0.075368
Maximum	0.643836
Minimum	-0.688229
Std. Dev.	0.175987
Skewness	-0.536946
Kurtosis	5.014699
Jarque-Bera	149.2007
Probability	0.000000

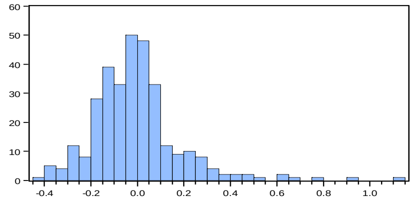
REST



Series: OBOS6MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 14047

Mean	0.026198
Median	0.027166
Maximum	4.776125
Minimum	-0.959455
Std. Dev.	0.373646
Skewness	8.309620
Kurtosis	110.3052
Jarque-Bera	6900947.
Probability	0.000000

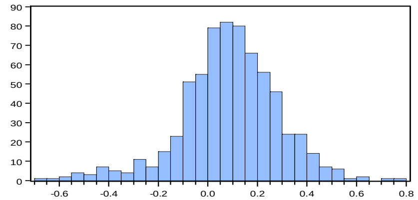
LOSERS



Series: OBOS6MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 317

Mean	-0.006742
Median	-0.022539
Maximum	1.100221
Minimum	-0.436314
Std. Dev.	0.193570
Skewness	1.615508
Kurtosis	8.982800
Jarque-Bera	610.6656
Probability	0.000000

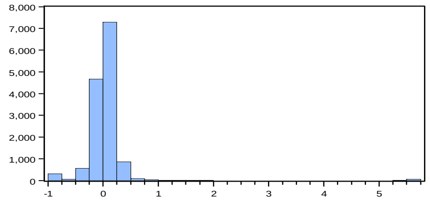
WINNERS



Series: OBOS7MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 678

Mean	0.087857
Median	0.091247
Maximum	0.755853
Minimum	-0.688748
Std. Dev.	0.198413
Skewness	-0.466769
Kurtosis	4.453866
Jarque-Bera	84.33241
Probability	0.000000

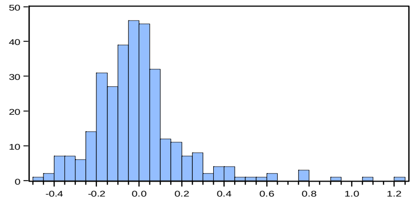
REST



Series: OBOS7MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 13941

Mean	0.035645
Median	0.031317
Maximum	5.695471
Minimum	-0.953116
Std. Dev.	0.430750
Skewness	9.326928
Kurtosis	124.6558
Jarque-Bera	8799157.
Probability	0.000000

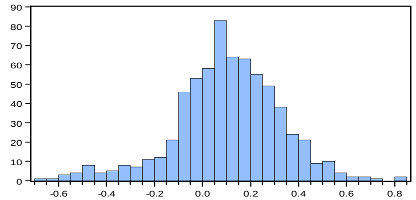
LOSERS



Series: OBOS7MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 316

Mean	-0.001991
Median	-0.018180
Maximum	1.223529
Minimum	-0.453453
Std. Dev.	0.217933
Skewness	1.788951
Kurtosis	9.404132
Jarque-Bera	708.5549
Probability	0.000000

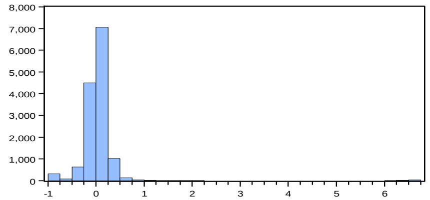
WINNERS



Series: OBOS8MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 669

Mean	0.105293
Median	0.112000
Maximum	0.837672
Minimum	-0.695179
Std. Dev.	0.220443
Skewness	-0.392638
Kurtosis	4.107250
Jarque-Bera	51.36417
Probability	0.000000

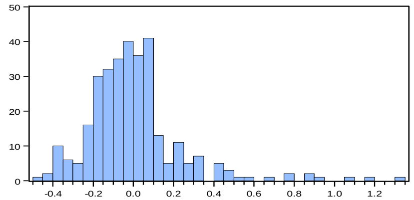
REST



Series: OBOS8MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 13836

Mean	0.045139
Median	0.035220
Maximum	6.608470
Minimum	-0.946855
Std. Dev.	0.488201
Skewness	10.04919
Kurtosis	135.3818
Jarque-Bera	10336000
Probability	0.000000

