University of the Western Cape

FACULTY OF ECONOMICS AND MANAGEMENT SCIENCES

APPLICATION OF CROSS-SECTOR STYLE ANALYSIS OF SOUTH AFRICAN EQUITIES IN ACTIVE PORTFOLIO MANAGEMENT

BY

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A Mini-Thesis prepared under the Supervision of Professor Heng-Hsing Hsieh and submitted in partial fulfilment for the Degree of Masters in Commerce to the School of Business and Finance in the Faculty of Economics and Management Sciences

Declaration

I, Wayne Small, declare that this mini-thesis is entirely my own work and is not being submitted for degree purposes at any other university. Except for the assistance which is duly acknowledged, all other work which is not my own is duly referenced in the text and the bibliography section of this thesis.

Wayne Small

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Dedication

Dedicated to my family and parents, Mr N.E. Small and the late Mrs E. Small

Acknowledgement

I would like to express my heartfelt gratitude to Professor Heng-Hsing Hsieh for his unconditional support and guidance through this humbling experience to complete my mini-thesis. Professor Hsieh has been instrumental to my personal growth development and provided invaluable insight to the investment universe. I would also like to thank Professor Kathleen Hodnett for her invaluable contributions.

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ABSTRACT

A distinctive phenomenon on the JSE Securities Exchange (JSE) is the market segmentation between the resource sector and the financial and industrial sectors. Criticisms also arise from employing a capitalization-weighted (cap-weighted) index such as the ALSI index when the market is less than perfectly efficient. A study conducted by Vardharah and Fabozzi (2007) also suggests that a correlation exists between sector allocation decisions and the investment styles inherent in portfolios. The uniqueness of the South African stock market is that it is dominated by three major sectors, namely, the financial sector, the industrial sector and the resources sector. The goal of this research is to examine the application of sector influences on the JSE over the examination period 1 January 2003 to 31 December 2013.

It is the contention that the cap-weighted ALSI index is price-sensitive and potentially mean-variance inefficient. The study therefore attempts to evaluate the relative mean-variance efficiency of alternative sector allocation strategies versus the cap-weighted ALSI as the optimal risky portfolio on the JSE. Two optimal long-only portfolios that maximises the Sharpe ratio are constructed and compared to the market proxy on the JSE over the examination period from 1 January 2003 to 31 December 2013. A long-only portfolio that comprises the JSE tradable sector indices and includes a cash allocation (risk-free proxy) and a long-only portfolio exclusive of the cash allocation are constructed. The research extends to cross-examine the inter-relationship between sector returns and the investment styles on the JSE using the Carhart (1997) four-factor model. The research further reexamines and updates the market segmentation phenomenon over the extended examination period from 1 January 2003 to 31 December 2013. The practicality of two sector-based multifactor APT models are examined and compared to the single-factor CAPM to determine which of the asset pricing models better explain JSE equity returns. A sector-based two-factor APT model proposed by Van Rensburg (2002) using the JSE sector indices FNDI and RESI as the sector proxies is reexamined and a sector-based three-factor APT model using the JSE tradable sector indices FINI, INDI and RESI as the sector proxies is explored. The optimal long-only portfolio with the cash allocation is found to offer the best mean-variance efficient allocation and the ALSI index represents the most mean-variance inefficient portfolio. The resource sector is found to be the worst performing sector and significantly influences the performance of ALSI. In terms of the style risk influences, the financial sector has a strong value bias and the industrial sector has a moderate value bias, small cap bias and a momentum bias. The resource sector, for the most part, is influenced by growth stocks and has a contrarian tilt. It is also found that the market segmentation phenomenon continues to exist on the JSE. Although the explanatory power of the three-factor APT model and the two-factor APT model is similar, the distinct advantage of the three-factor APT model is that systematic risks could be observed more closely by separating FINI and INDI in the asset pricing model.

Key words: sector analysis, sector allocations, mean-variance efficient portfolios, style risks, asset pricing models, market segmentation

Table of Contents

List of Figures and Tables

LIST OF FIGURES

LIST OF TABLES

1

INTRODUCTION

1.1 Background

Capital market theories laid the foundation for the development of capital asset pricing models. Markowitz (1952), who pioneered Modern Portfolio Theory (MPT), argues that all investors should hold mean-variance efficient portfolios on the efficient frontier of risky assets. The MPT assumes that all investors are risk-averse and completely rational in their decision making. Thus, risk-averse investors have homogeneous expectations regarding the mean, variance and covariance of risky asset returns, and would arrive at the same optimal risky portfolio. This optimal risky portfolio is termed the market portfolio. The separation theorem of Tobin (1958) suggests that investors will choose the optimal mix between the market portfolio and risk-free asset, depending on their risk preferences. An extension to the MPT and the separation theorem is the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM is a single-factor linear model that assists investors in estimating the equilibrium rate of returns on assets in an efficient capital market. Given that any unsystematic risk can be diversified away, the only relevant risk investors should be concerned about is the sensitivity of asset returns to systematic risk factors (that is, market risk), which is measured by the beta coefficient.

The efficient market hypothesis (EMH) of Fama (1965; 1970) is the theory that underpins efficient capital asset pricing models, such as the CAPM. The EMH postulates that investors are not able to outperform the market (that is, earning above risk-adjusted returns) in a consistent manner because of the efficient dissemination of information. Asset prices quickly and accurately reflect new information as it arrives in the market. As a result, asset prices are expected to accurately reflect their long-term intrinsic values in an efficient capital market. Tests of market efficiency, though, cannot be performed without testing the validity of the efficient pricing relationship depicted by the CAPM. This phenomenon is commonly known as the joint hypothesis problem.

Ross (1976) introduces a multifactor asset pricing model based on less stringent assumptions, compared to the CAPM, under the Arbitrage Pricing Theory (APT) framework. The APT is supported by Roll's (1977; 1978) critique that highlights the unobservable nature of the true market portfolio in MPT and CAPM. The APT calls for the decomposition of market risk into pervasive macro-economic risks that influence asset returns. The use of APT opens avenues for alternative risk budgeting approaches in asset allocation other than strictly indexing the market portfolio.

An alternative school of thought, behavioural finance, built on the likelihood of investors' behaviours, or investor prospects, challenges the assumptions of market efficiency, particularly investor rationality. Prospect theory of Kahneman and Tversky (1979) and the overreaction hypothesis of De Bondt and Thaler (1985; 1987) argue that investors are irrational in their decision making. Investors are often influenced by behavioural biases, which lead asset prices to deviate from their long-term intrinsic values.

Well known market anomalies (style risks) include the value effect of Basu (1977), size effect of Banz (1981), mean reversion of De Bondt and Thaler (1985; 1987) and the momentum effect of Jegadeesh and Titman (1993). These anomalies provide evidence against the EMH as investors are able to earn abnormal returns. Fama and French (1993) attempt to explain the market anomalies as risk factors omitted by the CAPM. By incorporating the size and value risk premia, in addition to the market risk premium, the Fama and French (1993) three-factor model is able to explain most of the above empirical anomalies. In addition to the size and value style risks, the momentum effect, employed in Carhart's (1997) four-factor model, is seen as the third style risk in explaining the movements of asset returns.

The challenge of pricing assets in the South African stock market (JSE Ltd) is that the performances of the resource stocks are driven by a different set of macro-economic factors compared to the industrial and financial stocks. This market segmentation phenomenon is highlighted by Van Rensburg and Slaney (1997) and Van Rensburg (2002). They argue that the pricing restrictions of the CAPM are violated when employing the FTSE/JSE All-Share Index (ALSI) as the proxy for the market portfolio. Cavaglia, Melas and Tsouderos (2000) argue that the sector allocation policy is a superior alternative to indexing the market portfolio. A study conducted by Vardharah and Fabozzi (2007) also reveals the strong correlation between sector allocation decisions and the investment styles inherent in the portfolios.

Criticisms also arise from employing cap-weighted indices such as the ALSI as the market proxy, as mean-variance efficiency cannot be achieved when the market is less than perfectly efficient. Empiricists such as Arnott, Hsu and Moore (2005) argue that cap-weighted indices are price-sensitive and are likely to be mean-variance inefficient in a market where investors overreact to the arrival of new information. In the presence of investor overreaction, the cap-weighting method overweighs overpriced assets and under-weighs underpriced assets, which introduces a performance drag in the index. Arnott *et al* (2005) introduce fundamental indices formed by price-insensitive measures of firm size, which successfully outperformed cap-weighted indices on a risk-adjusted basis.

The market segmentation phenomenon on the JSE, coupled with the observed performance drag in cap-weighted indices, suggest that the ALSI could potentially be mean-variance inefficient. This motivates the research to examine the practicality of sector-based APT models in explaining JSE equity returns. In addition, this study attempts to evaluate the relative mean-variance efficiency of alternative sector allocation strategies versus the cap-weighted ALSI as the optimal risky portfolio on the JSE. Based on arguments of sector and style allocations being inter-correlated, the research extends to cross-examine the inter-relationship between sector allocation and investment styles on the JSE.

1.2 Overview

Given the empirical evidence of market segmentation on the JSE and the observed criticisms of cap-weighted indices such as the ALSI, this research will endeavour to examine the mean-variance efficiency of alternative sector allocation strategies relative to the market capitalisation-weighted (cap-weighted) methodology employed by the ALSI. The prominent JSE sectors being examined by this research include the resource sector, financial sector and industrial sector due to their dominance in the total market capitalisation of the JSE.

An overview of the theories underlying this research is presented in Chapter 2. First, the theories relating to asset allocation decisions, such as MPT and the separation theorem with the assumption of market efficiency, are reviewed. Thereafter, the implications and relative comparisons between the CAPM and APT are evaluated. Behavioural finance as an alternative school of thought to the EMH, will also be discussed.

In Chapter 3, empirical evidence on capital market anomalies, including the value effect of Basu (1977), size effect of Banz (1981), overreaction hypothesis of De Bondt and Thaler (1985; 1987) and the momentum effect of Jegadeesh and Titman (1993) on international and local stock markets are examined. The Fama and French (1993) three-factor model and the Carhart (1997) four-factor model that attempt to explain the well-documented anomalies are also discussed in this chapter. The chapter also provides a discussion on alternative asset allocation strategies. In addition, the chapter reviews prior literature relating to style and sector allocation decisions, including the criticisms against cap-weighted indices, the rise of price-insensitive fundamental indexation and alternative weighting methodologies.

Chapter 4 presents the research problem statement, research objectives, the composition of the research sample and the methodology employed to achieve the stated objectives. The main objectives of this research are to examine the practical implications of sector-based asset pricing models and sector allocation strategies on the JSE. In addition, the research undertakes to cross-examine investment styles and JSE sector performance. An overview of the research sample, which includes the ALSI constituents and potential JSE sector indices are presented. Potential research biases relating to the research methodology will also be discussed in this chapter.

The test is initiated in Chapter 5 by performing portfolio optimisation employing the JSE tradable sector indices. The mean-variance efficiency achieved in the optimisation procedure for the sector-based portfolios will be examined against the performance of the ALSI, which is employed as the proxy for the market portfolio. The research results in this chapter provide an indication as to whether the ALSI remains as the appropriate market proxy given the market segmentation phenomenon on the JSE.

Based on the arguments of potential sector and style inter-correlations on the JSE, chapter 6 evaluates the primary investment styles that drive the performance of the JSE sector indices using the Carhart (1997) four-factor model.

Chapter 7 compares the explanatory power of the CAPM versus the APT on the JSE. The evidence of market segmentation coupled with the criticisms on the cap-weighted indices motivates this research to evaluate the significance of alternative asset pricing mechanisms on the JSE. Two sector-based APT models are constructed with their explanatory power evaluated against the CAPM. The first sector-based APT model consists of a three-factor APT model employing three prominent JSE tradable sector indices as its explanatory variables. The second APT model consists of a two-factor APT model proposed by Van Rensburg (2002) employing two prominent JSE tradable sector indices as its explanatory variables.

Chapter 8 presents the consolidated findings from the examination results performed in this research, outlining the pathway to the author's contributions and the ensuing recommendations that emerge from the research.

1.3 Contributions

In the evaluation of the market segmentation phenomenon highlighted in Van Rensburg and Slaney (1997) and Van Rensburg (2002), they assess the practical implications of a two-factor APT model against the CAPM. In Van Rensburg and Slaney (1997), the examination results of their two-factor APT model, employing the All-Gold index and Industrial index as observable proxies, provides a superior account to the pricing of asset returns compared to the CAPM over the period from 1985 to 1994. The reclassification of the JSE sectors in 2000 changed the composition and structure of the sector indices. In examining the impact of the JSE sector reclassification, Van Rensburg (2002) employs a similar methodology to that employed by Van Rensburg and Slaney (1997). This time round the resources index (RESI) and combined financial and industrial index (FNDI) are employed in a two-factor APT model. The examination results once again indicate that the two-factor model is a more appropriate model in explaining asset returns on the JSE over the period from 1993 to 2000. In support of the above view, the study conducted by Correia and Uliana (2004) reveals that FNDI serves as a more appropriate proxy in explaining JSE industrial company returns over the period from 1993 to 2000. The impact of market segmentation on asset pricing is revisited in this research over a more recent period from 1 January 2003 to 31 December 2013 to capture the impact of the global economic growth, the subsequent financial meltdown in 2008 and the global economic recovery thereafter. In addition, this study contributes to the empirical literature by decomposing the financial-industrial index into the financial index and industrial index and examining their explanatory power on JSE stock returns separately. This exercise is motivated by the possibility that the industrial sector could be segmented from the financial sector. Thus, separate market proxies could be required to explain the performances of financial and industrial shares respectively. The study further compares the explanatory power of the three-factor APT model against the two-factor APT model proposed by Van Rensburg (2002) to determine which of the two sector-based multifactor APT models have greater power in explaining JSE stock returns.

The study conducted by Van Rensburg and Robertson (2003a) suggest that the performance of the resources sector is primarily driven by growth stocks. On the other hand, the JSE value stocks are mostly from the financial and industrial sectors. This research undertakes to re-examine the interaction between sector performance and investment styles employing the Carhart (1997) four-factor model. The examination results contribute to the empirical literature by assisting investors to gain a better understanding of sector performance and style tilt over a more recent period.

To the author’s knowledge, comprehensive sector-based studies on the JSE have been limited to the aforementioned authors. This study contributes to the existing literature in providing solutions to alternative sector-based asset pricing and asset allocation decisions on the JSE.

1.4 Ethical Statement

The intention of the study is not to draw attention to any investor (especially institutional investors) or to make any critical remarks against any investor. Since information on ALSI constituents are publicly available and the study does not use private or inside information, there are no major ethical issues that arise during the study.

2

THEORETICAL OVERVIEW

2.1 Introduction

This chapter reviews the capital market theories that underlie the framework of the research, including the development and implications of modern portfolio theory (MPT); the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT), as well as the criticisms against the CAPM. The efficient market hypothesis (EMH) and the pervasive influences of behavioural finance on capital markets will also be examined.

A basic tenet embodied in capital market theories is that investors are risk-averse and completely rational. The MPT of Markowitz (1952) and the separation theorem of Tobin (1958) propose solutions to risk-averse investors in managing asset allocation decisions. MPT suggests that all investors ought to hold mean-variance efficient portfolios to diversify away firm-specific risks embedded in assets. For this reason, risk-averse investors have homogeneous expectations regarding the mean, variance and covariance of return. Investors should therefore arrive at the same optimal risky portfolio, which is referred to as the market portfolio. Tobin (1958) points out that the identity of a mean-variance efficient optimal portfolio is the first step in the asset allocation process. Moreover, the separation theorem proposes that an investment be split between the market portfolio and risk-free asset to create an optimal mix subject to the investor's risk preference.

The CAPM is the first asset pricing model to link risk to return. It is an extension of MPT, developed to assist investors in determining the equilibrium rate of return on assets in an efficient capital market. The only relevant risk parameter employed by the CAPM is the beta coefficient, which measure the sensitivity of asset returns to market risk. Ross (1976) introduces a multifactor model under Arbitrage Pricing Theory (APT) based on less stringent assumptions. Roll's (1977, 1978) critique, in support of APT, highlights the unobservable nature of the optimal risky portfolio in MPT and the CAPM. The APT is a flexible asset pricing model that allows investors to decompose market risk.

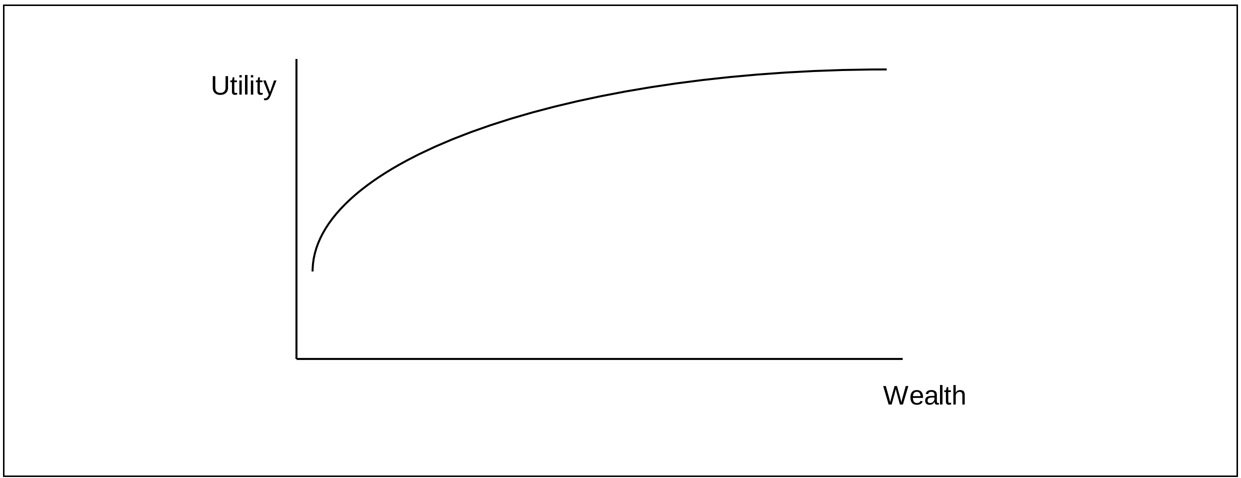
The efficient market hypothesis (EMH) is the fundamental theory that underpins all areas of finance in efficient capital markets. The EMH asserts that asset prices follow a random walk, that is, the successive movements in prices are independent of each other over time. In addition, new information is instantaneously and accurately absorbed into asset prices. As a result of the efficient dissemination of information, investors cannot earn abnormal returns consistently. Under EMH investors are assumed to behave rationally. Kahneman and Tversky (1979), however, assert that investors are subject to psychological biases. They point out that the psychological biases displayed by investors in their decision making have significant influences on the movements in asset prices and asset allocation decisions. They introduce prospect theory that describes how investors are likely to behave under conditions of uncertainty.

2.2 Asset Allocation Decisions under Conditions of Uncertainty

Markowitz (1952), the pioneer of modern portfolio theory (MPT), argues that uncertainty (risk) cannot be dismissed in optimising investors' portfolios. The approach of investors' towards risk is grounded on the principle of risk aversion and is described by the expected utility theory as depicted in Figure 2.1. Based on this notion, investors aim to maximise their expected utility. As the wealth of an investor increases, the utility assigned to any level of investor wealth increases, but at incrementally smaller amounts. The greater the wealth of an investor, the less is their appreciation for each extra dollar. Investors therefore exhibit diminishing marginal utility from each additional dollar payoff.

Figure 2.1 Risk Aversion and Marginal Utility

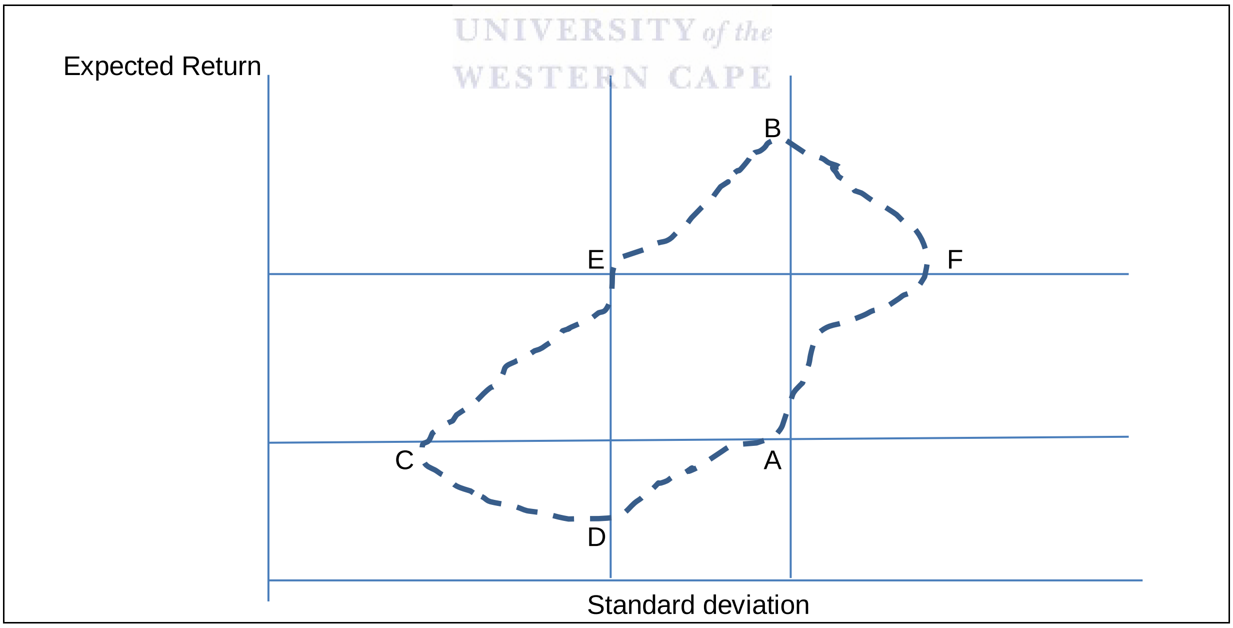
Figure 2.1 is adapted from Bodie *et al* (2005: 193). It illustrates the relationship between the wealth and the utility of wealth of risk-averse investors from an additional growth per dollar payoff.



The attitude of risk-averse investors is illustrated in Figure 2.2. Portfolio B is preferred to portfolio A as it offers more return at the same level of risk. Portfolio C is preferred to portfolio A as it offers less risk at the same level of return. Portfolio D can be eliminated given the existence of portfolio E, and similarly with portfolio F, which offers more risk than portfolio E at the same level of return. Portfolios B and C cannot be eliminated as these portfolios dominate all other portfolios in offering more return at less risk or less risk at the same return. In summary, investors are expected utility maximisers who prefer holding portfolios that offer a higher return for the same risk or lower risk for the same return.

Figure 2.2 Risk-Return Possibilities

Figure 2.2 is adapted from Elton *et al* (2011: 80) and illustrates and identifies the possible portfolios an investor could consider holding.



The process of portfolio selection, according to Markowitz (1952), should be approached by making probabilistic estimates of the future performances of stock returns. Thus, investors behave according to certain probability beliefs where no objective probabilities and (or) subjective probabilities are known. This suggests that investors exhibit rational investment behaviour. Equation 2.1 mathematically depicts the rational investor behaviour as follows (Bailey, 2005):

$$E(U) = p_1 u(x_1) + p_2 u(x_2) \ldots + p_n u(x_n) \qquad \textbf{... 2.1}$$

Where:

$x_1, x_2 \ldots x_n$ represents the various levels of wealth of the investment; and

$p_1, p_2 \ldots p_n$ represents the probabilities assigned to the various levels of wealth of the investments.