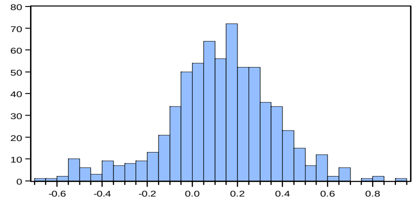
LOSERS



Series: OBOS8MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 314

Mean	0.002945
Median	-0.021075
Maximum	1.336538
Minimum	-0.456919
Std. Dev.	0.241153
Skewness	1.909173
Kurtosis	9.580389
Jarque-Bera	757.2801
Probability	0.000000

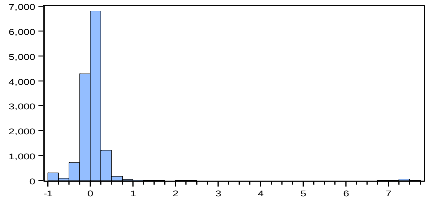
WINNERS



Series: OBOS9MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN
=1 AND CROSSID<>NA
Observations 663

Mean	0.122777
Median	0.137570
Maximum	0.912017
Minimum	-0.698976
Std. Dev.	0.241339
Skewness	-0.371211
Kurtosis	3.836272
Jarque-Bera	34.54617
Probability	0.000000

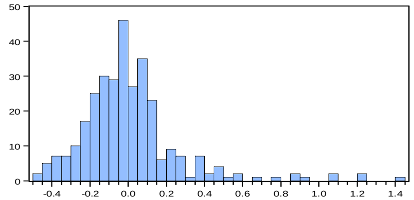
REST



Series: OBOS9MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0
AND DUM12MLOSE=0 AND
CROSSID<>NA
Observations 13730

Mean	0.054337
Median	0.040448
Maximum	7.511887
Minimum	-0.940887
Std. Dev.	0.545961
Skewness	10.57762
Kurtosis	143.4562
Jarque-Bera	11542062
Probability	0.000000

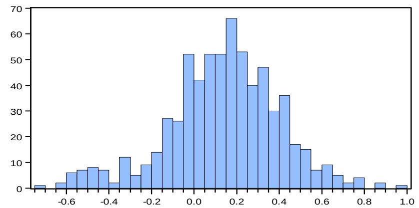
LOSERS



Series: OBOS9MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE
=1 AND CROSSID<>NA
Observations 312

Mean	0.008930
Median	-0.022281
Maximum	1.404177
Minimum	-0.460829
Std. Dev.	0.264303
Skewness	1.971656
Kurtosis	9.545709
Jarque-Bera	759.1484
Probability	0.000000

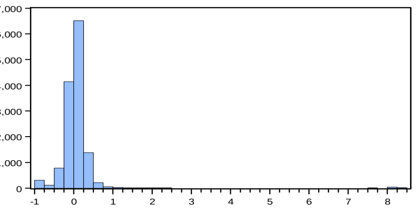
WINNERS



Series: OBOS10MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=1 AND CROSSID<>NA
Observations 658

Mean	0.137981
Median	0.155862
Maximum	0.981982
Minimum	-0.704997
Std. Dev.	0.262348
Skewness	-0.338311
Kurtosis	3.608453
Jarque-Bera	22.70187
Probability	0.000012

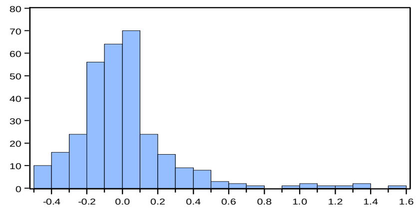
REST



Series: OBOS10MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 13623

Mean	0.063631
Median	0.045227
Maximum	8.407846
Minimum	-0.944403
Std. Dev.	0.603786
Skewness	10.97140
Kurtosis	149.5159
Jarque-Bera	12458456
Probability	0.000000

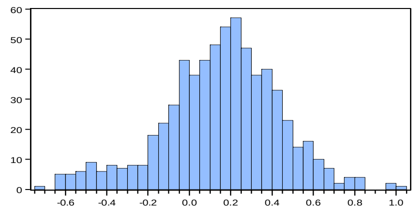
LOSERS



Series: OBOS10MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE=1 AND CROSSID<>NA
Observations 310

Mean	0.011934
Median	-0.022099
Maximum	1.513793
Minimum	-0.465174
Std. Dev.	0.285008
Skewness	2.052618
Kurtosis	9.995798
Jarque-Bera	849.8412
Probability	0.000000

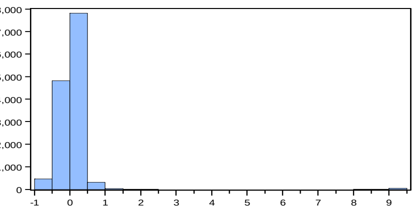
WINNERS



Series: OBOS11MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=1 AND CROSSID<>NA
Observations 655

Mean	0.153728
Median	0.172665
Maximum	1.043152
Minimum	-0.708963
Std. Dev.	0.283279
Skewness	-0.307244
Kurtosis	3.426076
Jarque-Bera	15.25974
Probability	0.000486

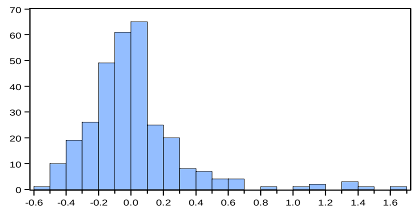
REST



Series: OBOS11MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 13514

Mean	0.073043
Median	0.049480
Maximum	9.297187
Minimum	-0.946388
Std. Dev.	0.661483
Skewness	11.26451
Kurtosis	153.9806
Jarque-Bera	13121354
Probability	0.000000

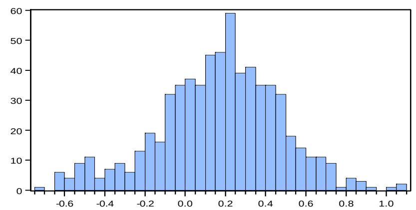
LOSERS



Series: OBOS11MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE=1 AND CROSSID<>NA
Observations 308

Mean	0.017817
Median	-0.015126
Maximum	1.618877
Minimum	-0.521346
Std. Dev.	0.308322
Skewness	2.046555
Kurtosis	9.868616
Jarque-Bera	820.4532
Probability	0.000000

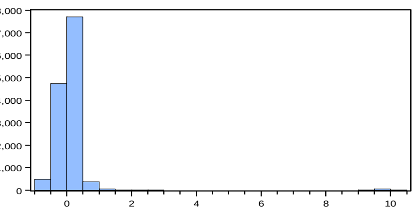
WINNERS



Series: OBOS12MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=1 AND CROSSID<>NA
Observations 651

Mean	0.168467
Median	0.187732
Maximum	1.083297
Minimum	-0.716216
Std. Dev.	0.302870
Skewness	-0.274435
Kurtosis	3.270544
Jarque-Bera	10.15702
Probability	0.006229

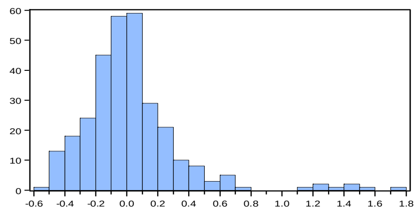
REST



Series: OBOS12MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 13410

Mean	0.081889
Median	0.055203
Maximum	10.18396
Minimum	-0.948565
Std. Dev.	0.714130
Skewness	11.54213
Kurtosis	159.2082
Jarque-Bera	13931810
Probability	0.000000

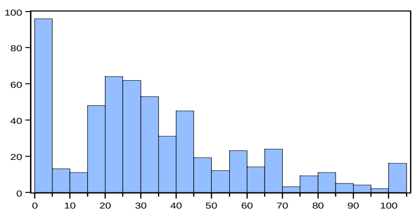
LOSERS



Series: OBOS12MMA
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE=1 AND CROSSID<>NA
Observations 303

Mean	0.021932
Median	-0.022610
Maximum	1.743180
Minimum	-0.553245
Std. Dev.	0.328178
Skewness	2.060076
Kurtosis	10.11522
Jarque-Bera	853.4747
Probability	0.000000

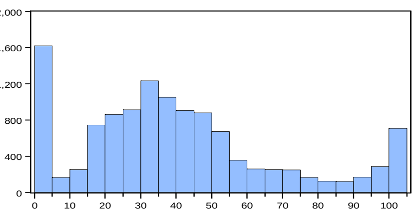
WINNERS



Series: POUTRAT
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=1 AND CROSSID<>NA
Observations 565

Mean	33.33635
Median	28.52736
Maximum	100.0000
Minimum	0.000000
Std. Dev.	25.27639
Skewness	0.755921
Kurtosis	3.178263
Jarque-Bera	54.55651
Probability	0.000000