The decision-making process illustrated by Equation 2.1 suggests that investor behaviour is grounded purely on the mathematical probabilities that investors assign to the various levels of wealth of investments.

MPT proposes that investors hold mean-variance efficient portfolios on the efficient frontier of risky assets. Based on the concept of risk aversion, rational investors will construct an efficient frontier based on all combinations of expected return and variance. The expected return and variance of a portfolio consists of two risky assets, *i* and *j*, are mathematically demonstrated as follows:

$$E(R_p) = (w_i \times E(R_i)) + (w_j \times E(R_j)) \qquad \textbf{... 2.2}$$

$$\sigma_p^2 = (w_i^2 \sigma_i^2) + (w_j^2 \sigma_j^2) + (2 w_i w_j \sigma_i \sigma_j \rho_{ij}) \qquad \textbf{... 2.3}$$

Where:

w_i and w_j represents the weights of constituents *i* and *j* in portfolio *P;*

σ_i and σ_j represents the standard deviations of constituents *i* and *j* in portfolio *P;* and

ρ_{ij} represents the correlation coefficient between the historical returns of the constituents *i* and *j* in portfolio *P.*

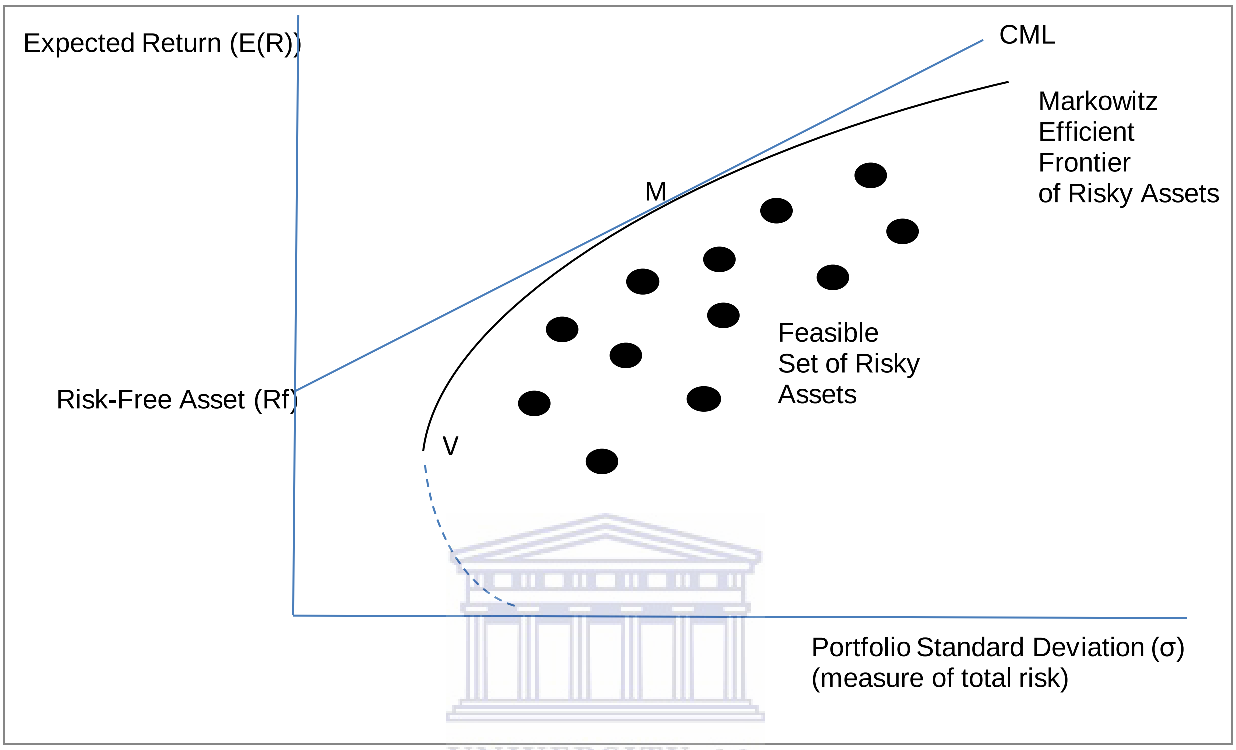
The expected return is a weighted average of historical returns on individual assets and the weights carried by the constituents are proportional to their relative market values. The correlation coefficient, ρ_{ij}, on the other hand, is derived from the covariance between assets *i* and *j.* MPT points out that the ultimate aim of investors is to create optimal diversified portfolios to remove any firm-specific risks. The correlation coefficient of returns, which is employed to determine the degree of diversification in portfolios, measures the co-movement between asset returns. The correlation coefficient of returns ranges between +1 and -1. Portfolios that contain assets that move in a similar direction are riskier (positive correlation) than assets that move in the opposite or dissimilar direction (negative correlation). Therefore, when assets move in a similar direction, the risk on portfolio *P*, as measured by the portfolio variance, will be a positively high value. Whereas portfolios that contain assets that move in the opposite direction will result in a portfolio variance of less than the weighted average variance on each asset. As a result, "*portfolios of less than perfectly correlated assets always offer better risk-return opportunities than the individual component securities on their own*" (Bodie, Kane and Marcus, 2005: 228). Investors that diversify their portfolios are rewarded with a higher expected return at a lower standard deviation (variance). In addition, as more assets are added to the portfolio, the impact of diversification is significantly increased as the effects of firm-specific risks (unsystematic risk) are reduced. However, all assets are affected by the pervasive influence of macro-economic factors. This is referred to as systematic risk.

2.2.1 Delineating the Efficient Frontier

Figure 2.3 presents the efficient frontier of risky assets. The hyperbola curve represents a mix of all possible portfolio expected return and standard deviation that can be formulated from the constituents *i* and *j*. The minimum variance portfolio, *V,* represents the lowest possible variance attainable in the feasible set of investments. Portfolios plotted above the minimum variance portfolio, represented by the solid concave curve, are mean-variance efficient as they provide the best possible risk-return combinations. Assets below the minimum variance portfolio, represented by the dotted concave curve, offer lower expected returns at higher standard deviations compared to assets on and above the minimum variance portfolio. Any assets to the right of the efficient frontier, represented by the black dots, are mean-variance inefficient as they provide more risk for a given level of expected return or less expected return for a given level of risk. Risk-averse investors will hold mean-variance efficient portfolios plotted on the Markowitz efficient frontier of risky assets in order to maximise their expected utility.

Figure 2.3 Markowitz's Portfolio Selection Model

Figure 2.3 is modified from Bodie *et al* (2005: 236). It presents the best risk-return combinations between risky assets, as well as the feasible set of risky assets along the efficient frontier.



Tobin (1958) introduces the possibility of investing or borrowing at the risk-free rate. Thus, the risk-free asset forms now part of the feasible set of investment opportunities. The separation theorem of Tobin (1958) asserts that investors face two separate decisions in the asset allocation process. Investors first identify the optimal risky portfolio on the Markowitz efficient frontier and subsequently allocate their capital between the optimal risky portfolio and the risk-free asset. The optimal risky portfolio is represented by *M* in Figure 2.3. The capital market line (CML) that connects the risk-free asset, R_f, and the optimal risky portfolio, *M,* represents the optimal capital allocation line (CAL) that dominates all other allocations between the risk-free asset and the mean-variance efficient portfolios on the efficient frontier. The optimal risky portfolio, *M,* is also the point of tangency to the efficient frontier. Due to the fact that investors have homogenous expectations regarding the mean, variance and covariance of returns, they will all arrive at the same conclusions on the identity of the optimal risky portfolio. The CML represents the efficient frontier of all assets, both risky and risk-free.

The CML is mathematically depicted in Equation 2.4. In essence the expected return on an efficient portfolio is proportional to the total risk of the portfolio, relative to the total risk of the market portfolio subject to the market risk premium plus the risk-free asset.

$$E(R_{p)}) = R_f + (\frac{E(R_m)-R_f}{\sigma_m^2})\sigma_p^2 \qquad \textbf{... 2.4}$$

Where:

$E(R_{p)})$ represents the expected return of portfolio *P;*

$E(R_m)$ represents the expected return of the market portfolio *M*;

R_f represents the return on the risk-free asset;

σ_p^2 represents the variance of portfolio *P*; and

σ_m^2 represents the variance of portfolio *M.*

All investors will end up with portfolios somewhere along the CML, as it represents the most efficient portfolios. Risk-averse investors will select a portfolio to the left of point *M* on the CML by placing some of their capital in a riskless asset and the balance in the market portfolio *M.* However, investors that prefer more risk will demand portfolios to the right of point *M* on the CML by borrowing at the riskless rate and placing their original capital plus the borrowed funds in the market portfolio *M.*

2.3 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is a single-factor linear equilibrium model developed independently by Sharpe (1964), Lintner (1965) and Mossin (1966). It is built on the insight of MPT and the separation theorem. MPT and the separation theorem provide no indication as to how individual assets or portfolios should be priced (Fuller, 1981). The CAPM, on the other hand, assists investors in estimating the equilibrium rate of return on assets and portfolios in an efficient capital market.

The CAPM postulates that the only relevant risk to the investor is systematic risk as unsystematic risk can be diversified away. The systematic risk could be measured by the covariance of an asset's returns to the market movements. Substituting the covariance of asset, i, to the market portfolio, $Cov_{i,M}$, for σ_p^2 in Equation 2.4 (Section 2.2), the expected return-systematic risk relationship can be expressed as follows:

$$E\big(R_{P)}\big) = R_f + \left(\frac{E(R_M) - R_f}{\sigma_M^2}\right)\sigma_{i,M} \qquad \textbf{... 2.5}$$

Defining $\frac{\sigma_{i,M}}{\sigma_M^2}$ as the beta coefficient, β_i, that measures the systematic risk of asset i, Equation 1.5 can be restated as follows:

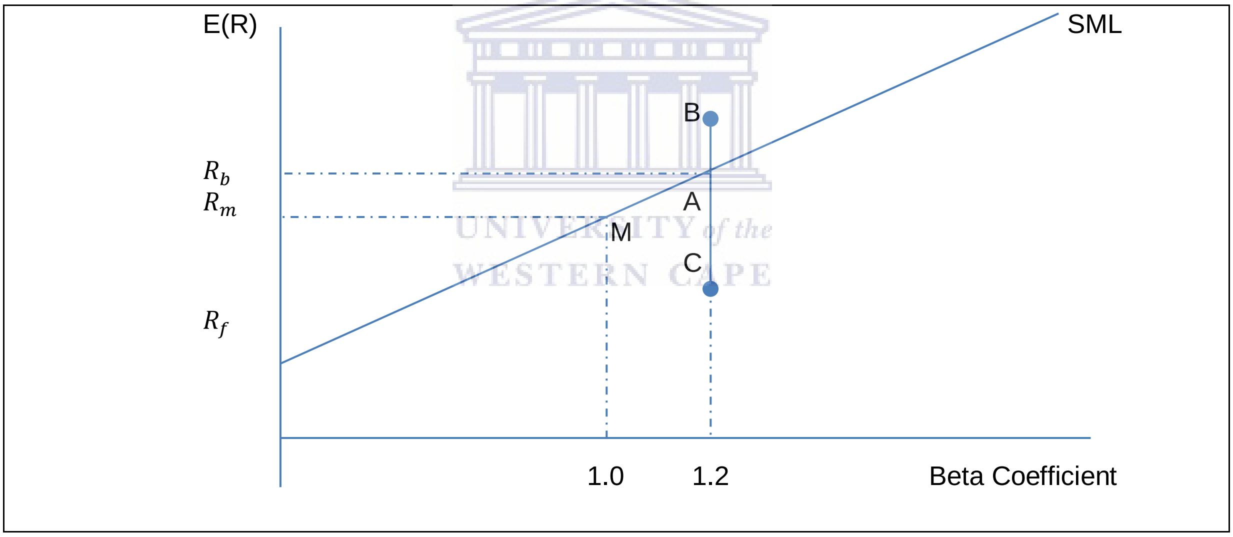
$$E\big(R_{P)}\big) = R_f + \beta_i(E(R_M) - R_f) \qquad \textbf{... 2.6}$$

Equation 2.6 is referred to as the security market line (SML). Under the notion of CAPM investors should be compensated at a higher rate of return for bearing more systematic risk. Figure 2.4 is a graphical depiction of the SML, where assets M and

A are fairly priced as they plot exactly on the SML. Asset B, however, is undervalued as it offers higher returns than its required rate of return indicated by the SML. Asset C is overvalued as it offers lower returns at the same level of systematic risk compared to asset A. Thus, there would be an increase in demand for asset B and an increase in supply for asset C. In equilibrium, the excess demand for asset B and excess supply for asset C, will restore their positions back to the SML respectively.

Figure 2.4 Security Market Line

Figure 2.4 is adapted from Elton *et al* (2011: 80). It illustrates and identifies the combination of portfolios plotted on the security market line.



The beta coefficient for asset, *M,* is the market beta in Figure 2.4 and is expressed as $\beta_m = \frac{Cov(R_m,R_m)}{\sigma_m^2} = \frac{\sigma_m^2}{\sigma_m^2} = 1.0$. It is also the weighted average value of beta coefficients across all assets. In summary, when the market (as measured by any widely available stock market index) goes up (down), all assets are expected to appreciate (depreciate) in price. The CAPM therefore assumes that assets move together due to their common co-movement with the market portfolio.

2.3.1 CAPM Critique

Roll (1977: 129) contends that "*no correct and unambiguous test of the CAPM theory has appeared in the literature, and there is practically no possibility that such a test can be accomplished in the future*". He argues that a true market portfolio is not observable as it must be representative of all assets in the universe subject to their respective market values. Empirical tests of the CAPM that employ general stock market indices as the proxy for the market portfolio are therefore ambiguous. Roll (1978) argues that the mis-specified market portfolio suffers from a benchmark error, suggesting that the SML is ambiguous as the estimated beta coefficients are significantly influenced by a mis-specified market proxy.

According to Sharpe (1965), individual assets are expected to respond to the same macro-economic risks. Therefore, it is expected that all assets move in tandem to any increase (decrease) with the market portfolio. However, Bodie *et al* (2005) argue that the CAPM does not capture the absolute sources of asset return uncertainty as important sources of micro-economic risks are overlooked. They point out that micro-economic risks may only affect firms within particular sectors, while the impact on the broad macro-economy is minimal. Furthermore, they point out that the CAPM places restrictions on the structure of asset return uncertainty as the beta coefficient is the only relevant risk measure. This phenomenon could therefore result in a biased beta estimate. Bodie *et al* (2005) also argue that sectors that are heavily weighted within the market portfolio places a significant degree of variance on the optimal portfolio. As a result, capitalisation-weighted indices that are employed as the market proxy are not mean-variance efficient.

2.4 The Arbitrage Pricing Theory

Arbitrage Pricing Theory (APT) is a multifactor asset pricing model developed by Ross (1976), and is seen as an alternative asset pricing model to the CAPM. Ross's (1976) APT description of equilibrium is more general, unlike the CAPM which is restrictive as it relies on the existence of an observable true market portfolio. Under APT, an asset's expected return is linearly related to a set of multiple risk factors. Investors are therefore able to tailor their investment needs to specific investment criteria (Elton, Gruber, Brown and Goetzman, 2011). Like the CAPM, an assumption of homogenous expectations is necessary.

2.4.1 The Law of One Price

The CAPM assumes that all investors hold mean-variance efficient portfolios. Any assets that are mispriced triggers investor demand for underpriced assets and the disposal of overpriced assets. Investors' effectively tilt their portfolios away from overpriced assets until market equilibrium is restored. This is referred to as asset prices mean-reverting. The guiding principle under APT is the law of one price. Ross (1976) points out that assets which are entirely equivalent economically should have the same price and expected returns. A violation of this law will result in an arbitrage opportunity for investors to earn riskless profits, simultaneously buying the underpriced asset and selling the overpriced asset. The underpriced asset is bid up and overpriced asset is forced down until the arbitrage opportunity is eliminated. Whereas the CAPM suggests that all investors take limited positions to restore market equilibrium, the APT proposes that all investors take infinite positions to bring about market equilibrium.

2.4.2 APT Derivation

The only relevant risk measure in the CAPM is the beta coefficient, whereas in APT multiple risk factors are capable of impacting returns of all assets. The APT has the flexibility to capture additional sources of market wide risk. Equation 2.7 demonstrates the linear relationship of asset i's return to the systematic risk exposures in a multifactor asset pricing model as follows (Reilly and Brown, 2003):

$$R_i = E(R_i) + b_{i1}\delta_1 + b_{i2}\delta_2 + \cdots + b_{ik}\delta_k + \varepsilon_i \; for \; i = 1 \; to \; n \qquad \textbf{... 2.7}$$

Where:

R_i represents the actual return on asset i during a specified time period, $i = 1,2,3, \ldots n$;

$E(R_i)$ represents the expected return for asset i if all the risk factors have zero changes;

δ_k represents a set of common factors or indexes with a zero mean that influences the returns on all assets;

b_{ik} represents the reaction in asset $i's$ return to movements in a common risk factor k;

ε_i represents the unsystematic risk of asset i, which has a mean of zero in well-diversified portfolios; and

n represents the number of assets.

The term δ represents the risk factors which influences asset returns, while the b term measures the degree of sensitivity of each asset's exposure to the kth common risk factor. Some notable examples of common risk factors include inflation or gross domestic product.

A distinctive characteristic embodied within the APT is that investors are able to gain additional insight into the return generating process. Practitioners are more capable of identifying the various asset return attributions and their comparative implications in estimating asset returns (Modigliani and Pogue, 1988). As a result, the APT allows investors to tailor their exposures to unexpected macro-economic shocks. For example, unexpected changes in interest rates could be offset with investors taking the appropriate investment strategy to offset any risk. The CAPM, on the other hand, assumes that all assets respond to the same macro-economic events. The APT recognises that the only relevant risk of an investment is the unexpected exposure to an asset (Ross, Westerfield and Jaffe, 1990). For this reason, the realised return of asset i in Equation 2.7 is apportioned between an expected return and an unexpected return which is influenced by the unanticipated movements in the kth risk factors. In equilibrium, the expected return-systematic risk relationship of the APT is depicted by Equation 2.8 when the unique effects of assets $i's$ return are diversified away:

$$E(R_i) = \gamma_0 + \gamma_1 b_{i1} + \gamma_2 b_{i2} + \cdots + \gamma_k b_{ik} \qquad \textbf{... 2.8}$$

Where:

γ_0 represents the expected return on an asset with zero systematic risk, which is proxied by the return on a risk-free asset;

γ_k represents the risk premium related to the *k*th common risk factor; and

b_{ik} represents the sensitivity of asset $i's$ expected return to movements in the risk premium on the risk factor *k.*

2.4.3 APT Potential Shortcoming

In as much as practitioners that employ the APT are able to tailor their exposures to various macro-economic causalities, the generality of the APT gives no indication as to the appropriate multifactor model. Chen, Roll and Ross (1986) examine the influences of macro-economic variables on major indices to determine if they explain equilibrium returns. Their examination results reveal that the unanticipated movements in the industrial production, inflation, yield spread between low-grade bond and government bond, and the slope of the term structure of interest rates are significant risk factors that determine asset returns. In addition, Chen *et al* (1986) point out that other factors may also influence asset returns but their impact could be explained through the above mentioned macro-economic factors. Similarly, independent tests conducted by Harrington (1987), and Burmeister and McElroy (1988) find statistically significant macro-economic evidence in favour of the APT model.

2.4.4 APT Going Forward

The CAPM requires a benchmark optimal portfolio to price asset returns. As a result, it is assumed that the CAPM risk premium subsumes all economic and firm characteristics. For this reason the CAPM is a restrictive asset pricing model. The APT, on the other hand, is more easily able to capture any additional economic and firm characteristic influences that affect asset returns (Reilly and Brown, 2003). Dhrymes, Friend and Gultekin (1984), for instance, find that a multifactor APT has greater explanatory power in explaining asset returns than the single-factor CAPM. Connor and Korajczyk (1986), Lehmann and Modest (1988), Fama and French (1993) and more recently Haugen (1996; 2010) and Haugen and Baker (1996; 2012) employ firm characteristics in a multifactor APT to successfully explain asset returns compared to the CAPM. The explanatory power of the APT in explaining asset returns, highlighted by the above empiricists, lends support for Roll's (1977; 1978) critique pertaining to an identifiable market portfolio. In a CAPM environment, residual risk plus the optimal portfolio which is employed as the market portfolio serves as the proxy for the true but unobservable market (Elton *et al*, 2011). Thus, the APT is able to capture additional sources of risk than the restrictive CAPM. Furthermore, Elton *et al* (2011) state that the APT, on a practical level, provide a better explanation for the variations in asset returns given the unobservable nature of the market proxy.

Given the flexibility of the APT, the beneficial implications are that risks are more easily identifiable. As a consequence, risks could be more closely controlled including risks to which assets exhibit greater sensitivity towards. The flexibility of the

APT also gives investors an opportunity to hedge or speculate on certain types of risk (Bodie *et al*, 2005). Another advantage of the APT is that important sources of return attributions could be employed to track a particular portfolio. This is particularly important to practitioners that adopt a passive management strategy. Elton *et al* (2011) point out that investors that employ the CAPM to match the market proxy are susceptible to conflicting sensitivities to the common factors that drive asset returns. As an example, cyclical stocks that are sensitive to unexpected changes in sales growth will negatively impact a portfolio that attempt to match a market proxy. This inevitably creates a mismatch in returns between an investor's portfolio and the market proxy. Another predicament of the CAPM is that stocks with conflicting sensitivities to the common risk factors, yet have the same beta coefficient, will be classified as equally risky. This will result in the CAPM incorrectly predicting a stock's return as having the same expected return (Elton *et al*, 2011). In addition, stocks that are more sensitive to the common risk factors should be compensating practitioners accordingly. For instance, stocks with an unanticipated positive risk premium to sales growth, practitioners are expected to be compensated with a higher risk premium relative to stocks which are indifferent to sales growth. These stocks would be seen as undervalued as they plot above the SML, which will effectively drive investors to pursue these assets. Therefore, any stocks which are sensitive to other unanticipated price influences will appear as overvalued or undervalued in relation to the SML (Elton *et al* (2011).

On the other hand, the APT derives an expected risk-return relationship differently to the SML of the CAPM. Reilly and Brown (2003) describes the APT expected risk-return relationship to that of a security market plane with two dimensions. The first dimension refers to an asset's anticipated expected return, whereas the second dimension represents the unanticipated returns as a result of the unique macro-economic and firm specific influences that drive asset returns. If one reviews the above sales growth example, from an APT standpoint, the expected risk-return premium would plot exactly on the security market plane on the APT framework. This effectively implies that a stock is neither undervalued nor overvalued as the equilibrium rate of return is denoted by the security market plane.

Seeing that the APT is a linear multifactor asset pricing model, it gives practitioners the opportunity to determine benchmark rates of return. Therefore, financial decisions based on APT benchmark rates of return could be employed in capital budgeting and security evaluation models (Bodie *et al*, 2005).

2.5 The Efficient Market Hypothesis

One of the underlying themes that have been dominant in the academic literature since the 1960s is the notion of efficient capital markets. Efficient capital markets imply that asset prices fully reflect all available information. The significance of whether capital markets are efficient, or inefficient, is central to investment valuation.