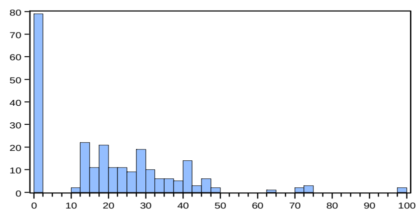
REST



Series: POUTRAT
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 11978

Mean	39.78912
Median	36.03350
Maximum	100.0000
Minimum	0.000000
Std. Dev.	27.95682
Skewness	0.625677
Kurtosis	2.813923
Jarque-Bera	798.7876
Probability	0.000000

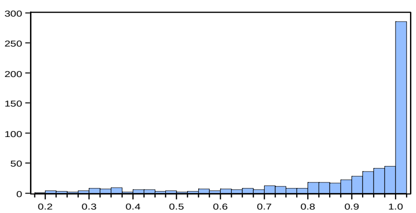
LOSERS



Series: POUTRAT
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE=1 AND CROSSID<>NA
Observations 245

Mean	19.44781
Median	18.00000
Maximum	99.71700
Minimum	0.000000
Std. Dev.	18.38338
Skewness	1.134945
Kurtosis	5.277616
Jarque-Bera	105.5535
Probability	0.000000

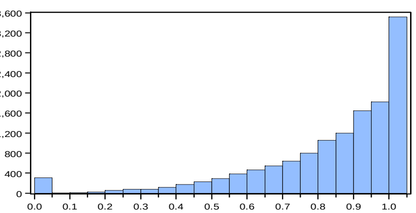
WINNERS



Series: PRICEREL12
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=1 AND CROSSID<>NA
Observations 651

Mean	0.872760
Median	0.979104
Maximum	1.000000
Minimum	0.181818
Std. Dev.	0.199884
Skewness	-1.785021
Kurtosis	5.200345
Jarque-Bera	477.0398
Probability	0.000000

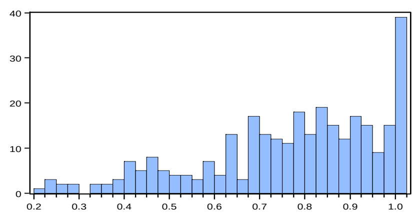
REST



Series: PRICEREL12
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 13410

Mean	0.829730
Median	0.909091
Maximum	1.000000
Minimum	0.007037
Std. Dev.	0.215032
Skewness	-1.841529
Kurtosis	6.586755
Jarque-Bera	14767.61
Probability	0.000000

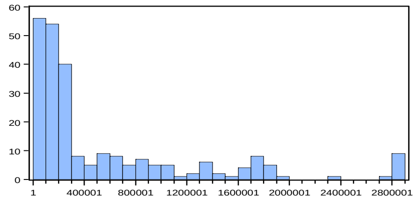
LOSERS



Series: PRICEREL12
Sample 1994M01 2011M05 IF
SMP_ONE=1 AND DUM12MLOSE=1 AND CROSSID<>NA
Observations 303

Mean	0.769275
Median	0.801408
Maximum	1.000000
Minimum	0.219371
Std. Dev.	0.194881
Skewness	-0.793327
Kurtosis	2.878603
Jarque-Bera	31.96914
Probability	0.000000

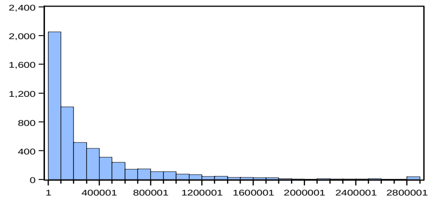
WINNERS



Series: PTSINV
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 243

Mean	552166.6
Median	226452.0
Maximum	2860279.
Minimum	12141.57
Std. Dev.	703344.8
Skewness	1.841165
Kurtosis	5.731467
Jarque-Bera	212.8322
Probability	0.000000

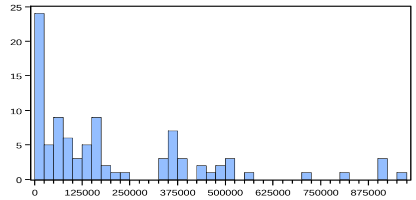
REST



Series: PTSINV
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 5466

Mean	338589.9
Median	160092.1
Maximum	2860279.
Minimum	11668.61
Std. Dev.	454742.6
Skewness	2.722932
Kurtosis	12.22995
Jarque-Bera	26156.95
Probability	0.000000