In independent inquiries into the predictability of asset return patterns, Samuelson (1965) and Mandelbrot (1966) statistically find that the time-series properties of asset returns follow a random walk. They show that price changes represent random departures from previous prices. This implies that if the flow of information is made available instantaneously, tomorrow's price change is only impacted by tomorrow's news. Therefore, tomorrow's price is independent of today's price. If prices follow a random walk, Malkiel (2003) argues that it equates to holding a randomly selected portfolio of individual assets with comparable risk. He therefore argues that it is unlikely that the average investor would consistently earn excess returns or beat the optimal market portfolio. Basu (1977), on the other hand, points out that in an efficient market the price of an asset is an objective estimate of the actual value on the investment. This implies that market prices can deviate from the true value as long as the deviations are random. Randonmess implies that assets could be equally undervalued or overvalued at any given point in time. In addition, the deviations should be uncorrelated with any observable variable (Damodaran, 2002).

Based on the notion that asset prices follow a random walk, Fama (1965; 1970) introduces the efficient market hypothesis (EMH) and defines three states of EMH, weak form; semi-strong form and strong form EMH. Fama (1970) argues that markets that are weak form EMH precludes technical analysts from earning positive abnormal returns in a consistent manner. He argues that positive price signals, which are based on historical price patterns that technical analysts employ to predict future price patterns, would already have been seized upon. All investors would have acted appropriately to any discernible patterns. In markets that are semi-strong form EMH, fundamental analysts that employ macro-economic news and company performance indicators are precluded from being profitable since all available public information would already have become widely known. When a market is strong form efficient, Fama (1970) argues that company insiders are prevented from trading on private information. Thus, no investors can make abnormal returns in a consistent manner. Furthermore, Fama (1991) argues that as capital markets become more sophisticated, the more efficient markets turn out to be. This inevitably increases trading activity. The aforementioned stems from the fact that the transaction costs in obtaining information and trading reduces significantly, which ultimately draw more investors into the market. The instantaneous availability of accurate information and the freedom to trade encourages investors to participate in the market.

The contribution of Fama (1991) to the theory of market efficiency emphasises the joint hypothesis problem hidden in the random walk of Samuelson (1965) and Mandelbrot (1966). Fama (1991) argues that market efficiency can only be evaluated in the presence of asset pricing models (that is, the CAPM) that emphasise equilibrium expected returns. For that matter, EMH underpins capital market theories. Thus, one cannot test the legitimacy of the EMH without involving tests of the validity of the CAPM.

2.6 Behavioural Finance

"*Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on the spontaneous optimism rather than mathematical expectations, whether moral or hedonistic or economic*" (Keynes, 1936).

Behavioural finance is the study of psychological biases on investor decision making that have pervasive influences on financial markets and is subject to investor irrationality.

The central challenge to investors is how decisions are made under conditions of uncertainty. In practice, many people make sub-optimal economic or financial decisions. For instance, people buy lottery tickets when the expected value of such an "investment" equates to less than the cost of the ticket. This behaviour is inconsistent with most common utility functions (Elton *et al*, 2011). Consequently, investors are subject to psychological biases in their economic and financial decision making. The conflicting comparisons between standard capital market theories and behavioural finance is that the former does not consider the implications of psychological decisions made by investors in financial markets. Behavioural finance, on the other hand, explores how financial markets function in reality.

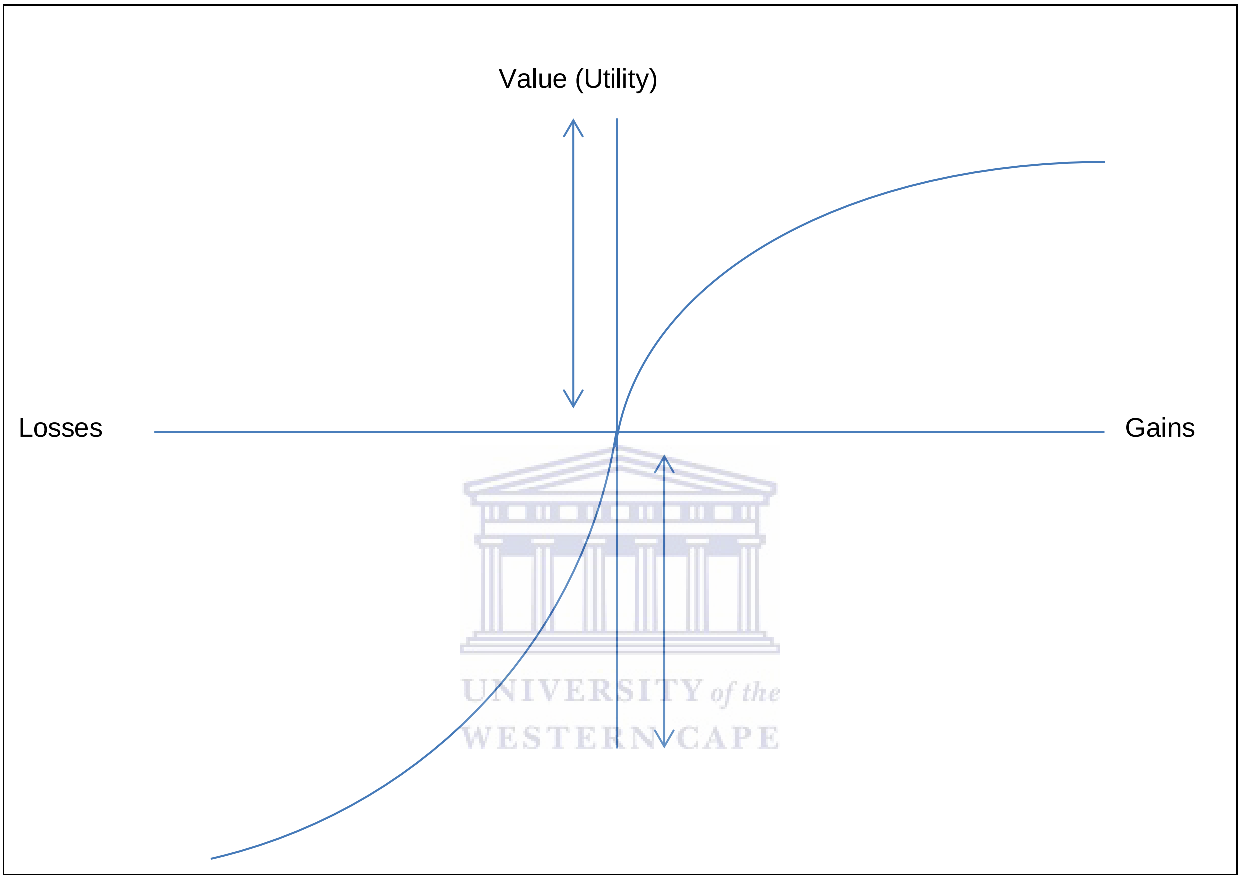
The expected utility theory has generally been seen as the prescriptive model in the analysis of optimising investor behaviour and rational choice under conditions of uncertainty (Kahneman and Tversky, 1979). Kahneman and Tversky's (1979) seminal work on behavioural finance evaluates how investors actually behave under conditions of uncertainty. They argue that the expected utility theory is an inappropriate model and present an alternative.

2.6.1 Prospect Theory

Kahneman and Tversky (1979) introduce prospect theory, which assesses investors' attitude towards risk that are inconsistent to Markowitz's (1952) standard utility model and rational probability assessments. Prospect theory suggests that investors' attitude towards risk is asymmetrical; however, it depends on how the potential gains and losses relate to a certain reference point. The reference point refers to the point of intersection where neither gains nor losses are realised. The prospect theory value function proposed by Kahneman and Tversky (1979) is a S-shaped utility value function and illustrates the attitude of investors towards risk as demonstrated in Figure 2.5. Similar to the expected utility theory in Figure 2.1, investors exhibit risk aversion above the reference point, indicated by the positive utility function. The marginal utility assigned to any level of investor wealth increases at a decreasing rate. In the negative utility region, the marginal utility exhibited by investors' declines at an increasing rate due to losses they experience. The larger the loss, the greater the displeasure investors experience for each additional dollar they lose. This is referred to as loss aversion. If one observes Figure 2.5, the slope for losses relative to gains is steeper, indicating that the disutility investors experience noticeably outweighs the utility in gains. This indicates that investors are motivated to lock in gains but not realise losses.

Figure 2.5 Utility Function of Loss Aversion

Figure 2.5 is adapted from Kahneman and Tversky (1979: 18). It illustrates that the utility of an investor from an investment is a function of estimated gains and losses relative to the specific reference point such as the purchase of an asset.



Kahneman and Tversky (1979) argue that changes in welfare cause individuals to approach gains and losses differently. Individuals behave irrationally when challenged with losses and rationally when faced with gains. This suggests that individuals experience great displeasure in losing money. In laboratory tests on respondents, they gave individuals the choice of an 80% chance of securing $4,000 or $3,000 with certainty. 80% of respondents chose the latter. When the prospects were reversed, in other words, respondents had a choice of 80% chance of losing $4,000 or simply losing $3,000. 92% of respondents chose the former even though the expected value was lower (80% of \$4,000 < \$3000). The evidence is in contradiction to the expected utility theory as utility outcomes are weighted by their probabilities. The chance of securing \$4,000 versus a certainty outcome of \$3,000 implies that individuals overweighed outcomes that they considered certain. Thus, investors' preferences are in violation of the expected utility theory. Kahneman and Tversky (1979) refer to this phenomenon as the certainty effect. The certainty effect implies a risk-averse preference for a sure gain relative to a larger probable gain. When the outcomes were reversed, the same effect lead to a risk-loving preference. The overweighting of certainty implies risk aversion for gains and loss aversion for losses. Investors prefer to gamble when it comes to losses and, hence, losses are steepest closest to the reference point.

In other laboratory experiments, Kahneman and Tversky (1979) found that subjects confronted with uncertainty use heuristics to guide their decision making. For instance, inferences are drawn from probability estimates without considering a wider range of issues such as sample size for example. They point out that subjects extrapolate beliefs from isolated experiences. In their conclusion, they argue that investors do not consider the entire range of relevant data to predict future returns as they base their decisions on recent or visible events in asset prices. Similarly, investors are overconfident when it comes to accurately estimating a range of outcomes to a risk venture. They are inclined to over-emphasise good news on firms evaluated, or overestimate growth rates and ignore negative news. Kahneman and Tversky (1979) argue that these heuristics lead to biased and poor decision making under conditions of uncertainty. In other heuristics, Shefrin and Statman (2000) argue that investors fail to consider all the elements of a portfolio as an integrated whole. They argue that investors conceptually place assets in separate accounts and treat them differently. This phenomenon is referred to as mental accounting. Shefrin and Statman (2000) find that this phenomenon leads investors to treat one part of their portfolio similar to a "*nest egg*" and another part of the portfolio as a "*lottery ticket*". Massa and Simonov (2003) test for this behavioural bias and find that investors have a propensity for treating the previous year's gains as "*house money*". The aforementioned phenomena are in contradiction to capital market theories as such behaviour, without considering all the elements of a portfolio as an integrated whole, will inevitably lead to sub-optimal decisions.

2.7 Conclusion

Capital market theories and the development of financial asset pricing models provide potential solutions to asset allocation decisions. The MPT suggest methods to manage risk and introduces the efficient frontier of risky assets. The separation theorem proposes that investors identify the optimal portfolio, namely the market portfolio. Also investors with different degrees of risk appetite choose an optimal mix based on a risk-free asset and the market portfolio. The underlying assumptions of the MPT and the separation theorem are that all investors are rational and risk-averse. In addition, investors have homogeneous expectations regarding the mean, variance and covariance of asset returns. As a result, they seek to maximise their expected utility when making investment decisions.

The CAPM, a single-factor linear model, is an extension of the MPT and the separation theorem. It is the first asset pricing model to link risk to return. Given that firm-specific risks can be diversified away, the only relevant risk is systematic risk. The beta coefficient of the CAPM measures systematic risk. The beta coefficient measures the sensitivity of an asset’s return to movements in the market portfolio. Ross (1976) introduces a multifactor asset pricing model developed under arbitrage pricing theory (APT), an alternative asset pricing model to the CAPM. Roll’s (1977; 1978) critique, in support of the APT, suggests that the true market portfolio is not observable. This suggests that the beta coefficient is a biased estimate. The distinct advantage of APT is that it is able to accommodate multiple sources of risk.

The fundamental theory that underpins capital market theories is the EMH. The EMH states that capital markets are efficient as asset prices fully reflect all available information. Furthermore, asset prices follow a random walk and that price changes represent random departures from previous prices.

Capital market theories are based on investor decision making in the perfect world. It presumes that decisions are based on investor rationality. Behavioural finance suggests that investors are irrational and focus on how investors actually make decisions. The architects of behavioural finance, Kahneman and Tversky (1979), and many others thereafter, argue that many people make sub-optimal economic or financial decisions. They suggest that investors are subject to psychological biases in their economic or financial decision making and argue that such behaviour is inconsistent with most common utility functions.

Prospect theory, developed by Kahneman and Tversky (1979), attempts to explain how investors actually behave. Under prospect theory, investors are risk-averse for gains but loss-averse towards losses. It is suggested that individuals' attitude to changes in welfare is that losses generally loom larger than gains. Individuals experience greater displeasure in losing money to experiencing the pleasure associated with the same amount of gains in money. Behavioural biases lead investors to violate the assumptions of traditional finance. Since investors use heuristics to guide their decision making, this behaviour have pervasive implications on asset prices which are in direct contradiction to efficient capital market theories.

3

LITERATURE REVIEW

3.1 Introduction

Compelling critique levelled at the capital asset pricing model (CAPM) and efficient market hypothesis (EMH) have been the value effect of Basu (1977), size effect of Banz (1981), overreaction hypothesis of De Bondt and Thaler (1985; 1987) and the momentum effect of Jegadeesh and Titman (1993). Banz (1981) documents that low market capitalisations (small caps) portfolios outperform large market capitalisations (large caps) portfolios. On the other hand, Basu (1977) finds that portfolios that consist of firms with low price-to-earnings (P/E) ratios outperform portfolios that consist of firms with high P/E ratios. De Bondt and Thaler (1985; 1987) reveal that investors could earn abnormal returns by acquiring prior 36-month loser portfolios. On the other hand, Jegadeesh and Titman (1993) indicate that abnormal returns are available to those investors that buy short-term winners based on prior 3- to 12-month prior returns.

Motivated by the critique levelled at the EMH, Fama and French (1993) introduce a three-factor asset pricing model that incorporates the size and value risk factors. The three-factor model, barring the momentum effect, adequately explains the returns of the portfolios formed by the capital market anomalies. Carhart (1997) extends the Fama and French (1993) three-factor model to include the momentum effect. The

Carhart (1997) four-factor model successfully explains the returns in United States (U.S) mutual funds.

As investors continue to search for methods to exploit market inefficiencies, Cavaglia, Melas and Tsouderos (2000) propose that investors should adopt a sector allocation investment strategy. They document superior reward-to-risk ratios to investors that espouse a sector allocation strategy relative those investors that index a market portfolio or embrace a security selection strategy. In addition, Vardharaj and Fabozzi (2007) point out that a strong relationship exists between sectors and investment styles. They therefore suggest that abnormal returns are available to those managers who seek to explore sector allocation strategies.

Empirical evidence suggests that the Johannesburg Stock Exchange (JSE) is subject to more than one security market line (Campbell, 1979; Bowie and Bradfield, 1993; Van Rensburg and Slaney, 1997; and Van Rensburg, 2002). This stems from the fact that the resources sector, especially the mining subsector, are highly influenced by global market-wide risks. The performance of firms in the resources sector is influenced by macro-economic factors which are different from factors that influence the industrial and financial sectors.

Cap-weighted indices, such as the ALSI that is employed as the market proxy on the JSE, have also come under scrutiny. Arnott, Hsu and Moore (2005) argue that cap-weighted indices are price-sensitive and are likely to be mean-variance inefficient due to the trading noises in markets where investor overreaction is present.

This chapter examines the empirical evidence on capital market anomalies, which includes the value effect of Basu (1977), size effect of Banz (1981), overreaction hypothesis of De Bondt and Thaler (1985; 1987) and the momentum effect of Jegadeesh and Titman (1993) on international and domestic stock markets. The chapter also reviews the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model that attempts to explain the well-documented anomalies. The prior literature on alternative asset allocation decisions, including style and sector allocation decisions are reviewed. In addition, the chapter evaluates the criticisms against cap-weighted indices and the development of price-insensitive fundamental indices and alternative weighting methodologies.

3.2 Market Anomalies: International Context

3.2.1 Size and Value Anomalies

A study conducted by Banz (1981) on the New York Stock Exchange (NYSE) over the period 1936 to 1977 examines the risk-adjusted returns of holding small caps versus large caps. The differences in the returns from buying and holding small caps relative to larger caps is 19.8% per annum, with the highest payoff coming from holding the smallest 20% of stocks. Similarly, Keim (1983) finds that small caps, on the NYSE and American Stock Exchange (AMEX) over the period 1963 to 1979, outperform large caps on a risk-adjusted basis.

Empiricists have attempted to evaluate the apparent excess returns appearing in the size effect with many pointing to the CAPM as an inappropriate asset pricing model to measure expected returns. Reinganum (1981), for instance, argue that the beta coefficients on small firms are downward biased. He points out that small caps trade less often than large caps. This inevitably leads to the beta coefficient being underestimated. As a result, the CAPM estimated expected return is exceedingly low, causing a difference between the actual expected return and required rate of return. Another reason presented for the beta coefficient being downward biased is offered by Christie and Hertzel (1981). They argue that firms that have become small have generally changed their economic charactistics, and accordingly, have become more sensitive to market-wide risks.

In examining the size effect, Keim (1983), Reinganum (1983), Roll (1983) and Schwert (2003), reveal that a substantial size effect occurs in January. They point out that the size effect in January, referred to as the January effect, contributes to at least half of the return differences between firms in the largest quintiles and smallest quintiles. Furthermore, they find that the size and January effect are strongly related. In explaining the January effect, Roll (1983) and Reinganum (1983) argue that small caps are subject to higher volatility, which inevitably causes small caps to experience substantial short-term capital losses. They posit the short-term capital losses to a tax-loss selling effect by investors. This phenomenon causes asset prices of small caps to reduce in price at the end of the year. As investors re-establish their investment positions by repurchasing these assets in early January, the demand pressure cause these asset prices to rebound.

Other critics, in explaining the small firm effect, introduce a multifactor model to explain expected returns. Chan, Chen and Hsieh (1985) on the NYSE over the period 1953 to 1977, for example, employ a multifactor model and examine the expected return on 20 portfolios formed on the basis of size. In an attempt to explain the size effect, corporate bond risk premiums is the additional variable they employ in their model. They find that when an appropriate model is employed to explain expected return, the size effect disappears. By contrast, they find that abnormal returns are available if the CAPM is used to measure expected returns.

Amihud and Mendleson (1991b) and Amihud (2002) examine the relationship between liquidity, size and bid-ask spreads and revise the result on the NYSE, over the period 1963 to 1997. They show that the size effect is in part compensation for illiquidity. Small caps are less liquid and, thus have higher transaction costs. Investors therefore demand a higher expected return. Their argument is based on the fact that small caps have higher bid-ask spreads and, hence, the demand for larger purchases are considerably smaller for small firms.

Chan and Chen (1991), on the other hand, evaluate small caps on the NYSE over the period 1956 to 1985 that have changed their structural characteristics. These are firms that have lost market share as a result of poor performance due to low production efficiency and high leverage. They argue that the change in structural characteristics have caused these firms to be riskier, effectively driving investors to seek larger firms which are highly liquid. As a result of the lack in trading activity, the increased risk due to the low probability of surviving economic hard times is essentially not captured by the beta coefficient.

Fama and French (1992) examine the size effect on the NYSE, AMEX and National Association of Securities Dealers (NASDAQ) over the period 1963 to 1990. Their results indicate that the small deciles outperform the large deciles on a risk-adjusted basis. In addition, they examine the average relationship between the beta coefficient and expected returns. Their results show that the small decile portfolios are characterised by low beta stocks and the large deciles consist primarily of high beta stocks. It is also observed that the SML relationship predicted by the ten different size portfolios are flatter than the standard SML. This implies a weak risk-return relationship when portfolios are formed based on market caps. Similarly, Fama and French (2004) on the NYSE, AMEX and NASDAQ over the examination period 1928 to 2003, re-examine the relationship between average returns and the beta coefficient. They conclude that firm size represents a better proxy for risk than the beta coefficient.

Haugen (1996; 2010) and Haugen and Baker (1996; 2012) examine the size effect in U.S. and non-U.S. markets and update their result over the period 1963 to 2011. Their results reveal that small caps are rewarded with higher returns at less risk, whereas large caps are rewarded with lower returns and more risk. This suggests that small caps offer superior risk-return benefits relative to large caps.

In addition to the well-documented size anomalies, several studies have suggested that value stocks outperform growth stocks. Firms with low price-to-earnings (P/E) ratios tend to have higher returns than firms with high P/E ratios. Accounting ratios such as the P/E, book-to-market (B/M), cash flow-to-price (C/P), debt-to-equity (D/E), earnings yield (EY), cash flow-to-debt (C/D) and dividend yield (DY) are common indicators used to classify value or growth stocks. Firms with lower prices relative to their fundamentals are classified as value firms as they are considered to have weaker future prospects. On the other hand, firms with higher prices to their fundamentals are generally perceived to be growth firms with ample future growth opportunities. Thus growth firms are expected to have higher returns compared to value firms.

The rationale for value firms outperforming growth firms is provided by Smidt (1968). He argues that investors are over-optimistic about the future prospects of firms and their trading behaviour leads to high P/E ratios. On the other hand, the exaggerated pessimism exhibited by investors towards value stocks results in lower P/E ratios.

Similarly, Basu (1977: 663) points out that "*returns on stocks with low P/E ratios are larger than warranted by the underlying risks… and would be inconsistent with the efficient market hypothesis".* Basu (1977) examines stocks on the NYSE over the period 1957 to 1971, using the CAPM to measure expected returns. He divides stocks between low and high P/E quintile portfolios. The results reveal that the bottom two P/E quintiles earn 16.3% per annum and 13.5% per annum compared to the top two P/E quintiles that earn 9.3% per annum and 9.5% per annum respectively. These results also indicate that the bottom two P/E quintiles have lower beta coefficients relative to the top two P/E quintiles. Thus, investors that invest in low P/E firms are able to achieve a better risk-adjusted performance, at lower risk, than investing in firms with high P/E ratios. In examining the relationship between the value and size effect on the NYSE and AMEX over the period 1967 to 1975, Reinganum (1981) finds that the value effect is highly correlated with the size effect.

Other accounting ratios have also been found to be useful predictors of future stock returns. Fama and French (1992) examine the value effect on their decile portfolios and employ the P/E, B/M, D/E ratios as value proxies. The results of their value portfolios achieve better risk-adjusted returns compared to their growth portfolios. In addition, value firms have lower beta coefficients relative to growth firms. They argue that value stocks are "*fallen angels*" and, therefore, fundamentally riskier. Their higher return premiums are compensation for bearing additional fundamental risk. As a result, the return premiums are expected and required given the additional fundamental risk.

Lakonishok, Shleifler and Vishny (1994) employ the B/M, C/P, EY and average historical 5-year growth rate of sales as benchmarks to construct value and growth portfolios on the NYSE and AMEX over the period 1963 to 1990. The results of their value portfolios achieve better risk-adjusted returns than their growth counterparts. They argue that investors extrapolate past earnings growth too far into the future or assume a trend in stock prices. This phenomenon consequently drives prices too high. When profits are driven to normal sustainable levels faster than what investors' had expected, they are disappointed with the performance results on growth stocks. On the other hand, they argue that the return premiums to value stocks are unexpected and, consequently, systematically surprise investors.

Lakonishok *et al* (1994) further examine the views presented by Fama and French (1992) pertaining to value stocks being fundamentally riskier. In their examination they review the frequency of superior (inferior) performance of value strategies. In addition, they evaluate value strategies during economic recessionary environments and poorly performing markets. Moreover, they review the beta coefficients and standard deviations of value and growth strategies over their examination period. Their results indicate that value strategies have consistently outperformed growth strategies, including during economic recessions and poorly performing markets. The results further indicate that value strategies are less risky than growth strategies. Lakonishok *et al* (1994) conclude that they find little support for Fama and French's (1992) view that value strategies are fundamentally riskier. Furthermore, Lakonishok *et al* (1994) point out that the results raise questions to the efficiency of the EMH.

Kothari, Shanken, and Sloan (1995); and Brown and Goetzmann (1995) argue that the evidence presented on value investing suffers from methodological issues and, hence, the results are flawed. They cite survivorship bias and look-ahead bias as a major problem, which apparently enhances the predictive power of the results. However, Chan, Jegadeesh, and Lakonishok (1995) re-evaluate the evidence to value investing. After considering for survival and look-ahead bias in their examination, they argue that no such bias is able to explain the differential performance between value and growth portfolios. Similarly, Haugen (1996; 2010) and Haugen and Baker (1996; 2012) examine the well-known documented anomalies and the reported criticisms related to methodological issues. They introduce a fifty six-factor model that explores the statistical relationship between 56 individual stock characteristics and returns. The characteristics included in their procedure are risk, liquidity, profitability, value and historical price performance. Similar to Lakonishok *et al* (1994) arguments' on value and risk, they find that the payoffs to risk are negative, whereas the payoffs to value are positive. They also argue that the market's overreaction to the successes and failures of businesses distort the presumed risk aversion implicit within investors. According to Kahneman and Riepe (1998), the value effect provides evidence that investors make irrational decisions. They argue that the value effect is a consequence of investors being inclined to be overconfident in their ability to project high earnings growth rates. In their opinion, investors are not risk-averse as growth stocks are priced higher than value stocks.

Fama and French (1998) extend their study to international markets that cover Europe, Australia and the Far East (EAFE) over the examination period 1975 to

1995. Significant value and size effects are found to that in the U.S. Other international evidence on the value and size anomalies are found in Japan (Chan, Hamao and Lakonishok, 1991); Australia (Beedles, 1992); Canada (Elfakhani, Lockwood, and Zaher, 1998); the United Kingdom (Bagella, Bechetti, and Carpentieri, 2000); Europe (Van Holle, Annaert, Crombez, and Spinel, 2002) and Chan and Lakonishok (2004) in the EAFE.

Rouwenhorst (1999: 1439) points out that the "*factors that drive cross-sectional differences in stock returns in emerging equity markets are qualitatively similar to those that have been documented for developed markets*". He examines 20 emerging market economies over the period 1975 to 1997. The empirical evidence indicates that small caps outperform large caps and value stocks outperform growth stocks on a risk-adjusted basis. Similarly, Barry, Goldreyer, Lockwood, and Rodriguez (2002), document value and size anomalies in 35 emerging market economies, over the period 1985 to 2000, and Drew, Naughton and Veeraraghavan (2003) in China from 1993 to 2000. In more recent work on international markets over the period 1996 to 2010, Hodnett and Hsieh (2011) find that the size and value effect continue to be prominent factors that consistently explain the cross-section of global equity returns.

3.2.2 Overreaction and Momentum Anomalies

According to the efficient market hypothesis (EMH) stock prices reflect all available information in a swift and impartial manner. Therefore stock prices represent an unbiased estimate of a firm's true underlying value (Basu, 1977). When information arises, the news spreads very quickly and is incorporated into prices without delay. However, many critics have questioned its validity from a behavioural perspective. De Bondt and Thaler (1985) examine the average cumulative abnormal returns (ACAR) of past winners and loser portfolios on the NYSE over the period 1 January 1926 to 31 December 1982. Their results indicate that the prior 36-month loser portfolios outperform the winner portfolios by 24.5%, 36 months on average since formation. The loser portfolios are found to accumulate positive abnormal returns relative to the winner portfolios that accumulate negative abnormal returns. In essence, selling the "*winners*" and buying the "*losers*" will earn positive expected profits in the presence of negative serial correlation to those investors that adopt a contrarian investment strategy. De Bondt and Thaler (1985) attribute long-term reversals in asset prices to investor overreaction. They argue that investors overreact to unexpected and dramatic news events, which is a direct result of investors' psychological biases. They further explain that investors afford too much weight to the most recent information, and too little is given to the long-term fundamental information inherent in a firm. Since the fundamental information of the firm remains a constant, asset prices that are overstated (understated) are expected to correct to their long-term fundamental values. For this reason, asset prices are expected to mean-revert. The overreaction hypothesis presented by De Bondt and Thaler (1985) is in direct contradiction to the EMH.

De Bondt and Thaler (1987), in their follow up paper on the overreaction hypothesis, test for the influence of firm size, seasonality and market risk (beta coefficients) on the NYSE over the period 1926 to 1982. Their results reveal that January excess returns are negatively related to December prior returns for past winners. They argue that the January effect serves as evidence of capital gains tax lock-in for past winners. However, they find no evidence of tax-loss selling for the loser portfolios in their study. Their results further reveal that factors such as size and market risk have no impact on the mean-reversal of past winners and past losers.

Chopra, Lakonishok, and Ritter (1992), on the NYSE over the period 1931 to 1986, examine the effect of market risk and size biases inherent in the De Bondt and Thaler (1985; 1987) study. In performing regression analysis on prior winners and prior losers, their results reveal large differences in abnormal returns between prior winners and prior losers, even after adjusting for time varying beta coefficients.

Fama (1998) evaluates the De Bondt and Thaler's (1985; 1987) overreaction hypothesis. According to Fama (1998: 284), "*if anomalies split randomly between underreaction and overreaction, they are consistent with market efficiency*". In essence, the long-term return anomalies are attributed to chance results. Fama (1998) argues that an efficient market generates categories of events. When these events are viewed individually, markets are expected to overreact (underreact) to information. Examples of categories of events include stock splits, initial public offerings, stock repurchases and dividend initiations. These anomalies, he points out, are effectively sensitive to methodology as they tend to disappear or become marginal when exposed to an appropriate model for expected return. The De Bondt and Thaler's (1985; 1987) long-term reversal anomalies can be explained by means of a rational multifactor asset pricing model (Fama, 1998).

Evidence of investor overreaction (underreaction) is observed in non-US markets, including emerging markets. In addition to the size and value effect in emerging markets, Rouwenhorst (1999) observes that in emerging markets stocks exhibit the momentum effect. Ang, Hodrick, Xing, and Zhang (2009), after controlling for size and value, find evidence that stocks with high past unsystematic risk have low expected future returns over 23 developed markets. Haugen and Baker (2012), on the other hand, find evidence of investor overreaction in stocks that cover 21 developed countries and 12 emerging markets.

It has also been revealed that asset prices with high returns over the past three to twelve months tend to have high returns over the following three to twelve months. This is referred to as the momentum effect. Jegadeesh and Titman (1993) examine the momentum effect on the NYSE and AMEX over the period 1 January 1965 to 31 December 1989. Their results reveal that abnormal returns are available in the short to medium term. Similarly, Haugen (1996; 2010) and Haugen and Baker (1996; 2012) find evidence of 12-month prior returns in U.S. and non-U.S. markets over the period 1963 to 2011. Motivated by the extraordinary increase in stock prices in the late 1990's, Shiller (2000) examines the stock market boom on the S&P 500 over the period from 1995 to 1999. His results suggest evidence of short-run momentum in asset prices and points out that it is consistent with psychological feedback mechanisms. For example, individuals that see stock prices rising are drawn into the market and this phenomenon inevitably creates a "*bandwagon effect*". He describes the rise in stock prices on the S&P 500 in the late 1990's as psychological contagion and refers to it as investor irrational exuberance. In more recent work covering four global equity markets, including the U.S, United Kingdom, continental Europe and

Japan over the period from 1972 to 2011 Asness, Moskowitz and Pedersen (2013) continue to find evidence of the momentum effect.

3.2.3 Style-based Asset Pricing Models

Given the criticism levelled at the joint hypothesis of the EMH, Fama and French (1992) argue that the size and value anomalies ought to be interpreted as missing risk factors. They argue that the anomalies should be considered evidence against the single-factor CAPM but not against the EMH. In their examination the well-documented size effect is proxied by market cap and the value effect is proxied by the B/M ratio. Fama and French (1992) point out that the risk captured by the B/M ratio is a relative distress factor. They further argue that the earnings prospects of firms are associated with a risk factor in returns. These are firms which are characterised with high B/M ratios. Firms that are subject to potential financial distress are characterised with higher cost of capital as investors demand a higher premium as compensation. Another reason given for high B/M ratios, are the irrational whims displayed by investors about the future prospects of firms (Fama and French, 1992). Consequently, they argue that critique levelled at the joint hypothesis of the EMH is mainly a result of methodology as the CAPM does not capture the different dimensions of risk (Fama and French, 1993).

Fama and French (1993) introduce a rational multifactor model incorporating value and size risk premiums in addition to the market risk in the CAPM. They argue that stock returns could be explained on the basis of loadings of stocks with respect to three factors. The size risk premiums is proxied by the difference between the rates of return to small stocks and large stocks and the value risk premium is proxied by the difference between the rates of return to high B/M ratios and low B/M ratios. The result of their three-factor model is able to successfully explain the common variation in stock returns. Moreover, their three-factor model adequately explains the returns of their portfolios based on the documented anomalies such as the long-term price reversal of De Bondt and Thaler (1985; 1987) and the C/P, EY and historical sales growth proxies of Lakonishok *et al* (1994) (Fama and French, 1996). Fama and French (1996) point out that the variables alluded to above are all scaled versions of a firm's value, with effects of some variables subsumed by the size effect and the other by the value effect. The momentum effect of Jegadeesh and Titman (1993) is not captured by the Fama and French three-factor model. In explaining the absence of the momentum effect in their rational multifactor model, Fama and French (1996) argue the momentum effect is a consequence of data-snooping or survivorship bias. However, Chan, Jegadeesh, and Lakonishok (1996) argue that the momentum anomaly is a market inefficiency due to the slow reaction of investors to new information.

Haugen (1996) and Haugen and Baker (1996; 2012) employ and replicate Fama and French's (1993) three-factor model to determine if the same result holds in their examination. Similar to Lakonishok *et al* (1994) findings, their examination results reveal that value stocks are rewarded with a risk premium of low risk relative to growth stocks that are rewarded with a risk premium of high risk.

Carhart (1997) extends Fama and French's (1993) three-factor model to develop a four-factor model that accommodates Jegadeesh and Titman's (1993) short-term momentum risk premium, which is proxied by prior 12-month returns. The Carhart (1997) four-factor model is employed to examine the persistence of mutual fund returns on the NYSE, AMEX and NASDAQ over the period 1962 to 1993. The Carhart (1997) four-factor model significantly improves upon Fama and French (1993) three-factor model as it explains a higher degree of variation in mutual fund returns. More importantly, it is able to explain the momentum effect that could not be explained by the Fama and French (1993) model.

3.2.4 South African Evidence

Page and Way (1992; 1993) test De Bondt and Thaler's (1985; 1987) overreaction hypothesis on the JSE over the period 1974 to 1989. Their results are consistent with international findings in that the loser portfolios outperform the winner portfolios by 14.5%, on average, 36 months after formation. In addition, the loser portfolios are found to generate abnormal returns 12 months after formation, which is consistent with international studies. Furthermore, the results provide evidence of asset prices mean-reverting, similar to De Bondt and Thaler's (1985; 1987) findings. They conclude that investor overreaction exists on the JSE, and indicate that the JSE is less than weak-form efficient over the examination period.

Muller (1999) examines the overreaction hypothesis on the JSE over the period from 1985 to 1998. To avoid the seasonality bias, the middle third of the examination period is divided into 30 equally-spaced sub–periods which provide 30 randomly-chosen portfolio formation dates within the respective sub-periods. Unlike the January effect exhibited in the U.S. studies, South African companies are free to choose their financial year end calendar month. As a consequence, tests conducted on the JSE are unlikely to be impacted by any seasonality bias pertaining to the January effect. Muller (1999) employs the 200 largest shares by market cap as the research sample and the size of the winner and loser portfolios are kept to 30 or 60 stocks. Employing computer simulations, the formation and holding periods are varied from 60 days to four years. The results of both the winner and loser portfolios yield positive abnormal returns initially. However, the winner portfolios lose their initial momentum after approximately 600 days, whereas, the loser portfolios are optimised at a holding period of 340 days. To conclude, Muller (1999) suggests that the asymmetrical reversals of the loser and winner portfolios are subject to their unique timings in market correction.

Fraser and Page (2000) on the South African stock market, examine the pervasiveness of value and momentum strategies over the period from 1978 to 1997 on the JSE. Their cross-sectional regression analysis reveals that the value and momentum anomalies independently explain the cross-sectional returns on the JSE. Van Rensburg (2001), on the other hand, develops style-mimicking portfolios and tests their influences and exposure on JSE returns over the period 1983 to 1999. An enumerate number of market anomalies related to value, future earnings growth, and other neglect/irrationality style categories are examined in his study. The returns on the style portfolios were cluster analysed. The study suggests that the CAPM anomalies such as EY, DY, leverage, C/D, turnover, prior 3-month, prior 6-month and prior 12-month returns documented in international markets are prevalent on the JSE. The results of the cluster analysis reveal that market cap, EY, and prior 12-months returns represent major style risks on the JSE. Van Rensburg and Robertson

(2003a) employ a characteristic approach and re-evaluate the risk factors tested by Van Rensburg (2001) on the JSE over the period 1990 to 2000. The objective of their empirical investigation is to identify the style-based factors that drive the cross-section of JSE returns. The time-series factor payoffs to the style characteristics are identified using a univariate test. Thereafter, the factor payoffs that represent significant effects are filtered from a set of 24 fundamental and technical attributes and employed in a multivariate analysis. Similar to Van Rensburg (2001) study, the multifactor results reveal that EY and market cap represent the two major sources of style risks on the JSE over the examination period. In addition, the multifactor results support a two-factor APT model with size and value as explanatory variables. Furthermore, EY and market cap subsume all other factors such as B/M, DY, and C/P ratios. Unlike the momentum factors identified in Van Rensburg (2001) study, the factors receive no significant factor payoffs in the initial univariate test. Van Rensburg (2003b) extends the research of Van Rensburg and Robertson (2003a) adopting the methodology of Fama and French’s (1992) to cross-examine the EY and market cap as the major sources of style risks on the JSE. Similar to the results of international studies, the results indicate that value stocks have high returns and low beta. Moreover, they find that the size and value effects operate independently of each other on the JSE, similar to the results of Fraser and Page (2000). Overall, the results reveal that neither the CAPM nor the two-factor APT model succeed in removing the anomalies identified in the study.

Rousseau and Van Rensburg (2004) examine the potential payoffs of longer holding periods on value portfolios on the JSE over the period 1982 to 1998. The results indicate that returns on portfolios beyond 12 months holding periods are more robust. This indicates that value investing is best employed as a long-term strategy. However, for such a strategy to achieve outstanding performance they suggest a diversified value portfolio. They point out that the rewards to value stocks are not evenly distributed. As a consequence, the returns are strongly right skewed. Rousseau and Van Rensburg (2004) argue that abnormal returns earned by the value portfolios are dominated by a few members of the portfolios only.

Basiewicz and Auret (2010) examine the feasibility of employing Fama and French's (1993) three-factor model on the JSE. In time-series tests, over the period 1992 to 2005, the three-factor model is able to explain both the value and size effects. Based on their empirical evidence, they find that the Fama and French three-factor model has greater explanatory power in explaining expected returns on the JSE relative to the standard CAPM. As a consequence, they propose that the Fama and French (1993) three-factor model be adopted for asset pricing on the JSE. Auret and Cline (2011), on the other hand, evaluate the inter-relationship between the value, size and January effect over the period from 1988 to 2006. In constructing portfolios that represent the cross-sectional factors under examination, the results of their regression analysis reveal that no significant value, size or January effects exist over the examination period. Whereas Strugnell, Gilbert and Kruger (2011), over the period from 1994 to 2007, examine Van Rensburg and Robertson (2003a) conclusions based on the value, size and beta interrelationship. In their examination, they employ the Dimson Aggregated Coefficients method with a lead and lag of 3 months to estimate the beta coefficient on their portfolios. They argue that stocks on the JSE are subject to thin trading. Therefore, employing ordinary least square regressions to estimate beta coefficients is an inappropriate methodology. Similar to

Van Rensburg and Robertson (2003a) results, they find that the value and size effects are able to explain the cross-section of expected returns on the JSE. Similar to Van Rensburg and Robertson (2003a) and other international studies, they find that the beta coefficients on their portfolios have an inverse relationship with the size effect and value effect, In their conclusion, they declare that the CAPM is an inappropriate model to determine expected returns on the JSE.

Muller and Ward (2013) examine the well-documented anomalies found in international and South African studies. Their research is motivated by the fact that local studies suffer from methodology shortcomings. To overcome any methodology shortcomings, they extend their examination period from 1985 to 2011. Their portfolios are rebalanced every quarter and financial year-end data is lagged 3-months to overcome any biases. In addition, only the top 160 firms ranked by market cap are included in their examination to minimise liquidity constraints. They further argue that the use of average monthly or quarterly returns is a methodology weakness. Cumulative returns are thus employed over the examination period. Their style portfolios show significant and persistent abnormal returns for momentum, P/E, DY, B/M, C/P, liquidity, return on capital, return on equity and interest cover. Contrary to other reported empirical evidence on the size effect, their portfolios formed on the basis of size only outperform the ALSI over the period from 2000 to 2002. Beyond 2002 the size effect disappears. They also show that the introduction of electronic trading and the subsequent lower transaction costs renders illiquidity premiums as zero after the restructuring of the JSE in early 2000.

Hodnett (2014) evaluates the cyclical nature of the value-growth spread on the JSE over the period from 1997 to 2013. The relative valuation measures used to define value and growth stocks in the study includes EY ratio, B/M ratio and sales-to-price (S/P) ratio. The study results show that the median ratio between the value and growth portfolios for the S/P ratio is the highest and most volatile over the examination period. Hodnett (2014) points out that this indicates that the S/P ratio could be a useful indicator regarding market sentiments and degrees of risk aversion over various phases of the business cycle.

In more recent evidence on the South African stock market, Hsieh (2015) examines whether the value effect continues to exist on the JSE over the period from 1997 to 2013. Similar to the relative valuation measures employed by Hodnett (2014), the study includes the EY ratio, B/M ratio and S/P ratio to define value and growth stocks. Unlike prior studies that sort portfolios into quintiles or quartiles, portfolios are divided into tertiles to distinguish the performance of value and growth portfolios. Hsieh (2015) indicates that the advantage of dividing portfolios into tertiles is that sufficient sample sizes could be obtained that effectively dilutes the effect of extreme outliers. Examining the value effect independently within the large cap segment and the small cap segment on the JSE, the results show no significant value effect and growth effect over the entire sample period and within the different size segments. On the other hand, the results display a significant size effect on the JSE over the sample period. Hsieh (2015) attributes the size effect to the tertile analysis undertaken in the research.

Examining the persistence of the momentum effect on the JSE, La Grange and Krige (2015) show that the momentum anomaly continue to be a prominent factor in explaining the cross-section of equity returns on the South African stock market. Their study evaluates the profitability of momentum strategies against the benchmark ALSI Top 40 index over the period from 1998 to 2013. The results show that their momentum strategies are able to earn an annualised return of 8.7% risk-adjusted, inclusive of transaction costs, in excess of the benchmark portfolio.

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3.3 Alternative Asset Allocation Strategies

3.3.1 Fundamental Indexation

Market cap is often employed as a weighting methodology used on global market indices, including the ALSI on the JSE, to reflect the performance of established firms in the market. In terms of the EMH, market caps of firms self-adjust to reflect a firm's intrinsic value. Hsu (2006) highlights some of the most notable benefits of cap-weighting. Cap-weighting is 1) a passive strategy which requires little or no active management, hence, no transaction costs; 2) cap-weighted portfolios self-adjust as stock prices fluctuate, as a result, there are no rebalancing costs associated with this methodology except for replacing a constituent stock in the portfolio; 3) cap-weighting methodologies assign the greatest weights to the largest companies. Thus, market caps are highly correlated with liquidity. A cap-weighting methodology, therefore, ensures that the portfolio is invested in stocks that are highly liquid, hence, reduces expected portfolio transactions; and 4) finally, a broad based cap-weighted portfolio is automatically Sharpe Ratio maximised or mean-variance efficient in terms of the standard conditions as specified under CAPM.

Cap-weighted indices have not been without its critics though. Haugen and Baker (1991), for instance, argue that cap-weighted portfolios are inefficient investment portfolios when investors disagree on risk, expected returns, when short selling is restricted, income investment is taxed, or in the presence of investment opportunities to foreign investors in domestic capital markets. On the other hand, Arnott, Hsu, and

Moore (2005) argue that cap-weighted portfolios are price-sensitive measures of firm size and are subject to a pricing noise. They point out that cap-weighting methodologies overweigh stocks that are overpriced relative to their true fair values and underweighs stocks trading below their true fair values. Accordingly, "*this mismatch leads to a natural performance drag in cap-weighted and other price sensitive portfolios*" (Arnott *el al*, 2005: 84). The mismatch in performance drag is ascribed to investor overreaction (Arnott *et al*, 2005; and Hsieh, Hodnett, and Van Rensburg, 2012), which cause asset prices to overshoot (undershoot). This leads to market prices to be more volatile than is warranted by changes in a firm's fundamentals. Effectively, a disproportionate amount of weight is assigned to overvalued stocks in comparison to undervalued stocks. Given investor overreaction and the overweighting of overvalued stocks, they point out that overvalued stocks are positively correlated with portfolio weights. As a consequence, cap-weighted portfolios do not capture the full premium commensurate with their risk (Hsu, 2006). It is thus argued that cap-weighting is a sub-optimal strategy (Arnott *et al*, 2005 and Hsu, 2006). Siegel (2006) referred to this phenomenon as the noisy market hypothesis.

The associated asset allocation shortcomings related to cap-weighted portfolios have prompted practitioners to search for alternative weighting methodologies. Various studies have explored the potential benefits of alternative weighting methodologies that take into account real-life constraints that improve mean-variance efficiency. Motivated by the shortcomings in cap-weighted portfolios, Arnott *et al* (2005) introduce price-insensitive measures that reflect the fundamentals underlying a firm's intrinsic value in its weighting methodology. This is commonly referred to as fundamental indexation. The price-insensitive measures of firm size they propose include book value, revenue, cash flow, sales and dividends. The fundamental indexes they introduce are primarily concentrated in large and well established firms and, hence, preserve the liquidity and traditional capacity benefits of cap-weighted indices. Based on stocks on the S&P 500 and a reference cap-weighted index similar to the Russel 1,000 over the examination period from 1962 to 2004, their fundamental indices outperform the cap-weighted indices on a risk-adjusted basis. Similarly, Hsieh *et al* (2012) employ the Dow Jones Composite Sector Index, encompassing all the first world and major emerging market economies including South Africa in their database. Their results, over the examination period from 1991 to 2008, indicate that fundamental-weighted indices outperform cap-weighted indices. Hemminki and Puttonen (2008) examine fundamental indexes employing the Dow Jones Euro Stoxx 50 Index, which covers the 12 major Eurozone economies, over the examination period from 1996 to 2006. Their results indicate that fundamental-weighted indices outperform cap-weighted indices on a risk-adjusted basis.