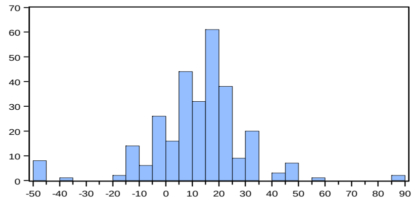
LOSERS



Series: PTSINV
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 93

Mean	206931.5
Median	116922.2
Maximum	967754.9
Minimum	11668.61
Std. Dev.	235165.9
Skewness	1.554363
Kurtosis	4.934066
Jarque-Bera	51.94358
Probability	0.000000

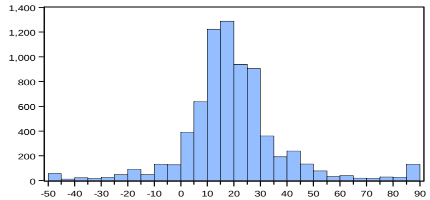
WINNERS



Series: ROE
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 290

Mean	12.11697
Median	14.12000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	17.77559
Skewness	-0.458457
Kurtosis	6.730025
Jarque-Bera	178.2753
Probability	0.000000

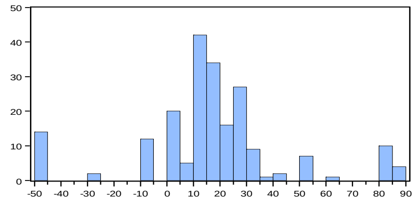
REST



Series: ROE
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 7236

Mean	19.46539
Median	17.80000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	18.91927
Skewness	0.501463
Kurtosis	6.524041
Jarque-Bera	4047.555
Probability	0.000000

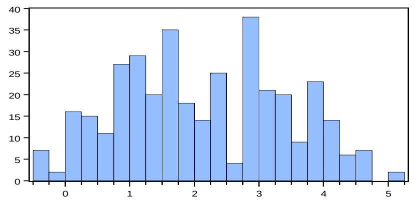
LOSERS



Series: ROE
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 206

Mean	16.91791
Median	16.03000
Maximum	85.00500
Minimum	-47.48000
Std. Dev.	27.44083
Skewness	0.125304
Kurtosis	4.738715
Jarque-Bera	26.48759
Probability	0.000002

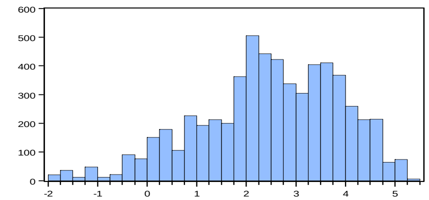
WINNERS



Series: SPSLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN =1 AND CROSSID<>NA
Observations 363

Mean	2.118643
Median	2.065355
Maximum	5.041470
Minimum	-0.493969
Std. Dev.	1.280557
Skewness	0.077536
Kurtosis	2.085136
Jarque-Bera	13.02299
Probability	0.001486

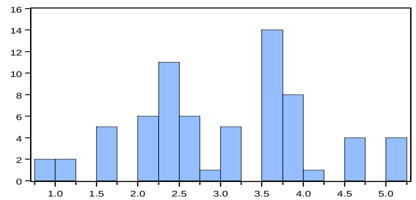
REST



Series: SPSLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MWIN=0 AND DUM12MLOSE=0 AND CROSSID<>NA
Observations 5969

Mean	2.478331
Median	2.545767
Maximum	5.286503
Minimum	-2.000000
Std. Dev.	1.421486
Skewness	-0.507224
Kurtosis	2.911952
Jarque-Bera	257.8750
Probability	0.000000

LOSERS



Series: SPSLOG
Sample 1994M01 2011M05 IF SMP_ONE=1 AND DUM12MLOSE =1 AND CROSSID<>NA
Observations 69

Mean	3.060311
Median	3.068444
Maximum	5.193976
Minimum	0.929010
Std. Dev.	1.083064
Skewness	0.073443
Kurtosis	2.357928
Jarque-Bera	1.247266
Probability	0.535994

Appendix F.2: Forward stepwise regression results for 12-month holding period: Winner shares