Perold (2007) challenges the noisy market hypothesis as suggested by Arnott *et al* (2005) and Hsu (2006). Perold (2007) provides a theoretical argument to the noisy market hypothesis and argues that if stock prices follow a random walk without mean-reversion, cap-weighted indices would not experience a performance drag. Furthermore, Perold (2007) argues that cap-weighting would not have a return drag if the fair value was randomly distributed around stock prices. Chow, Hsu, Kalesnik and Little (2011) contradicts Perold (2007) argument and indicate that it is practically more intuitive to think that prices are distributed around the fair value of a company and not the other way around.

Arnott and Hsu (2008) re-evaluate the noisy market hypothesis. They mathematically show that asset prices are noisy proxies of an asset's fair value. Their exercise also reveals that the market portfolio is mean-variance inefficient, which causes an asset's beta coefficient to be misrepresented. Whereas Fama and French (1992; 1993) argue that the size and value anomalies are hidden risk proxies not captured by the CAPM, Arnott and Hsu (2008) attribute these anomalies to the pricing noise imminent in cap-weighted portfolios. They further argue that large caps and growth stocks tend to underperform because these stocks exhibit a positive pricing error. They posit that models such as the disposition effect and the information herding effect are able to explain the value and size puzzle. Moreover, when prices are noisy, the value and size effects are expected to arise naturally as investor overreaction cause prices to overshoot (undershoot). In essence, they point out that capital markets are not efficient as investors behave irrationally.

Ferreira and Krige (2011) examine the application of fundamental indexing on the South African stock market over the period from 1996 to 2009. The price-insensitive measures they include to construct their fundamental indexes are book value, cash flow, sales and dividends. The results of their fundamental index outperform the ALSI by 4.7% per annum risk-adjusted over the examination period.

According to Arnott and Shepherd (2012), the application of fundamental indexing is also applicable in emerging markets that experience a significant degree of volatility and are less efficient. Using the FTSE RAFI (Research Affiliates Fundamental Index) Emerging Market Index over the period from 1994 to 2009 as their sample, their results achieve an annual return of 15.9% compared to the benchmark that achieves an annual return of 6.9% on a risk-adjusted basis.

Hsieh (2013) examines the merits of fundamental indexation in global emerging stock markets over the period from 1996 to 2009. Based on Fama and French (1993) three-factor model, Hsieh (2013) analyses the influence of the value and size risk factors on fundamental indexes. His results reveal that the majority of fundamental indexes have significant exposures to the value and size risk factors. On the other hand, once the value and size risks are controlled for, the fundamental indexes earn negative abnormal returns. The results further reveal that the fundamental indexes accumulate positive residuals during the information technology bubble crash of 2000 and the financial market crash of 2008 but at the expense of severe drawdown.

3.3.2 Portfolio Optimisation and Style Allocation Strategies

Haugen and Baker (1991) perform an alternative weighting procedure using the largest 1,000 U.S. stocks in terms of market cap over the period 1972 to 1989. To ensure diversification, they constrain their portfolio to a maximum of 1.5% of the portfolio invested into any stock and 15% of the portfolio invested in any industry. Furthermore, they employ a long-only constraint. Using the Wilshire 5,000 as the benchmark portfolio, their results show that their optimised portfolio offers a similar return at lower volatility against the benchmark portfolio. Haugen (2010) re-examine the implications of alternative weighting methodologies using a long-only constraint. They construct optimal portfolios based on the largest 1,000 U.S. stocks in terms of market cap and compare the performance of their optimal portfolios against the S&P 500 index. Haugen (2010) evaluate four portfolios from lowest volatility with increasing intent in favour of higher expected returns achieved through increasing the average annual turnover on each portfolio. The results show that three of their optimised portfolios achieve less risk and higher excess returns than the benchmark S&P 500 index. The portfolio with the highest turnover achieves the highest excess return to all the constructed portfolios including the benchmark, however at higher risk.

If one considers Markowitz's (1952) appraisal that the inputs such as expected returns, risk and covariance of returns in the portfolio selection process be based on a set of probability beliefs, one could argue that these inputs are subject to the quality of the estimation of the input parameters. For this reason one can only gauge an approximation of a true optimal portfolio (Jorion, 1992). Moreover, the input parameters employed in mean-variance analysis is based on historical data. To this end, the inherent uncertainties surrounding these parameters are overlooked. Jorion (1992) refers to these phenomena as estimation risk that influences the portfolio optimisation process. Motivated by these shortcomings in the optimisation process, Jorion (1992) sets out to provide insight into the construction of an *ex post* randomised optimal portfolio. Accounting for sampling variability made up of 1000 iterations in the optimisation procedure, Jorion (1992) evaluates an *ex post* optimal portfolio of U.S. and global bonds, incorporating all the major developed countries in his simulation. He further compares the optimal portfolio against a global bond index and U.S. bond index over the period from 1978 to 1988. The portfolios are further evaluated with and without a short sales constraint. The optimisation procedure, without short sales successfully outperforms the U.S. index but is unsuccessful in outperforming the global index. In relaxing the constraint to include short sales, Jorion (1992) points out that the performance of the optimal portfolio is subject to an estimation error as it leads to imprecise portfolio results.

Amenc, Malaise, Martellini and Sfeir (2003) evaluate the application of style timing strategies on a market neutral hedge fund using the S&P 500 indexes over the period from 2000 to 2002. They employ a multifactor model with style attributes as the observable proxies in their style timing strategy. The observable proxies used in their procedure include the S&P 500 Large Cap Index, the S&P Large Cap Growth Index, the S&P Large Cap Value Index and the Russell 2000 Small Cap Index. The results reveal that the market neutral hedge fund is able to outperform the S&P 500 Index with significantly lower historical drawdowns. Similarly, Hsieh, Hodnett and Van Rensburg (2012) examine the application of tactical style allocation (TSA) strategies on global equity portfolios. The objective for their research is to evaluate the risk-adjusted performance on global equity portfolios and hedge fund strategies over several phases of the global economic cycle. They evaluate two style-based portfolios, one which is optimised employing a global value index and the global momentum index, and the other includes a risk-free proxy (cash component) in addition to the value and momentum constituents. In comparing their examination results to the MSCI World Index and the Global Value Index and Global Momentum Index over the period 1994 to 2009, their optimised TSA style-based portfolios are able to outperform the benchmark portfolios on a risk-adjusted. The results further reveal that the portfolio with the cash component provides additional protection during the financial market crises in 2008.

Encouraged by the increasing popularity of alternative weighting methodologies, including the equal weighting and price-insensitive weighting methodologies, Chow, Hsu, Kalesnik, and Little (2011) evaluate a back-test of several alternative weighting methodologies. Their examination included the top 1,000 stocks made up of stocks in the U.S. and global equity markets over the period from 1964 to 2009 and from 1987 to 2009 respectively. The performance results of their optimisation procedure reveal that the alternative weighting methodologies successfully outperform the traditional cap-weighted indices. However, they attribute the outperformance to a positive exposure to the value and size factors.

3.3.3 Market Segmentation and Sector Allocation

The unique empirical feature of the JSE is that more than one security market line (SML) exists. Campbell (1979) finds that the CAPM beta coefficient of the industrial index, with the ALSI as the market proxy, fell from the mid-1960s to the mid-1970s relative to the Gold Index that rose over the same period. The same relationship is found on individual shares in the same index. However, the individual beta coefficients were more stable when measured against their respective indices. Campbell (1979) argues that different economic forces affected each set of shares over the 10-year period and proposed that a different SML existed for each sector, with the sector index playing the role of the market proxy. Bowie and Bradfield (1993) corroborate Campbell's (1979) findings and argue that ALSI is an inappropriate market proxy employed in the CAPM on the JSE. The problems highlighted by Campbell (1979) and Bowie and Bradfield (1993) is that the JSE is dominated by mining companies in terms of market cap, especially the gold and diamond firms. This phenomenon is unlike other global stock markets. When international political conflicts or significant macro-economic events appear, the fortunes of such companies are impacted.

In an attempt to explain the persistent returns generated by the JSE, Van Rensburg and Slaney (1997) introduce a two-factor APT model. Employing a factor analytic procedure, they identify that the most influential sectors to be employed as observable proxies in their two-factor model, include the JSE Actuaries All-Gold and industrial indices over the examination period from 1985 to 1995. Their time-series regression results reveal that the two-factor APT model comprehensively explains the stock returns on the JSE. Furthermore, they argue that the different sources of risk are rewarded with a different risk premia and that the large majority of JSE shares are either influenced by the mining sector or industrial sector, but not both. Whereas Bowie and Bradfield (1993) propose that an appropriate sector index be employed in the CAPM, Van Rensburg and Slaney (1997) argue that the two-factor APT is a more appropriate model to explain stock returns on the JSE. They point out that their model captures all the benefits of the two SML approach suggested by Bowie and Bradfield (1993). Furthermore, they propose that the two-factor APT model employing the JSE Actuaries All-Gold and industrial indices should be adopted in asset pricing applications as it provides a superior account to asset pricing relative to the CAPM.

The Johannesburg Stock Exchange was renamed to the Johannesburg Securities Exchange and sectors were reclassified in 2000. The All-Gold sector and other mineral sub-sectors were subsumed into a resources sector. Chemicals, Oil, Paper, and Steel sub-sectors were reclassified from the industrial sector and included in the resources sector as well. Motivated by the reclassification of sectors on the JSE, Van Rensburg (2002) updates the work of Van Rensburg and Slaney (1997) and adopts a similar examination procedure. The factor analytic procedure identifies the resources sector (RESI) and the combined financial and industrial sectors (FNDI) as the most influential sectors. The RESI and FNDI are employed as observable proxies in his two-factor APT model over the examination period from 1993 to 2000. The results reveal that the model gives a superior account in explaining stock returns on the JSE. When the possibility of investing offshore is considered, Van Rensburg (2002) argues that the CAPM is an inappropriate model in asset pricing on the JSE. He points out that the ALSI, employed as the optimal portfolio in the CAPM, is mean-variance inefficient. Unlike other global equity markets, the JSE is unique in that it is influenced by a minority of shares with pervasive influences on the SML. These influences suggest that the CAPM is an inappropriate model to employ in the determination of stock prices. The results further suggest that a two-factor APT, with RESI and FNDI as observable proxies, significantly improves the explanatory power driving the returns on the JSE.

As investors continue to search for superior alternatives to maximise returns, Cavaglia, Melas, and Tsouderos (2000) and Cavaglia and Morez (2002) argue that a sector allocation strategy may be an effective alternative. They reason that the increased integration into the global economy due to globalisation may potentially benefit those investors that diversify their portfolios across country and across industry. They further point out that the rewards-to-risk ratios and return payoffs to those investors that adopt a sector allocation strategy is superior relative to those that adopt a passive investment strategy within countries.

Vardharah and Fabozzi (2007) argue that an asset allocation strategy based on economic sectors and allocation based on styles should not be considered separate exercises. They argue that sectors, over time, mimic the behaviour inherent in certain styles in comparison to other sectors. An example was the technology bubble when the returns of the technology sector outpaced all other sectors. The pattern severely reversed when the bubble burst. They further argue that a sector allocation strategy is equivalent to a style allocation strategy as the behaviour within sectors adopts the attributes of a particular style. For this reason they argue that sectors and styles are intercorrelated as investors are driven by the underlying macro-economic risks during the course of an economic cycle. Vardharaj and Fabozzi (2007) examine the performance attribution on U.S. and global stock markets, including emerging market equity funds, over the period from 1995 to 2007. Their results reveal that 90% of the variations in equity returns are explained by the economic sector indices, size and value indices.

Hodnett and Hsieh (2011) examine the well-documented efficient market anomalies across different sectors in the global equity market over the period from 1999 to 2009. The results of their univariate analysis indicates that market cap, B/M ratio and the market beta coefficient are prominent factors that consistently explain the persistent returns in global equity markets. Furthermore, they suggest that the value effect and mean reversals are significant influences on sectors, especially during turbulent economic times. Their results suggest that investors that adopt a sector allocation strategy are more superior to a country allocation strategy that seeks to employ a passive investment strategy.

Yu (2008) provides support from a South African perspective. Yu (2008) employs Sharpe (1992) return decomposition methodology on the JSE over the period from 2001 to 2008. The RESI, industrial sector index (INDI), and financial sector index (FINI), as well as three constructed style proxies are employed in her evaluation procedure. The results indicate that the performances of South African unit trusts are driven by their inherent investment styles and sector allocation strategies relative to a manager's stock picking ability.

3.4 Conclusion

The well-documented anomalies have spawned significant debate related to the joint hypothesis problem of the EMH. There are those that argue that asset pricing models based on investor rationally are subject to pricing irregularities as a result of the well-documented anomalies. They point out that in the presence of investor irrationality, investors either overreact/underreact to the arrival of new information. This has prompted many observers to argue that the anomalies provide evidence against the EMH as investors are able to earn abnormal returns. Fama and French (1992; 1993), on the other hand, provide a risk-based explanation for the anomalies. They argue that the anomalies should only be considered evidence against the CAPM. In an attempt to explain the anomalies, they introduce a rational multifactor model which substantially captures risks unexplained by the CAPM.

The rational multifactor model that Fama and French (1993) introduce is a three-factor model, which is an extension of the CAPM and includes the size and value style risks. The only style risk unaccounted for in their model is the momentum effect of Jegadeesh and Titman (1993). Carhart (1997), on the other hand, introduces a four-factor model which includes the Fama and French (1993) four-factor model as well as the momentum style risk of Jegadeesh and Titman (1993). The four-factor model is able to explain a higher degree of variation in asset returns and manages to explain the abnormal returns in the momentum portfolio.

In the presence of investor overreaction, it is found that cap-weighted indices are sub-optimal strategies. Cap-weighted portfolios overweigh stocks that are overpriced and underweigh stocks trading below their true fair value, which leads to a performance drag in the portfolios (Arnott et al, 2005). Arnott *et al* (2005) show that fundamental indices, formed on the basis of fundamental values, are able to outperform cap-weighted indices. Similarly, it is found that optimisation-weighted portfolios are a superior alternative to cap-weighted indices.

The well-documented anomalies in international studies have also been found to be a recurrent theme in the South African market. As a consequence, Van Rensburg and Slaney (1997) and Van Rensburg (2002) argue that market segmentation exists on the JSE. Employing a two-factor APT asset pricing model, with RESI and FNDI as sector risk proxies, Van Rensburg (2002) sector-based APT model is able to explain stock returns more comprehensively than the CAPM. Furthermore, Van Rensburg (2002) argues that the JSE ALSI is not mean-variance efficient when offshore investing is included in the analysis. As a result, the CAPM is not an appropriate model for pricing assets on the JSE.

Cavaglia, Melas, and Tsouderos (2000) and Cavaglia and Morez (2002) argue that a sector allocation strategy may be a superior alternative investment strategy to a passive investment strategy. On the other hand, Vardharah and Fabozzi (2007) argue that an asset allocation strategy based on sectors mimic the behaviour inherent in certain styles in comparison to other sectors. For this reason, they point out that sectors and styles are intercorrelated as investors are driven by the underlying macro-economic risks during the course of an economic cycle.

4

DATA AND METHODOLOGY

4.1 Introduction

The theoretical foundation of capitalisation-weighted (cap-weighted) indices is based on the belief that the market is efficient in that stock prices are unbiased estimates of their intrinsic values at all time. As a cap-weighted index, the market portfolio is presumed to be mean-variance efficient in capital market theories as it offers the best risk-return trade-off amongst all risky assets and portfolios. However, empirical evidence based on real world constraints have produced an enumerate number of capital market anomalies. The noisy market hypothesis of Siegel (2006) suggests that stock prices are subject to trading activities which are unrelated to their intrinsic values, and cap-weighted indices have a tendency to overweigh overvalued stocks and underweigh undervalued stocks. Arnott *et al* (2005) ascribe this phenomenon to investor overreaction. As a result of the price-sensitivity inherent in cap-weighted indices, empiricists have searched for alternative asset allocation methodologies. For instance, fundamental indexation pioneered by Arnott *et al* (2005) has been shown to exhibit superior risk-return characteristics to investors in comparison to cap-weighted indices.

The market segmentation phenomenon documented by Van Rensburg and Slaney (1997) and Van Rensburg (2002) on the JSE indicates that the performances of different sectors are driven by different sets of macro-economic forces. This suggests that the FTSE/JSE All Share Index (ALSI) could potentially be sub-optimal to be employed by the capital asset pricing model (CAPM) to explain stock returns from various sectors on the JSE. The noisy market hypothesis coupled with the market segmentation phenomenon on the JSE has two conundrums. Given the potential mean-variance inefficiency of the ALSI, the first conundrum is to determine what might constitute an optimal mean-variance sector-based allocation. The second conundrum is that a sector-based asset pricing model might have better power than CAPM in explaining JSE stock returns.

The aim of this chapter is to highlight the research problem and to delineate the goals and objectives of the research problem. The methodologies to be carried out to conduct the research are also presented. In addition, the rationale behind the database and sample selection, challenges and biases in the research procedure are presented.

4.2 Problem Statement and Research Objectives

This research attempts to answer the question as to whether the sector allocation of ALSI as the market proxy is mean-variance efficient; and if stock returns are better explained by their exposures to the market risk as a whole or the risks inherent in the prominent sectors on the JSE. In addition, this study attempts to establish the correlation between sector performance and the underlying investment styles on the JSE.

The goals of this research are to be achieved through the following objectives:

1. Construct an optimal portfolio of risky assets on the JSE that maximises the Sharpe ratio over the examination period from 1 January 2003 to 31 December 2013, using JSE tradable sector indices as its constituents.
2. Construct an optimal portfolio that consists of both risky tradable sector indices and the risk-free asset on the JSE over the examination period.
3. Compare and contrast the performance of the optimised portfolios to that of the ALSI index as the market proxy over the examination period.
4. Conduct performance attribution analysis on the sector allocation between the optimised portfolios and the ALSI index over the examination period.
5. Evaluate the influence of style risks on the JSE sector returns based on the Carhart (1997) four-factor model regression results.
6. Evaluate the predictability of sector-based multifactor APT models in explaining JSE stock returns relative to the single-factor CAPM over the examination period.

The outcomes of the tests conducted in this research provide insights into alternative asset allocation decisions and asset pricing models relevant to investors on the JSE.

4.3 Research Database and Sample selection

According to Fama (1970: 383), a perfectly efficient capital market 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*". Thus, an efficient capital market entails that accurate information is available to all interested parties instantaneously and subject to there being no barriers to trade.

The JSE prior to 1994 was beset of the qualities that could be considered to be an efficient capital market. Evidence suggests that the JSE was constrained by issues such as illiquidity, lack of accurate information, inefficiency of price information and high transaction costs (Mkhize and Mswell-Mbanga, 2006). Mkhize and Mswell-Mbanga (2006) attribute these inefficiencies to economic and political instability brought about by international sanctions against the South African regime at the time. Listed firms on the JSE which were acquired by large corporations with financial clout could more easily tap into external financing for long-term capital projects to the detriment and subsequent death warrant of the majority of other listed firms. The JSE was characterised by thin trading as institutional investors focused their investment strategies on a few select stocks, which effectively discouraged entrepreneurial risk-taking and the development of new infrastructure in South Africa.

According to Mkhize and Mswell-Mbanga (2006), another problem on the JSE was the efficient dissemination of information to all parties. Member stockbrokers of the

JSE were permitted to act in a single capacity and trade stocks on the market trading floor, hence, were privy to information on shares prior to it being made public. All other parties were marginalised as they were forced to trade through a member stockbroker and were subjected to high transaction costs.

After international sanctions, post 1994, the JSE went through a deregulation phase to align its stock market with international trends and participate in global capital markets. The JSE undertook numerous restructuring reforms to improve market efficiency, liquidity and subsequent competitiveness. In 1996 the JSE introduced an automated trading platform, known as the Johannesburg Equities Trading (JET) system, to eliminate the open outcry trading floor. The Shares Transactions Totally Electronic (Strate) was introduced in 1997. This is an electronic clearing and settlement system that initiated closer links with South African Development Community (SADC) bourses. In addition, the Exchange News Service (SENS) was introduced to manage the dissemination of company announcements and price sensitive information in realtime. As a consequence, JSE listing requirements was amended to enhance transparency and investor confidence in the South African market. Furthermore, Deutsche Bank introduced warrants to the JSE near the end of 1997.

In 2001, the JSE and London Stock Exchange (LSE) came to an agreement which enabled cross-dealing between the bourses. This led to the implementation of the FTSE/JSE Africa Index series in 2002 which brought about a change in philosophy and methodology for calculating indices and sector classifications. FTSE's unique methodology effectively meant that indices were liquid, tradable, of a relevant market size and free float market caps. At the same time, the LSE electronic trading system, SETS, was introduced to increase competitiveness on the JSE.

Table 4.1, sourced from Mkhize and Mswell-Mbanga (2006), presents evidence of the impact of the restructuring process on the JSE. The evidence shows that the restructuring reforms had a significantly positive impact on the performance of the JSE from 1994 to 2002. Over the initial eight year restructuring period, value and volume traded increased by a staggering 1011% and 867% respectively, and number of deals and liquidity increased by 350% and 420% respectively. The positive effects of the JSE restructuring program are further highlighted in Muller and Ward (2013). They find that the illiquidity premium over their examination period is zero and point to the success of the restructuring reforms undertook by the JSE.