The table below presents the results of the forward stepwise logistic regression approach as discussed in Chapter 8, Section 8.4.2. The variables included at each step (until the process is terminated) are listed below the table. The variable coefficient (B) and standard error (S.E.) are reported after each successive step. The significance of each variable is determined by comparing the Wald statistic to the critical value obtained from the chi-squared distribution table with the appropriate degrees of freedom. The associated p-value is reported as well (Sig.) It can be seen that all variables included are statistically significant at the 1% level. The exponent of the coefficient value is reported in the last column. This value is interpreted as an "odds ratio". Specifically, the probability of the binary dependent variable taking on the value of one is e^B times as likely for a one unit increase in the value of the independent variable. For example, the Exp(B) of 28.98 associated with CFTP reported in step 3 means that the probability that a share is classified as a winner is approximately 29 times as likely with a one unit increase in CFTP.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CFTP	3.690	.401	84.775	1	.000	40.063
	Constant	-3.640	.100	1313.394	1	.000	.026
Step 2[b]	CFTP	4.004	.414	93.503	1	.000	54.792
	MOM6	1.698	.220	59.413	1	.000	5.462
	Constant	-3.971	.116	1174.064	1	.000	.019
Step 3[c]	CFTP	3.367	.420	64.149	1	.000	28.980
	LNP	-.345	.053	42.881	1	.000	.708
	MOM6	1.681	.217	60.146	1	.000	5.373
	Constant	-2.880	.190	228.570	1	.000	.056

a. Variable(s) entered on step 1: CFTP.

b. Variable(s) entered on step 2: MOM6.

c. Variable(s) entered on step 3: LNP.

The table below reports the goodness-of-fit measures (as discussed in Chapter 8, section 8.4.1.3) for each logit model after every successive step. From the table it is seen that the different measures improve for each successive model. The pseudo R-squared values are quite low, however this may be due to the fact that the logistic regression models are based on single shares. These values could easily be increased by using portfolios of shares instead.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2230.043[a]	.012	.038
2	2172.278[a]	.021	.068
3	2128.801[a]	.028	.090

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

The last table reports percentage correctly predicted values based on the specific logit model created during each successive step and the threshold value used (which is obtained through the process described in Chapter 8 (section 8.4.2) and reported below the table). The objective is to obtain a threshold value such that the percentage correctly predicted for both values of the binary dependent variable is optimised. The values within the cells indicate the number of times the binary dependent variable was observed to be 1 or 0 versus the number of times it was predicted to be 1 or 0 for each step. Taking Step 3 for example, the binary dependent variable was predicted to be zero 4122 times while the actual number of times it was equal to zero is 4122 + 1698 = 5 820. Hence the percentage of binary variables correctly predicted to be zero equals 4122/5820 = 70.8%. Similarly, the binary dependent variable value was predicted to equal one 178 times while the actual number of times it was equal to one is 107+178 = 285. Hence the percentage of binary variables correctly predicted to equal one is 178/285 = 62.5%.

Classification Table[a]

Observed			Predicted DUM12MWIN 0	Predicted DUM12MWIN 1	Percentage Correct
Step 1	DUM12MWIN	0	4278	1542	73.5
		1	145	140	49.1
	Overall Percentage				72.4
Step 2	DUM12MWIN	0	4086	1734	70.2
		1	112	173	60.7
	Overall Percentage				69.8
Step 3	DUM12MWIN	0	4122	1698	70.8
		1	107	178	62.5
	Overall Percentage				70.4

a. The cut value is .049

Appendix F.3: Forward stepwise regression results for 12-month holding period: Loser shares

The tables below present the results of the forward stepwise regression approach followed to derive the logit model for the loser shares. The interpretation of each table is similar to that discussed in Appendix E.2.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CFTP	-4.812	.576	69.831	1	.000	.008
	Constant	-3.011	.078	1495.861	1	.000	.049
Step 2[b]	CFTP	-4.436	.557	63.359	1	.000	.012
	MOM6	-1.175	.222	27.902	1	.000	.309
	Constant	-2.970	.077	1487.089	1	.000	.051
Step 3[c]	CFTP	-4.492	.580	59.915	1	.000	.011
	LNP	.202	.045	19.871	1	.000	1.224
	MOM6	-1.322	.231	32.801	1	.000	.267
	Constant	-3.556	.159	499.084	1	.000	.029

a. Variable(s) entered on step 1: CFTP.

b. Variable(s) entered on step 2: MOM6.

c. Variable(s) entered on step 3: LNP.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2487.556[a]	.007	.033
2	2458.787[a]	.010	.046
3	2438.958[a]	.012	.054

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted DUM12MLOSE 0	Predicted DUM12MLOSE 1	Percentage Correct
Step 1	DUM12MLOSE	0	6050	3686	62.1
		1	86	195	69.4
	Overall Percentage				62.3
Step 2	DUM12MLOSE	0	6572	3164	67.5
		1	108	173	61.6
	Overall Percentage				67.3
Step 3	DUM12MLOSE	0	6517	3219	66.9
		1	89	192	68.3
	Overall Percentage				67.0

a. The cut value is .030