Table 4.1 Restructuring Performance Indicators on the JSE

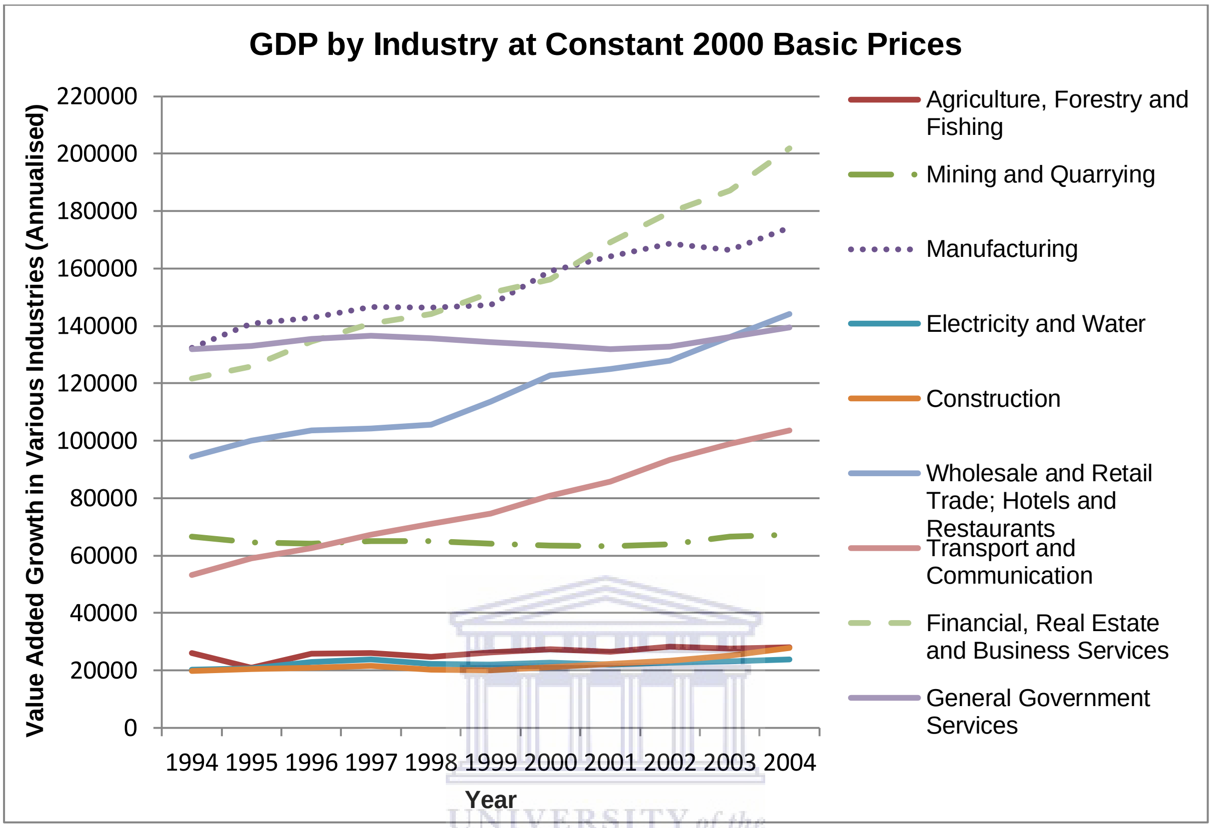
The data provides an overview of the major performance indicators, value traded, volume traded, number of deals and liquidity from 1994 to 2002 as a result of the restructuring reforms undertook post 1994 to improve market efficiency, liquidity and competitiveness on the JSE.

Year	Value Traded (R billion)	Volume Traded (billion shares)	Number of deals (million)	Liquidity (%)
1994	72	6	0.8	7.5
1995	63	5	0.8	7
1996	117	9	1.4	10.9
1997	206	18	2.3	16.9
1998	319	34	3.7	26.7
1999	440	42	3.7	34
2000	570	50	4.2	35
2001	600	60	4.1	38.4
2002	800	58	3.6	39

Yartey and Adjasi (2007) argue that stock markets and the development thereof, positively influence economic growth as it encourages savings amongst individuals and provides avenues for financing. This is attributed to investors increasingly tailoring their risk preferences and liquidity to specific needs and companies are able to unlock capital for long-term projects at lower costs. They further argue that threats of takeovers encourage financial discipline as it acts as an incentive for management to pursue projects that maximise firm value. In addition, stock market liquidity improves the allocation of capital and enhances prospects for long-term growth as investors have confidence knowing that their stake in a company could easily, quickly and cheaply be sold. Another important characteristic for stock market development is a well-functioning financial intermediary sector. Demirguc-Kunt and Levine (1996) empirically point out that most stock market indicators are highly correlated with banking sector development. It is a well-known fact that South Africa’s banking sector is highly sophisticated and on par with banks in developed economic zones.

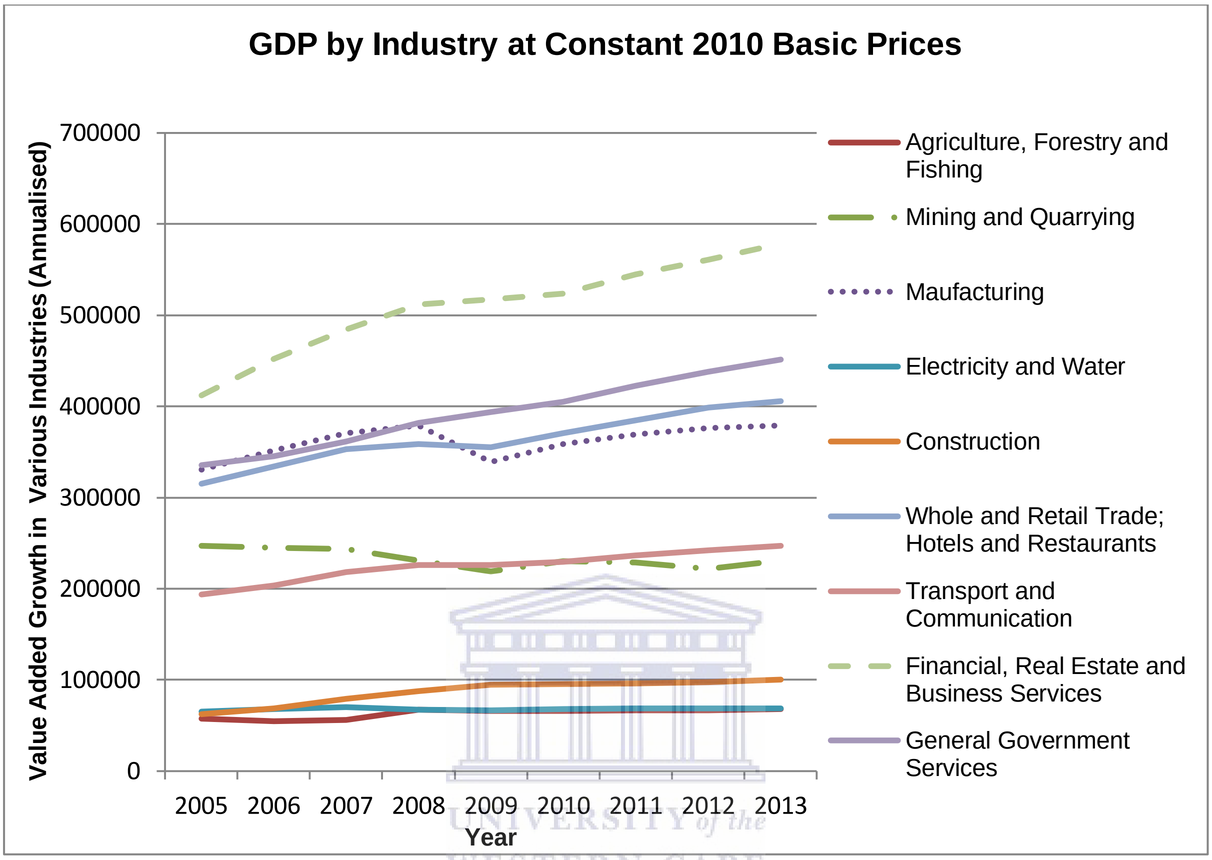
Figure 4.1 and Figure 4.2 presents and illuminates the contribution of the various industries to real gross domestic product (GDP) in South Africa over the period 1994 to 2004 and thereafter from 2005 to 2013 based on constant 2000 and 2010 basic prices respectively. Of interest are mining and quarrying, manufacturing and financial, real estate and business services industries as defined by the International Standards Classification of all Economic Acitivities (ISIC). The best performing industry, illuminated by the steepness in slope, is financial, real estate and business services which significantly outperform all the industries as illustrated in Figure 1 and Figure 2. Furthermore, the steepness in slope is an indication of the growth in the financial, real estate and business services industry over the period 1994 to 2013. The manufacturing industry also experienced growth but to a lesser extent to that of the financial, real estate and business services industry. On the other hand, the mining and quarrying industry trend line is generally flat over the period 1994 to 2013, which indicates that the industry experienced minimal growth and illustrates its insignificance in adding value to GDP in South Africa. The strong showing by the financial, real estate and business services industry suggest that the internationalisation of the JSE due to the restructuring reforms has had a significant and positive influence on this industry.

Figure 4.1 Contribution of Industries to GDP in South Africa from 1994 to 2004 at Constant 2000 Basic Prices



Source: www.statssa.gov.za

Figure 4.2 Contribution of Industries to GDP in South Africa from 2005 to 2013 at Constant 2010 Basic Prices



Source: www.statssa.gov.za

In early 2000, the JSE sector indices were reclassified. Van Rensburg (2002) provides a summary of the reclassification philosophy. Companies whose core business was the production and sale of commodities and whose prices are influenced by global demand and supply factors were regrouped to form the resources sector. For instance, subsectors such as Chemicals, Oil and Paper, Plastics and Steel were removed from the industrial sector and grouped with the mining sector to be renamed the resources sector. Two important subsectors, Information Technology and Telecommunications, were created and included in the industrial sector. The financial sector had grown to over 30% prior to the reclassification. This prompted Banks and Financial Services to be split into two separate sectors due to the increasing significance in favour of Banks (Van Rensburg, 2002). Motivated by the reclassification of JSE sector indices in early 2000, Van Rensburg (2002) re-examines the empirical evidence of the market segmentation phenomenon by Van Rensburg and Slaney (1997) on the JSE. Based on his factor analytic procedure, the resources sector index (RESI) and combined financial-industrial sector index (FNDI) are used as observable proxies in his sector-based two-factor APT model to explain asset returns on the JSE. Van Rensburg (2002) points out that the sector-based two-factor APT with RESI and FNDI as observable proxies should be used in future applications as opposed to CAPM in explaining stock returns on the JSE.

The significance in growth and contribution of the financial, real estate and business services industry and to a lesser extent the manufacturing industry to GDP, suggests that these industries have become important and meaningful economic performers in South Africa. In as much as Chemicals, Oil and Paper, Plastics and Steel subsectors are included in the manufacturing industry for ISIC measuring purposes, these subsectors alone does not explain the phenomenal degree in growth in the manufacturing industry. Similar to the performance exhibited by the financial, real estate and business services industry, the holistic performance of the manufacturing industry is attributed to the internationalisation of South Africa coupled with the restructuring process on the JSE. The overwhelming contribution of financial, real estate and business services and to a lesser extent the manufacturing industries to macro-economic performance in South Africa, particularly over the period 2000 to 2013 (illustrated in Figure 4.1 and Figure 4.2), suggest that these industries have significantly contributed to South Africa's economic growth. Thus, the contention of this research is that FNDI should be split into separate indices, namely, a financial sector index (FINI) and an industrial sector index (INDI). In the empirical study of Yu (2008), the application of sector indices have also been identified. The application of FINI, INDI and RESI is documented by Yu (2008) who analyses the return attribution of South African unit trusts over the period 2001 to 2006. For the purpose of this research, FINI, INDI and RESI as defined by the Industry Classification Benchmark (ICB) is adopted since the aforementioned sector indices is an embodiment of the major sectors on the JSE. A sector-based three-factor APT model is consequently explored using FINI, INDI and RESI as observable proxies to determine if stock returns on the JSE are explained.

The examination period from 1 January 2003 to 31 December 2013 is unique for a number of reasons. Firstly, the examination period is influenced by two momentous meltdowns. The first is the information technology (IT) bubble crash at the turn of 2000 and the other is the sub-prime market crash of 2008 with both events spilling across the majority of global economic markets including South Africa. Economic recovery only came about towards the end of 2002 and thereafter gained momentum and accelerated, eventually leading to one of the most prominent historical global bull markets. The bull market finally came to an end with the culmination of the sub-prime market crash of 2008 with markets only recovering towards the end of 2009. Thereafter, global markets entered and experienced a completely different economic cycle up to and including 2013 as a result of the sub-prime market crash of 2008 with markets being characterised by bear market conditions.

Global economic events could be viewed and measured by economic cycles. Furthermore, economic relationships are more easily identifiable through economic cycles. Macro-economic activity such as economic growth and subsequent unemployment levels, for example, are factors that significantly affect the overall performance of sectors. The distinctive advantage and choice of examination period is that the outcomes of the tests conducted in this research are based over two distinct economic phases. The growth exhibited by the various industries is greatly amplified in magnitude from 2003 to 2008 (Figure 4.1 and Figure 4.2). This is mainly attributed to the restructuring program undertaken by the JSE post 1994 to increase competitiveness and minimise illiquidity, coupled with the strong economic growth experienced globally from 2003 and ending 2008. On the other hand, the performances of those industries that continue to influence GDP, post 2008, provide insight to their resilience as a result of the bear market conditions (Figure 4.2). For these reasons the research explores the influence and application of sector indices over two distinct economic periods.

4.3.1 Sample Selection

Indexes face a direct trade-off between breadth and investability (Lawton and Jankowski, 2009). Breadth refers to the number of constituents in an index whereas investability refers to the ability of investors to trade stocks at minimum price pressures and transaction costs. Indexes that are widely used and most popular are those that offer less breadth and have greater liquidity or (and) offer a basket of constituents that resemble an actively managed basket. The establishment of highly liquid, transparent, easily tradable strict rules based indexes governed by country specific stock exchanges have opened avenues for active managers. More innovative investment strategies and added value are available to active managers as to replicating the market portfolio (Sippel, 2015).

Indices that embody the aforementioned viewpoints include the FTSE/JSE Top 40 (ALSI Top 40) index, which is a tradable index and consists of the sum of the constituents that comprises the tradable sector indices, namely, the FINI Top 15 index, the INDI 25 index and the RESI Top 10 index. If one considers the uniqueness of the South African stock market, is that a minority of stocks have an overriding influence to the performance of the ALSI index (Van Rensburg and Slaney, 1997 and Auret, 2010). The top 10 JSE constituents, for example, accounts for at least 57% of ALSI index ranked by market cap as at 30 September 2008. The ALSI Top 40 is the most prominent index on the JSE and barometer for the wider market. In unreported results on the performance of ALSI Top 40 versus the ALSI, the performance of ALSI Top 40 index mirrors the performance and at times outperforms the ALSI index over the period 2002 to 2008. This is an indication of the dominance and scale in performance of the Capi40 index compared to the ALSI index. This phenomenon is further illustrated with the FTSE/JSE Top 40 index mirroring, and at times outperforming the FTSE/JSE ALSI index between the periods 2010 and 2015. The ALSI Top 40 index together with the FINI Top 15 index, the INDI

Footnote:

(30 September 2008) *FTSE/JSE Capped Top 40 and All Share Indices,* Available at:*www.jse.co.za* (Accessed: 15 April 2015)

(31 October 2015) *FTSE/JSE Top 40 and FTSE/JSE All Share indices*, Available at www.ftse.com (Accessed: 22 November 2015)

Top 25 index and the RESI Top 10 index are indices that are used as performance benchmarks, in derivatives and for use in the creation of exchange traded funds (ETF) as at 30 April 2015. Thus, these tradable indices have significant practical applications. For the purposes of this study, the aforementioned tradable indices provide ample justification to examine sector allocation exposures, the correlation between sector performance and the underlying investment styles, and the application of asset pricing models on the South African stock market. The monthly firm-specific data that comprises the ALSI Top 40 index, the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index are extracted from Stockground and spans the period 1 January 2003 to 31 December 2013. Additional data sourced and downloaded include the risk-free returns from yields based on the South African 3-month Treasury bill.

The JSE consists of roughly 400 listed companies whereas the ALSI index consists of 164 companies but represents at least 99% ranked by total market cap in May 2014. However, over the entire sample period from 1 January 2003 to 31 December 2013, the ALSI index comprised of companies that have delisted, have been suspended or no longer exist. To minimise the impact of survivorship bias, the examination consists of all the companies that comprises the ALSI index over the entire sample period. This represents 199 companies. Companies not included in ALSI ranked by market cap are considered too small and subject to liquidity risk. A big issue and on numerous occasions has been highlighted in various studies undertaken on the JSE has been issues related to liquidity problems and subsequent

Footnote:

(June 2015) *FTSE/JSE InfoMax User Manual,* Available at: www.jse.co.za (Accessed: 27 September 2015).

thin trading. The empirical studies of Mkhize and Mswell-Mbanga (2006) and Muller and Ward (2013) suggest that liquidity related concerns may no longer be a concern due to the restructuring process undertaken on the JSE. Therefore the structure and composition of the ALSI consists only of the most liquid constituents. For this reason all constituents that comprises the ALSI over the entire sample period are included for this examination. The monthly firm-specific attributes of each company that comprises the constituents on ALSI has been downloaded from the database of Stockground and covers a period of 132 months. This represents an overall examination period from 1 January 2003 to 31 December 2013 and consists of 199 constituents in total.

4.4 Methodology

The study consists of three primary tests to examine the application of sector-based investment influences. The first primary test sets out to evaluate the mean-variance efficiency of the capitalisation-based sector allocation of the ALSI index. This objective is achieved by conducting two tests. The objective of the first test is twofold. The test first aims to determine the best optimal sector allocation through the accomplishment of a Sharpe ratio sector-based portfolio optimisation procedure over the entire sample period from 1 January 2003 to 31 December 2013. Thereafter, the test aims to evaluate the performance of the ALSI index against the optimal portfolios. The optimisation procedure is adopted from Hsieh, Hodnett and Van Rensburg (2012) methodology. The justification for adopting Hsieh *et al* (2012) optimisation methodology is that the procedure undertaken in this research is similar to the methodology which they used for their research. In addition, their procedure represents one of the latest techniques in terms of Sharpe ratio optimisation.

The Sharpe ratio optimisation procedure searches for the optimal weight allocations that maximise the portfolio Sharpe ratio at each level of portfolio excess return. In the second test, the study aims to examine the historical comparison between the optimal sector composition and the sector allocation of the ALSI index on an annual basis.

The objective of the second test is to analyse the performance attribution of the sector allocation of the ALSI index and to compare the effective sector allocation against the optimal sector composition. Sharpe (1992) return decomposition model is employed to determine the performance attribution of the sector allocation of the ALSI index and Hsieh *et al* (2012) methodology is employed to determine the optimal portfolios. Sharpe (1992) return decomposition methodology is one of the most widely used methodologies and continues to be a methodology that offers robust results. For this reason, it is adopted for this research to determine the return variability of the ALSI index.

The benefit of maximising the Sharpe ratio at each level of portfolio excess returns is robust as it is based on risk-adjusted returns. Two sets of asset mixes are developed, one that includes a cash allocation, proxied by the South African 3-month Treasury bill, and the other a non-cash allocation, to examine their impact on sector-based portfolio diversification. The test is initiated by finding the average returns and standard deviations on each of the pre-specified constituent indices of ALSI Top 40, namely, the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index and risk-free proxy. Thereafter, portfolios are developed using a long-only constraint with the weight on each of the constituent indices restricted to be between 0% and 100% and the sum thereof maximised to 100%. The procedure constructs a series of long-only portfolios by solving for the optimal weights that maximises the Sharpe ratio at each level of incremental portfolio excess returns for the two asset mixes. The optimised excess returns are bound by an upper limit and lower limit, determined by the highest and lowest arithmetic annualised constituent returns respectively. The upper and lower limits are determined by finding the difference between the respective constituent indices and the risk-free proxy.

The purpose of the second test is to infer as much as possible about ALSI exposure to the pre-specified sector return variations that impact ALSI performance over the sample period. To do so, Sharpe (1992) return decomposition model is employed to find the optimal sector allocations of the ALSI Top 40 index that minimises the standard deviation of the tracking error of the ALSI index on an annual basis. The training procedure is constructed each year based on the monthly pre-specified sector indices with the weights of the sector allocations constrained to lie between 0% and 100% and the sum of the weights aggregated to be 100%.

The second primary test evaluates the primary investment styles, namely; value, size and momentum that could explain the performance of the financial, industrial and resources sectors on the JSE. The indices identified for this test includes ALSI, RESI, FINI and INDI. Time-series regressions are performed using the Carhart (1997) four-factor model to determine whether the style risks identified for this evaluation captures the different dimensions of risk embodied within the pre-specified sector indices. The choice of Carhart (1997) four-factor model is based on the fact that it is an extension of the Fama and French (1993) three-factor model, which is a well-cited and widely used model.

The factors employed by Carhart (1997) include the market risk premium (MRP), the value risk premium (HML), the small cap risk premium (SML) and the momentum risk premium (WML). The proxy for HML is the difference between the rates of return to high B/M ratios and low B/M ratios and proxy for SMB is the difference between the rates of return to small caps and large caps. The proxy for WML is the difference between the rates of return to winner prior 12-month returns and loser prior 12-month returns.

Similar to empirical evidence in international and South African literature, the aforementioned style risks are shown to be prevalent on the South African stock market. The evaluation is initiated by constructing arithmetic mean returns in the factor mimicking portfolios based on the highest and lowest percentiles capped at 75% and 25% respectively. Whereas Carhart (1997) employ quintiles to his risk proxies, quartiles are chosen due to the sample size for this examination being much smaller to the sample size he employs in his examination.

The descriptive statistics based on the time-series regressions inclusive of R-Squared and the factor loadings on style mimicking portfolios are expected to explain the power of the style risks in driving sector performance. According to Fama and French (1993), alpha as proxied by the regression intercept, is expected to be zero if an appropriate model is used to explain stock returns. The signs of the factor loadings, exhibited by positive or negative values, are expected to provide evidence of the style risks that could explain sector performance. On the other hand, R-Squared values measure the degree in variation in stock returns as explained by the factors employed in the model.

The third primary test examines and analyses the comparative practicality of alternative asset pricing mechanisms on the JSE. The study attempts to examine the significance of the explanatory power of the single-factor CAPM relative to two sector-based multifactor APT models in explaining stock returns. The ALSI index, which is adopted as the market proxy on the JSE, is used to track JSE equity market performance. It is also assumed that the ALSI index is driven by the same macro-economic movements inherent in the systematic risk factors. The market segmentation phenomenon highlighted in Van Rensburg and Slaney (1997) and Van Rensburg (2002) shows that stock returns on the JSE are influenced by a different set of economic forces.

The examination re-evaluates and updates the market segmentation phenomenon on the JSE. To do so, two sector-based APT models are constructed: a three-factor APT model using the JSE tradable sector indices FINI, INDI and RESI as its explanatory variables; and a two-factor APT model proposed by Van Rensburg (2002) using the JSE tradable sector indices FNDI and RESI as its explanatory variables. The methodology adopted for this test is similar to that used by Van Rensburg and Slaney (1997) and Van Rensburg (2002). Van Rensburg and Slaney (1997) and Van Rensburg (2002) perform time-series regressions and use a similar methodology to the methodology proposed by this research to test for the applicability of alternative asset pricing models.

As a result of the growing importance of the financial sector, the three-factor model decomposes FNDI into FINI and INDI sector indices. The financial sector index (FINI) and the industrial sector index (INDI), together with RESI are employed as explanatory variables in the three-factor APT model. The evaluation is instigated by determining the excess returns on the monthly ALSI constituents and the excess returns on ALSI and pre-specified sector indices. Time-series regressions are performed based on the monthly ALSI constituents over the sample period from 1

January 2003 to 31 December 2013. The suitability of alternative asset pricing models on the JSE are examined using descriptive statistics including alpha, beta coefficients and R-Squared to establish the relative appropriateness in determining JSE stock returns.

4.5 Potential Research Biases

The potential biases that might influence the results of this research are data-snooping bias, look-ahead bias and survivorship biases. Data-snooping bias arises when researchers examine the properties of a database or review the results of a database, and build predictive models which offer favourable results and test those models on the same database. The problem of data-snooping bias can be addressed if data from new markets or different time periods are employed. Data-snooping bias in this research is mitigated for three reasons. The time period employed for this examination, 1 January 2003 to 31 December 2013, covers two distinct economic phases. The period between 2003 and 2008 is characterised by bull market conditions whereas the period from 2008 to 2013 is characterised by bear market conditions. More importantly, the examination period includes the global financial crises of 2008 which affected all economies. Furthermore, the market segmentation analysis undertaken by Van Rensburg and Slaney (1997) and Van Rensburg (2002) was accomplished on time periods prior to 2002 and to the author's knowledge had not been examined thereafter. Also the database employed for this research is somewhat different as it is highly influenced by the significant impact of the restructuring process undertaken on the JSE

Look-ahead bias arises when data elements are used as predictive factors and those values are assumed to be unknown when the predictions are made. This is mainly due to the difference in the dates the values are reported and the dates the predictions are made. Financial statement data of companies are usually reported at financial year-end dates; however, the final audited values of South African companies are only released a few weeks or months after their official year-end dates. Although the sample for this study includes accounting variables (for example, B/M financial ratios), the impact of look-ahead bias is expected to be minimal. The unique feature of Stockground's database is that all accounting variables are lagged three months. Furthermore, the database reports share prices without any delay.

Survivorship bias is a consequence of firms that have become inactive and systematically excluded from the research database at the time of data collection. The significance of excluding inactive firms in the research database will potentially result in distorted examination results. For the purposes of this study, the impact of survivorship bias is mitigated as the research database includes all firms, including those that have become inactive over the entire sample period.

5

PORTFOLIO OPTIMISATION

5.1 Introduction

The primary objective of this chapter is to evaluate the mean-variance efficiency of the capitalisation-based sector allocation of the ALSI index. The market segmentation phenomenon on the JSE and the criticisms of the price-sensitive cap-weighted indices documented by Arnott, Hsu and Moore (2005) suggest that the cap-weighted ALSI index that overweights the resources sector could potentially be mean-variance inefficient. Thus, the chapter performs sector-based portfolio optimisation and evaluates the mean-variance efficiency of the sector allocation of the ALSI index against its optimal sector allocation derived historically.

Two tests are conducted in this chapter. The first test adopts the methodology proposed by Hsieh, Hodnett and Van Rensburg (2012) to construct optimal long-only portfolios that maximise the Sharpe ratio over the entire examination period from 1 January 2003 through 31 December 2013 and evaluates the performance of the ALSI index relative to that of the optimal portfolio. The second test focuses on the comparison between the optimal sector composition and the sector allocation of the ALSI index on an annual basis over the examination period. The pre-specified tradable indices identified as the constituent indices for the optimisation procedures include the ALSI Top 40 index, the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index.

Section 5.2 presents a summary of the descriptive statistics and performance measures to be employed for this research. The results of the optimisation procedure and the evaluation of the performance of ALSI against the optimal portfolio are presented in Section 5.3. The historical evaluation of the sector allocation of the ALSI index against the optimal sector composition is presented in Section 5.4. The chapter concludes by providing a summary of the various results in Section 5.5.

5.2 Descriptive and Performance Statistics

Hsieh *et al* (2012) propose the use of Sharpe (1992) return decomposition model to find the optimal allocations (weights) that maximises the Sharpe ratio of the mean-variance efficient portfolio. Two long-only optimal portfolios are constructed using the JSE tradable sector indices, namely, the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index. The first portfolio includes a cash allocation with investments allocated in the risk-free asset and constituent sector indices. The risk-free asset is proxied by the returns on the South African 3-month Treasury Bills. The second portfolio excludes a cash allocation with investments exclusively allocated to the constituent sector indices. The objective of the procedure is to maximise the Sharpe ratio over 132 months from 1 January 2003 to 31 December 2013.

Based on the arithmetic return for each sector index and risk-free proxy, the return on the sector-based optimal long-only portfolio inclusive of the cash allocation in month *t* is thus computed using Equation 5.1 as follows:

$$r_{p,t} = \left(w_{fini} \times r_{fini,t}\right) + \left(w_{indi} \times r_{indi,t}\right) + \left(w_{resi} \times r_{resi,t}\right) + \left(w_{Rf} \times r_{Rf,t}\right) \qquad \textbf{... 5.1}$$

Where:

$r_{fini,t},\ r_{indi,t},\ r_{resi,t}, r_{Rf,t}$ represents the returns on the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index and the risk-free proxy on portfolio *P* in month *t*; and

$w_{fini}, w_{indi}, w_{resi}, w_{Rf}$ represents the optimal weights on the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index and risk-free proxy on portfolio *P.*

On the other hand, the return on the sector-based portfolio exclusive of the cash allocation in month *t* is computed using Equation 5.2 as follows:

$$r_{p,t} = (w_{fini} \times r_{fini,t}) + (w_{indi} \times r_{indi,t}) + (w_{resi} \times r_{resi,t}) \quad \text{… 5.2}$$

The *T*-month standard deviations for the two optimal long-only portfolios are computed using Equation 5.3 as follows:

$$\sigma_p = \sqrt{\frac{\sum_{t=1}^{T}(r_{p,t} - R_p)}{T-1}} \quad \text{… 5.3}$$

Where:

$r_{p,t}$ represents the return for the sector-based portfolio *P* in month *t*;

R_p represents the *T*-month arithmetic return for the sector-based portfolio *P*; and

T represents the number of months in the holding period.

Annualising the portfolio returns computed in Equation 5.1 and Equation 5.2, and standard deviations for the portfolios computed in Equation 5.3, the Sharpe ratios for the two optimal long-only portfolios are thus computed as shown in Equation 5.4. The procedure maximises the Sharpe ratio by searching for the optimal allocations into the constituent tradable sector indices and cash equivalents. The implementation procedure of the two optimal long-only portfolios are constrained with the weight on each of the constituent sector indices restricted to be between 0% and 100% and the sum thereof maximised to 100%.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \quad \text{… 5.4}$$

Where:

$R_p - R_f$ represents the annualised excess return with R_p representing the annualised portfolio return and R_f representing the annualised arithmetic return for the risk-free proxy; and

σ_p represents the annualised portfolio standard deviation on portfolio *P*.

5.2.1 Performance Evaluation Measures

In an attempt to determine the impact and influence of the constituent indices on the JSE, risk and return performance statistics are estimated for each of the sector indexes and the ALSI Top 40 index. The risk and return performance statistics estimated includes the annualised arithmetic returns, annualised standard deviations and beta coefficients. Using time-series regressions, the beta coefficient for each sector index, X, is computed using Equation 5.5 as follows:

$$r_X - r_f = \alpha_X + \beta_X \times (r_M - r_f) + \varepsilon_X \qquad \textbf{... 5.5}$$

Where:

$R_X - R_f$ represents the monthly excess return on sector index, X;

α_X represents the regression intercept as a constant deviation from the required rate of return for sector index, X, as predicted by the CAPM;

$R_m - R_f$ represents the market risk premium with the ALSI Top 40 employed as the market proxy;

β_X represents the beta coefficient that measures the systematic risk of sector index X;

R_f represents the risk-free rate proxied by the return on the South African 3-month Treasury Bill rate; and

ε_X represents the unsystematic risk of sector index, X, that is uncorrelated with returns on the ALSI Top 40 index.

In addition to the risk and return performance statistics used to evaluate sector performance, risk-adjusted performance statistics such as the Sharpe ratio, the Treynor measure and Jensen's alpha are also estimated for each sector index and the ALSI Top 40 index. Similar to Equation 5.4 which is used to compute the portfolio Sharpe ratio, the portfolio return is swapped out for an index annualised arithmetic return and the portfolio standard deviation is swapped out for an index annualised standard deviation. The Sharpe ratio used to examine sector performance represents an index excess return per unit of total risk. Unlike the Sharpe ratio that measures excess returns per unit of total risk, the Treynor ratio measures excess returns per unit of systematic risk. Based on the beta coefficient estimated from Equation 5.5, the Treynor ratio is computed using Equation 5.6 as follows:

$$Treynor\ ratio = \frac{R_X - R_f}{\beta_X} \qquad \textbf{… 5.6}$$

Where:

$R_X - R_f$ represents the annualised arithmetic return above the risk-free proxy for index X; and

β_X represents the beta coefficient that measures the systematic risk of sector index X.

Jensen's alpha, on the other hand, measures abnormal returns in excess to what the standard CAPM is expected to predict and represents the intercept term, α_X, which is estimated by Equation 5.5.

In addition, the evaluation examines the potential diversification benefits between each of the constituent sector indices and the ALSI Top 40 index. This is achieved by estimating the correlation coefficient, which measures the strength and linear relationships between two variables, and is computed using Equation 5.7 as follows:

$$\rho_{xy} = \frac{Cov(r_{X,t}, r_{Y,t})}{\sigma_X \sigma_Y} \qquad \textbf{… 5.7}$$

Where:

$Cov(r_X, r_Y)$ represents the covariance of the monthly return on the first index, X, against the monthly return on the second index, Y; and

$\sigma_X \sigma_Y$ represents the product of the standard deviation on the first index, X, and the standard deviation on the second index, Y.

The risk and return performance statistics in combination with the risk-adjusted performance measures are expected to provide insight into the distinctive sector risks inherent in each sector and the influence of each sector in comparison to the ALSI Top 40 index.

5.3 Results: Performance of ALSI Compared to Optimal Portfolios

5.3.1 Descriptive Statistics and Performance Measures of Constituent Indices

The risk and return performance statistics across the constituent indices are presented in Table 5.1. The INDI Top 25 index offers the highest annualised arithmetic return of 23.95% and the lowest annualised standard deviation of 16.18% over the sample period. On the other hand, the RESI Top 10 index offers the lowest annualised return of 12.92% and the highest standard deviation of 25.53%. In terms of the Sharpe ratio risk-adjusted performance, the INDI Top 25 index is the only index that outperforms the ALSI Top 40 index at 1.002 compared to 0.502. The ALSI index represents the market proxy in South Africa. The Sharpe ratio of the RESI Top 10 index is the worst performing sector at 0.203, which is less than half the risk-adjusted performance of the ALSI Top 40 index and the FINI Top 15 index (0.502 and 0.414 respectively).

In terms of the systematic risks of the constituent sector indices, the beta coefficient for the RESI Top 10 index is substantially higher than the market proxy at 1.30. On the other hand, the beta coefficients for the FINI Top 15 index and the INDI Top 25 index are substantially lower than the RESI Top 10 index at 0.64 and 0.74 respectively. The Treynor ratios reveal that both the INDI Top 25 index and the FINI Top 15 index outperform the ALSI Top 40 index (0.218 and 0.113 respectively compared to 0.094) with the INDI Top 25 index the best performing sector. Similar to the Sharpe ratio risk-adjusted performance measures, the Treynor ratio for the RESI Top 10 index is the worst performing sector at 0.040. Although the regression results reveal that Jensen's alpha across all three sectors is approximately 0.00, the INDI Top 25 index and the RESI Top 10 are the only sectors that achieve statistical significance.

Table 5.1 Summary of Cross-Sector Performance Statistics

Table 5.1 presents a summary of the descriptive statistics and risk-adjusted performance measures of the constituent indices over the sample period from 1 January 2003 to 31 December 2013.

	Basic Performance Statistics			
	FINI Top 15	**INDI Top 25**	**RESI Top 10**	**ALSI Top 40**
Arithmetic Return p.a.	14.94%	23.95%	12.92%	17.13%
Standard Deviation p.a.	17.39%	16.18%	25.53%	18.06%
Beta	0.64	0.74	1.30	1.00
	Risk-Adjusted Performance Statistics			
Sharpe p.a.	0.414	1.002	0.203	0.502
Treynor p.a.	0.113	0.218	0.040	0.094
Jensen	0.001	0.007	-0.006	0.000
t-stats	0.273	2.845	-2.049	0.000
p-value	0.785	0.005	0.042	1.000

5.3.2 Optimal Portfolios vs ALSI Index

The portfolio compositions of the two optimal long-only portfolios that maximise the Sharpe ratio over the entire examination period from 1 January to 31 December 2013 are presented in Figure 5.1. The portfolio composition of the portfolio consisting of the cash allocation is illustrated in Chart (A) and the portfolio composition of the portfolio exclusive of the cash allocation is illustrated in Chart (B) of Figure 5.1. On the other hand, Table 5.2 presents the risk and return portfolio characteristics based on the portfolio compositions of the two optimal long-only portfolios and the ALSI Top 40 index.

The Sharpe ratio for the portfolio consisting of the cash allocation is optimised at 107.24% when 15.38%, 46.22%, 4.37%, and 34.03% of the investment capital is allocated to the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index and the risk-free proxy respectively. The annualised portfolio return and annualised standard deviation for the optimised portfolio based on the aforementioned portfolio compositions are 16.56% and 8.23% respectively. The Sharpe ratio for the portfolio exclusive of the cash allocation is optimised at 107.18% when 23.96%, 68.95%, and 7.09% of the capital is allocated to the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index respectively. The annualised portfolio return and annualised standard deviation based on the optimised portfolio compositions are 21.01%, and 12.39% respectively.

Although the Sharpe ratios for both the long-only portfolios are almost identical at 107.24% and 107.18%, the portfolio with the cash allocation has a much lower standard deviation of 8.23% compared to the portfolio with the non-cash allocation which has a standard deviation of 12.39%. This is mainly due to 34.03% of the investment capital allocated to the risk-free proxy. The implications of this observation suggest that the portfolio with the cash allocation offers a more mean-variance efficient allocation. If one considers that the upside of holding a cash allocation in a portfolio is that the return of a risk-free asset is generally uncorrelated with holding any set of risky assets due to the certainty nature the return of the risk-free asset offers. Thus, the results of the portfolio compositions suggest that the portfolio with the cash allocation is capable of being more resilient to significant downturns in financial markets without surrendering its risk-adjusted return potential.

Based on the Sharpe ratios of 107.24% and 107.18% for the portfolio with the cash allocation and the portfolio exclusive of the cash allocation respectively, the Sharpe ratio for the ALSI Top 40 index is 52.00%. This represents portfolio Sharpe ratios which are more than double the market proxy. This suggests that the ALSI Top 40 index is mean-variance inefficient compared to the two optimal long-only portfolios. Although the portfolio with the cash allocation achieves the lowest annualised arithmetic return of 16.56%, its arithmetic return is similar to that of the ALSI Top 40 index which achieves an annualised arithmetic return of 17.13% over the sample period. Furthermore, the ALSI Top 40 index annualised standard deviation is more than double to that of the annualised standard deviation of the portfolio with the cash allocation, 18.06% compared to 8.23% respectively. The portfolio exclusive of the cash allocation, on the other hand, achieves a higher annualised return of 21.01% compared to the ALSI Top 40 index and a lower annualised standard deviation of 12.39%. Overall, the results indicate that the portfolio with the cash allocation offers the best mean-variance efficient allocation and the ALSI Top 40 index is the least mean-variance efficient of the three portfolios.

The beta coefficients of the two optimal long-only portfolios both achieve lower beta coefficients compared to the ALSI Top 40 index. The portfolio with the cash allocation achieves a beta coefficient of 0.50, which is half to that of the ALSI Top index, whereas the portfolio exclusive of the cash allocation achieves a beta coefficient of 0.76. In essence, when the risk-free proxy is included in the portfolio composition, systematic risk is reduced significantly. This highlights the fact that the risk-free proxy is least correlated with the returns of the constituent sector indices. Overall, the risk and return statistics between the optimal portfolios and the ALSI Top 40 index indicate that the sector-based portfolios offer superior returns at lower risk compared to the ALSI Top 40 index. The results suggest that the risk and return benefits on offer to those investors that tilt their portfolios in favour of a sector allocation are superior to those that hold the ALSI Top 40 index.

Figure 5.1 Portfolio Compositions of the Optimal Long-only Portfolios

Figure 5.1 presents an illustration of the portfolio compositions of the optimal long-only portfolios. Chart (A) illustrates the portfolio composition of the portfolio consisting of the cash allocation and Chart (B) illustrates the portfolio composition of the portfolio exclusive of the cash allocation. The optimisation procedure is implemented over the sample period from 1 January 2003 to 31 December 2013. The constituent sector indices included in the procedure include the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index and the risk-free rate proxied by the 3 month Treasury Bill rate. The optimisation procedure is implemented by altering the weights of the constituent sector indices with the aim maximising the Sharpe ratio. The constraints based on the long-only strategy for both portfolios restricts the weight on each of the constituent sector indices to be between 0% and 100% but aggregated to 100%.

Chart (A): Portfolio Composition of Portfolio with Cash Allocation

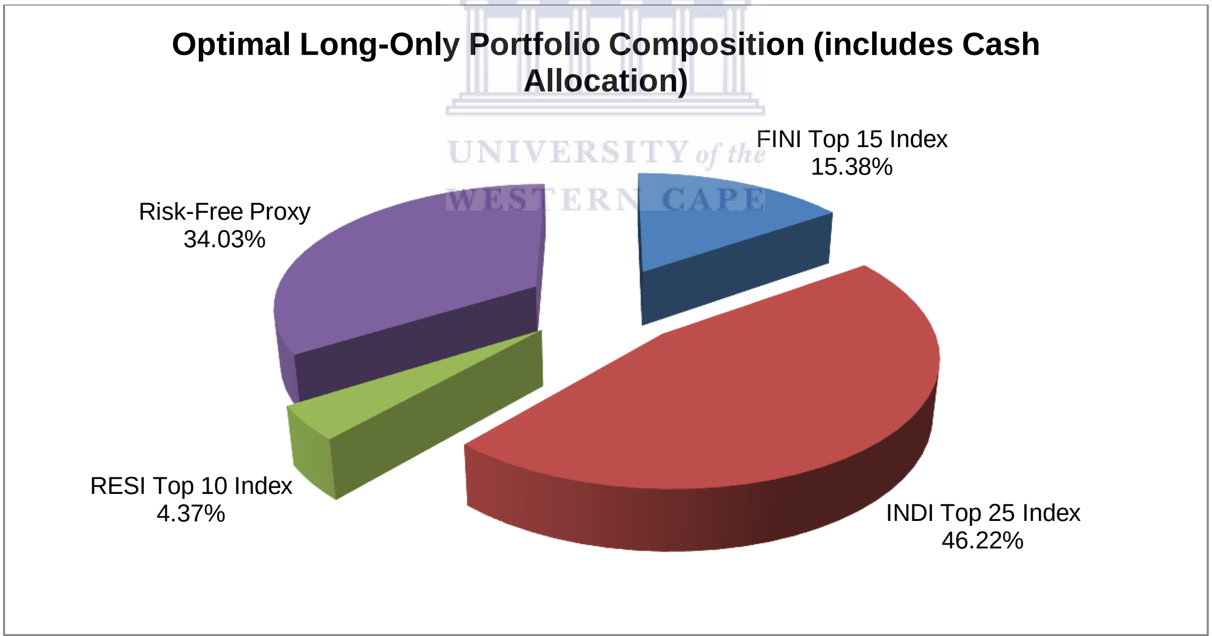


Chart (B): Portfolio Composition of Portfolio without Cash Allocation

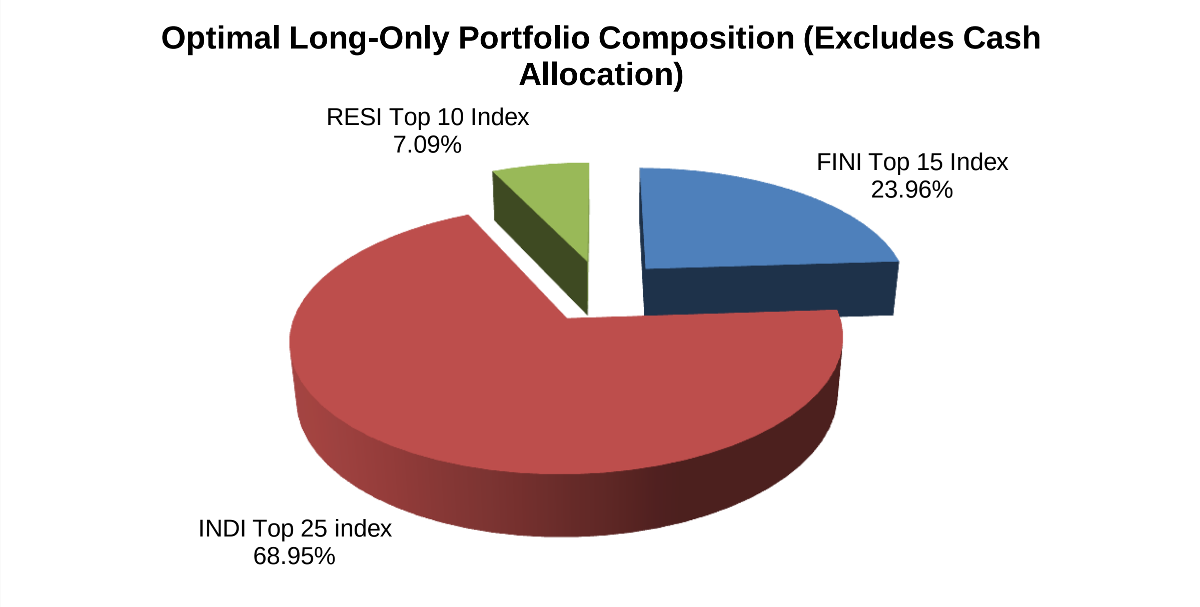


Table 5.2 Risk and Return Statistics of Optimal Long-Only Portfolios Compared to the ALSI Top 40 Index

Table 5.2 presents the summarised statistics of the two optimal portfolios compared to the ALSI Top index over the examination period from 1 January 2003 to 31 December 2013. The first portfolio includes the constituent sector indices with a cash allocation and the second portfolio includes the constituent sector indices exclusive of a cash allocation. The summarised statistics includes the annualised the annualised Sharpe ratio, annualised portfolio returns, annualised standard deviations and beta coefficients of the optimal portfolios and the ALSI Top 40 index.

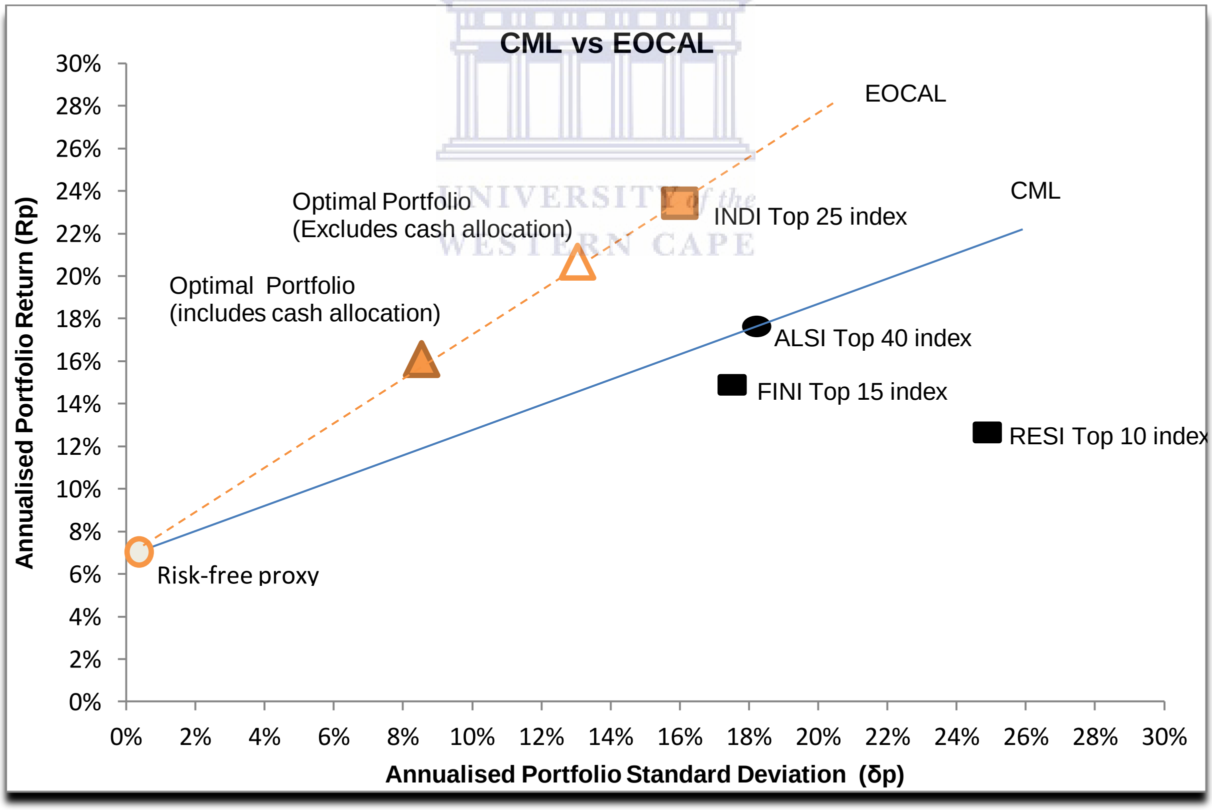
Summarised Statistics for the South African Sharpe Ratio Optimised Portfolios

Portfolio No.	(1) Long-Only	(2) Long-Only	
Constraints	Mean-Variance (Includes Cash)	Mean-Variance (Excludes Cash)	ALSI
Performance Statistics:			
Portfolio Return p.a.	16.56%	21.01%	17.13%
Std Deviation p.a.	8.23%	12.39%	18.06%
Sharpe Ratio p.a.	107.24%	107.18%	52.00%
Beta	0.50	0.76	1.00
Leverage	N/A	N/A	

Figure 5.2 illustrates the capital market line (CML) and the empirical optimal allocation line (EOCAL). Included in the illustration are the optimal long-only portfolio with the cash allocation, the optimal long-only portfolio exclusive of the cash allocation, the ALSI Top 40 index and the stand-alone constituent sector indices. The results depicted in Figure 5.2 suggest a couple of conundrums. According to Tobin (1958) separation theorem, the CML represents the optimal allocation line (OCAL) and the optimal risky portfolio (market portfolio) offers the best mean-variance portfolio. Further, one of the main implications of the CAPM is the use of an appropriate market proxy to represent the market portfolio. In South Africa, the ALSI index is employed to represent the market proxy. Thus, the line that connects the risk-free proxy, marked by a circle, and the ALSI Top 40 index, marked by an oval-shaped black dot, are expected to represent the OCAL, hence the CML. The dotted line that connects the risk-free proxy, the optimal long-only portfolio with the cash allocation, marked by a lightly shaded triangle, the optimal long-only portfolio exclusive of the cash allocation, marked by a white shaded triangle and the INDI Top 25 index, marked by a square, represents the EOCAL. Portfolios that plot on the EOCAL dominate all other portfolios, including the stand-alone constituent sector indices, as it plots above the CML. Thus, the sector-based optimal long-only portfolios are representative of the true optimal risky portfolios as their reward-to-risk ratios are superior to the ALSI index. The results in Figure 5.2 further show that the RESI Top 10 index is the most inefficient index as it is furthest to the bottom right and below the CML.

Figure 5.2 CML versus EOCAL

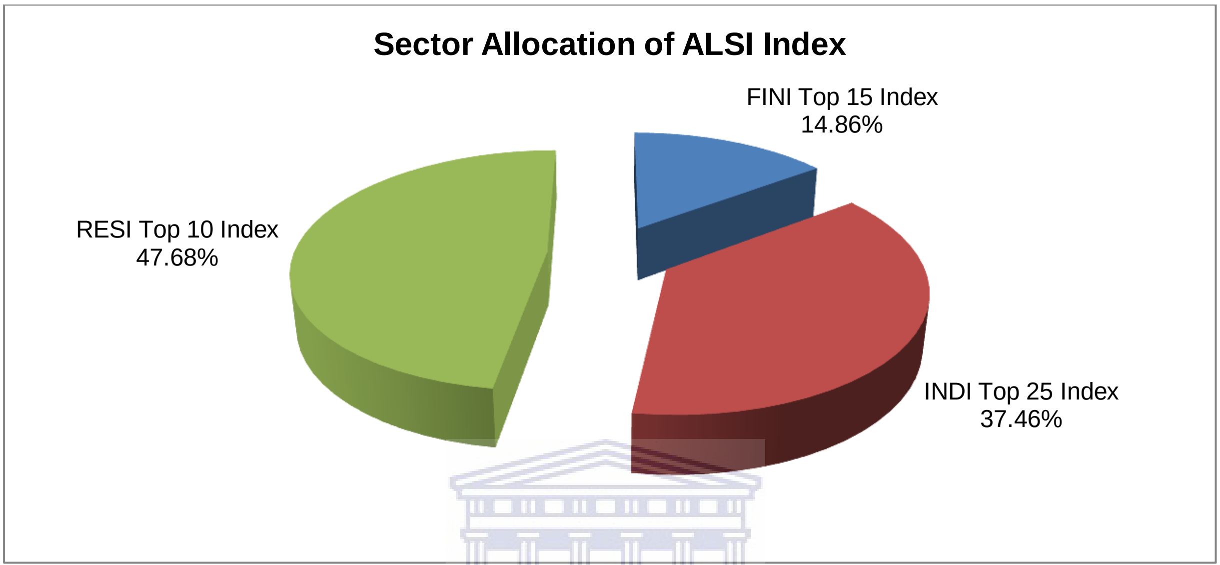
Figure 5.2 demonstrates the graphical relationship between the CML and EOCAL. The procedure is implemented over the examination period over 132 months from 1 January 2003 to 31 December 2013. The constituent indices included in the examination include the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index, risk-free rate proxied by the 3 month Treasury Bill rate and the market proxy proxied by the ALSI Top 40 index. The annualised Sharpe ratio for the long-only optimal portfolio with the cash allocation, marked by a lightly shaded triangle, is 107.24%, with the annualised portfolio return 16.56% and annualised standard deviation 8.23%. The optimal portfolio composition for the portfolio with the cash allocation is 15.38%, 46.22%, 4.37% and 34.03% for the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index and the risk-free proxy respectively. The annualised Sharpe ratio for the long-only optimal portfolio exclusive of the cash allocation, marked by a white shaded triangle, is 107.18%, with the annualised portfolio return 21.01% and annualised standard deviation 12.39%. The optimal portfolio composition for the portfolio exclusive of the cash allocation is 23.96%, 68.95%, 7.09% for the FINI Top 15 index, the INDI Top 25 index, the RESI Top 10 index respectively. The line that intersects the risk-free proxy and the ALSI Top 40 index represents the CML and the dotted line that intersects the risk-free proxy, optimal portfolios and the INDI Top 25 index represent the EOCAL. The optimal portfolios represent the portfolios that achieve the highest risk premium per unit of total risk. Constituent indices plotted below and farthest to the right of the EOCAL represent assets that are mean-variance inefficient.



Based on the criticisms of price-sensitive capitalisation-weighted indices documented by Arnott, Hsu and Moore (2005), the sector-based allocation of the capitalisation-based ALSI Top 40 index points to a performance drag. The underperformance of the RESI Top 10 index suggests that the ALSI index is overweighted by the resources sector and significantly impacts the performance of the market proxy. Employing Sharpe (1992) return decomposition model, the effective sector allocation that accounts for the return variation of the ALSI index over the entire sample period is illustrated in Figure 5.3 (Sharpe (1992) return decomposition methodology is demonstrated in Section 5.4). The FINI Top 15 index provides the lowest sector allocation of 14.86% followed by the INDI Top 25 that offers a sector allocation of 37.46%. The RESI Top 10 index, on the other hand, offers the highest sector allocation of 47.86%. Overall, the results in Figure 5.3 highlight the fact that the resources sector accounts for approximately half the sector allocation of the ALSI index. The insight provided by the sector composition of the ALSI index and the underperformance of the RESI Top 10 index corroborates the criticisms of price-sensitive capitalisation-weighted indices documented by Arnott *et al* (2005).

Figure 5.3 Sector Allocation of the ALSI Index

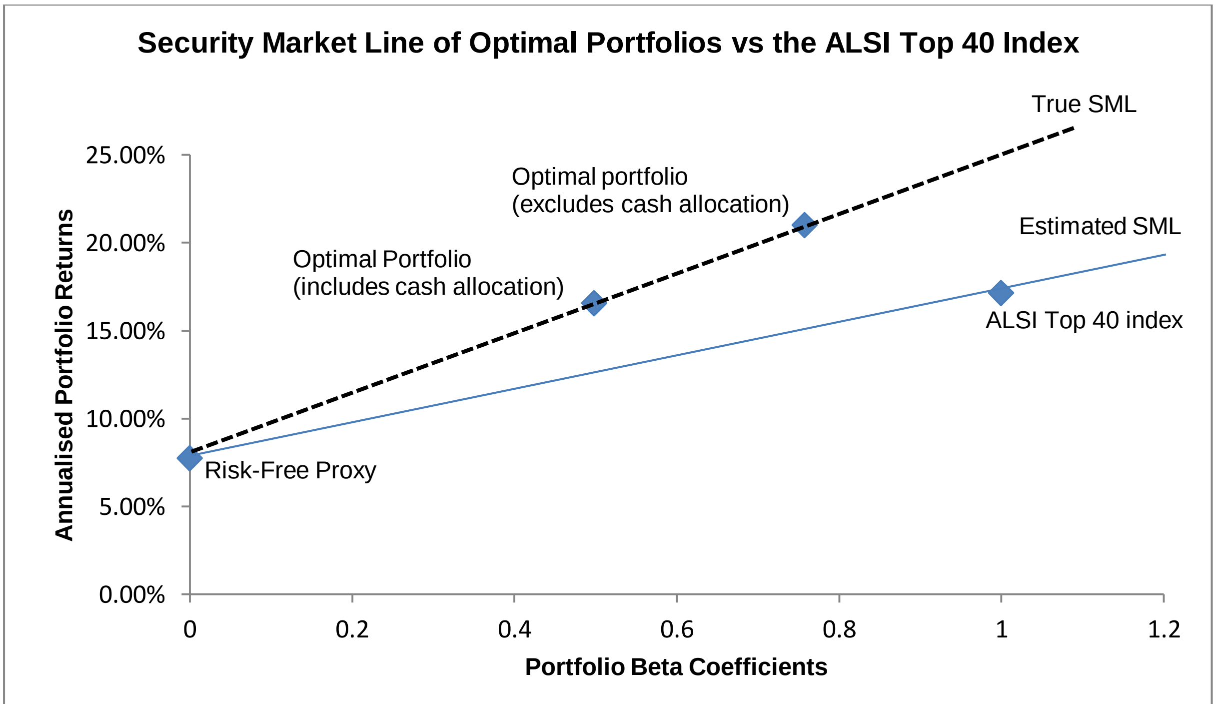
Figure 5.3 presents an illustration of the sector allocation of the ALSI index over the entire examination period from 1 January 2003 to 31 December 2013. This represents the effective sector allocation that accounts for the return variation of the ALSI and is based on Sharpe (1992) return decomposition model.



Based on the mean-variance inefficient ALSI index, the imminent implications of holding the market proxy indicates that the CAPM is an inappropriate asset pricing model to use to price assets on the JSE. Given that the beta coefficient is the only relevant risk factor and is highly dependent on an optimal risky portfolio, the mean-variance inefficient ALSI index implies that a stock's beta coefficient is mis-represented. Figure 5.4 presents the security market line (SML) and highlights the mis-representation of stocks' beta-coefficients on the JSE. The line that connects the risk-free proxy and the ALSI Top 40 index represents the estimated SML as it is based on the mean-variance inefficient cap-weighted sector allocation of the ALSI index. The dotted line that connects the risk-free proxy, the optimal long-only portfolio with the cash allocation and the optimal long-only portfolio exclusive of the cash allocation is referred to as the true SML. The optimal sector compositions of the long-only portfolios represent the optimal risky portfolios as it is more representative of a mean-variance efficient allocation. Under the notion of CAPM, stocks, in equilibrium, plot along the SML. However, the estimated SML plots below the true SML. Thus, the evaluation of stocks on the JSE will be seen to be overvalued. Further, the estimated SML is more flat to the true SML. This suggests that the computation of beta coefficients are biased downwards and points to investors not being compensated appropriately at higher rates of return for bearing more systematic risk. In addition, performance measures used to evaluate the performance of portfolio managers will be incorrectly computed as the performance measures are based on an inappropriate benchmark.

Figure 5.4 Security Market Line

Figure 5.4 presents the security market line (SML). The dotted line that connects the risk-free proxy to the optimal portfolio with the cash allocation and the optimal portfolio exclusive of the cash allocation represents the true SML. The line that connects the risk-free proxy to the ALSI Top 40 index represents the estimated SML as it is based on a mean-variance inefficient market proxy. The procedure is implemented over the examination period from 1 January 2003 to 31 December 2013.



The results presented in Table 5.3 provide further insight into the diversification benefits on offer on the JSE. The correlation coefficient between the FINI Top 15 index and the ALSI Top 40 index is lowest at 0.66 and the correlation coefficient between the RESI Top 10 index and the ALSI Top 40 index is highest at 0.92. This suggests that the FINI Top 15 index is the least sensitive to movements in the ALSI Top 40 index compared to the RESI Top 10 index that almost mirrors the movements in the ALSI Top 40 index. The RESI Top 10 index offers the lowest annualised arithmetic returns (12.92%) and the highest annualised standard deviation (25.53%) compared to the FINI Top 15 index (14.94% and 17.39% respectively) and the INDI Top 25 index (23.95% and 16.18%). Based on Arnott *et al* (2005) criticisms pertaining to price-sensitive capitalisation-weighted indices, the annualised arithmetic return and the annualised standard deviation of the RESI Top 10 index coupled with a correlation coefficient of 0.92 between the RESI Top 10 index and the ALSI Top 40 index suggests that the ALSI Top 40 index is highly and negatively influenced by movements in the RESI Top 10 index.

The correlation coefficient between the FINI Top 15 and the RESI Top 10 index and the correlation coefficient between the INDI Top 25 index and the RESI Top 10 index are 0.40 and 0.58 respectively. These observations indicate that the correlation co-efficients between these constituent sector proxies are the lowest on offer. The observations suggest that the constituent sectors are driven by unique underlying macro-economic influences. On the other hand, the correlation coefficient between the FINI Top 15 index and the INDI Top 25 index is 0.76. This suggests that these proxies are driven by relatively similar underlying macro-economic influences.

Overall, the observations suggest that potential diversification benefits exist to those investors that tilt their portfolios between the constituent sectors. The correlation coefficients between the risk-free proxy and either of the constituent indices are negative. This suggests that investors should tilt their portfolios in favour of a cash allocation in their portfolios as it presents investors with an opportunity to offset a significant degree of total risk including systematic risks, especially during times of turbulent market conditions.

Table 5.3 Correlation Coefficients of Constituent Sector Indices

Table 5.3 presents a summary of the correlation coefficients of the constituent indices covering the examination period 1 January 2003 to 31 December 2013.

	All Share Index	FINI Top 15	INDI Top 25	RESI Top 10	Three month Treasury Bill Rate
All Share Index	1.00				
FINI Top 15	0.66	1.00			
INDI Top 25	0.83	0.76	1.00		
RESI Top 10	0.92	0.40	0.58	1.00	
Three month Treasury Bill Rate	-0.22	-0.22	-0.26	-0.12	1.00

5.4 Sector Allocation of ALSI index vs Optimal Sector Composition

The focus in this section of the chapter shifts to evaluating the sector allocation of the ALSI Top 40 index against the optimal sector composition on an annual basis from 1 January 2003 to 31 December 2013. The objective of the evaluation is to analyse the performance attribution of the sector allocation of the ALSI Top 40 index using Sharpe (1992) return decomposition model and to compare the effective sector allocation against the optimal sector composition. The methodology employed to determine the optimal sector composition is adopted from Hsieh *et al* (2012) to find the optimal sector allocations that maximises the Sharpe ratio on an annual basis. Equation 5.2, 5.3 and 5.4 are employed to determine the optimal sector compositions. An optimal long-only portfolio is constructed each year based on the monthly pre-specified sector indices where the sector weights are constrained to lie between 0% and 100%, and the sum of the weights are aggregated to 100%.

Employing Sharpe (1992) return decomposition model, the aim is to find the optimal sector allocations of the ALSI Top 40 index that minimises the standard deviation of the tracking error of the ALSI index on an annual basis. The goal is to infer as much as possible about ALSI exposure to the pre-specified sector return variations that impact ALSI performance over the examination period. The training procedure is constructed each year based on the monthly pre-specified sector indices with the weights of the sector allocations constrained to lie between 0% and 100% and the sum of the weights aggregated to be 100%. Based on Sharpe (1992) return decomposition model, the return on the ALSI index in month *t* is computed using Equation 5.8 as follows:

$$r_{alsi,t} = \left[(w_{fini} \times r_{fini,t}) + (w_{indi,t} \times r_{indi,t}) + (w_{resi,t} \times r_{resi,t})\right] + \varepsilon_{alsi,t} \qquad \textbf{... 5.8}$$

Where:

$r_{alsi,t}$ represents the returns on the ALSI Top 40 index in month *t*; and

$\varepsilon_{alsi,t}$ represents the part of the return that cannot be explained by the ALSI Top 40 index in month *t.*

Equation 5.8 is rearranged to compute the tracking error using Equation 5.9 as follows:

$$\varepsilon_{alsi,t} = r_{alsi,t} - \left[(w_{fini} \times r_{fini,t}) + (w_{indi,t} \times r_{indi,t}) + (w_{resi,t} \times r_{resi,t})\right] \qquad \textbf{... 5.9}$$

Based on the tracking error computed by Equation 5.9, the standard deviation is thereafter computed.

5.4.1 Results

The time-series portfolio composition for the Sharpe ratio long-only portfolio is illustrated in Chart (A) of Figure 5.5. The dark shaded area represents the sector allocation of the FINI Top 15 index, the white shaded area represents the sector allocation of the INDI Top 25 index and the lightly shaded area represents the sector allocation of the RESI Top 10 index. The Sharpe ratio model allocates substantial weight to the FINI Top 15 index at the beginning of the examination period. This is indicative of the steady growth experienced in the financial sector. However, as the imminent risks associated with holding financial stocks leading up to the impending financial crises of 2008 increases, portfolios are repositioned to mitigate the imminent risks. This eventually results in the gradual decline in the FINI Top 15 index towards the end of 2006. Another period of substantial weight allocation to the FINI Top 15 index is over the period 2011 to 2013 with the sector allocation peaking to approximately 40% over this period. Another sector that enjoys initial sector allocation success is the resources sector. The Sharpe ratio model allocates substantial weight to the RESI Top 10 index in 2005, gradually increasing until 100% is allocated in 2008. This is indicative of the strong global economic growth experienced and the subsequent demand for resources over this period. The INDI Top 25, on the other hand, dominates the sector composition over the examination period, except for 2005 and 2008. This implies that the INDI Top 25 index offers the best mean-variance efficient allocation. Similar to the FINI Top 15 experience, the weight in the INDI Top 25 index shifts in favour of the RESI Top 10 index. This is due to the impending volatility in the global financial markets as a result of the financial crises of 2008.

The time-series sector composition of the ALSI Top 40 index using Sharpe (1992) return decomposition model is illustrated in Chart (B) of Figure 5.5. Similar to the portfolio composition in Chart (A), the dark shaded area represents the sector allocation of the FINI Top 15 index. Similarly, the white shaded area represents the sector allocation of the INDI Top 25 index and the lightly shaded area represents the sector allocation of the RESI Top 10 index. Chart (B) addresses the impact of the sector composition on ALSI performance and represents the effective sector allocation which accounts for the return variation of the ALSI index. Overall, the sector composition depicted in Chart (B) among the constituent sector indices remains more or less constant over the examination period. The results indicate that the RESI Top 10 index dominates the sector composition over the entire sample period except for 2012 and 2013 with the sector exposure gradually tilting in favour of the INDI Top 25 index. Both the FINI Top 15 index and the INDI Top 25 index experience a gradual decline in sector exposure leading up to the financial crises of 2008 with investors increasing their exposure in the RESI Top 10 index over this period. In an attempt to mitigate global and domestic systematic risks immediately after the financial crises of 2008, the sector allocation in the FINI Top 15 index increases significantly in 2009 (represented by the steep incline) as investors pursue undervalued stocks. Another period of gradual decline in the FINI Top 15 is experienced after 2009 with the sector exposure gradually increasing in favour of the INDI Top 25 index. However, the sector exposure in the FINI Top 15 index gradually increases from 2012 to 2013 which suggest that investors sought to diversify their portfolios.

Figure 5.5 Sharpe Ratio Optimal Sector Composition Compared to Sector Allocation of ALSI Index

Figure 5.5 presents the time-series optimal portfolio composition and the time-series sector allocation of the ALSI index on an annual basis over the sample period from 1 January 2003 to 31 December 2013. Chart (A) illustrates the time-series portfolio composition for the Sharpe ratio long-only portfolio. Chart (B) illustrates the time-series sector composition of the ALSI Top 40 index using Sharpe (1992) return decomposition model.

Chart (A): Sharpe Ratio Optimal Sector Composition

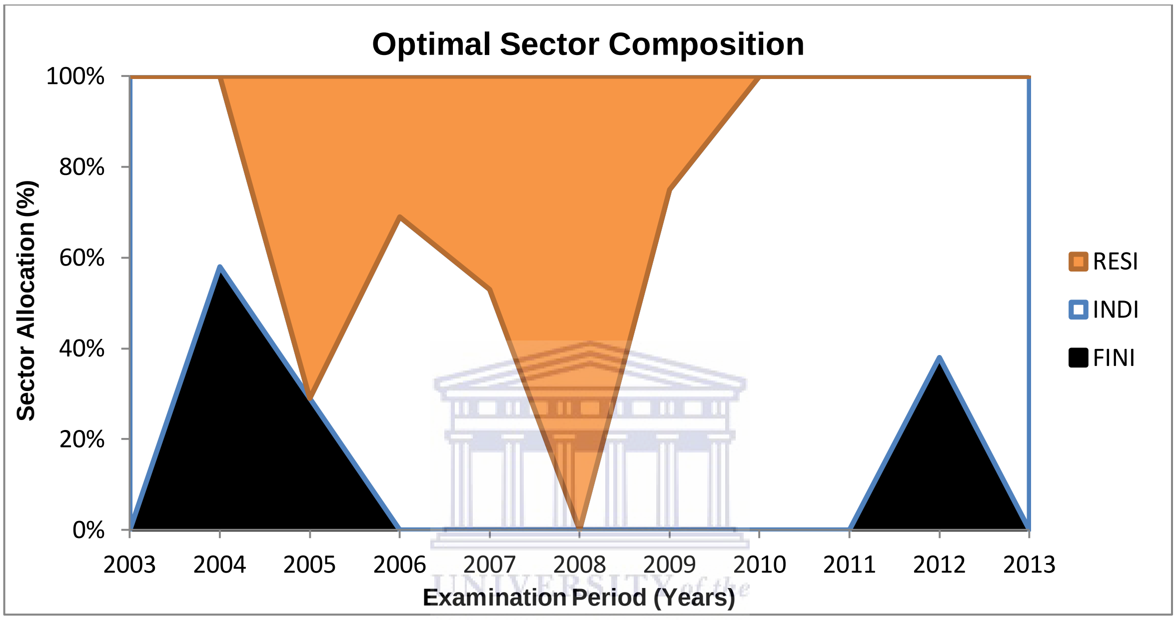


Chart (B): Sector Allocation of ALSI index

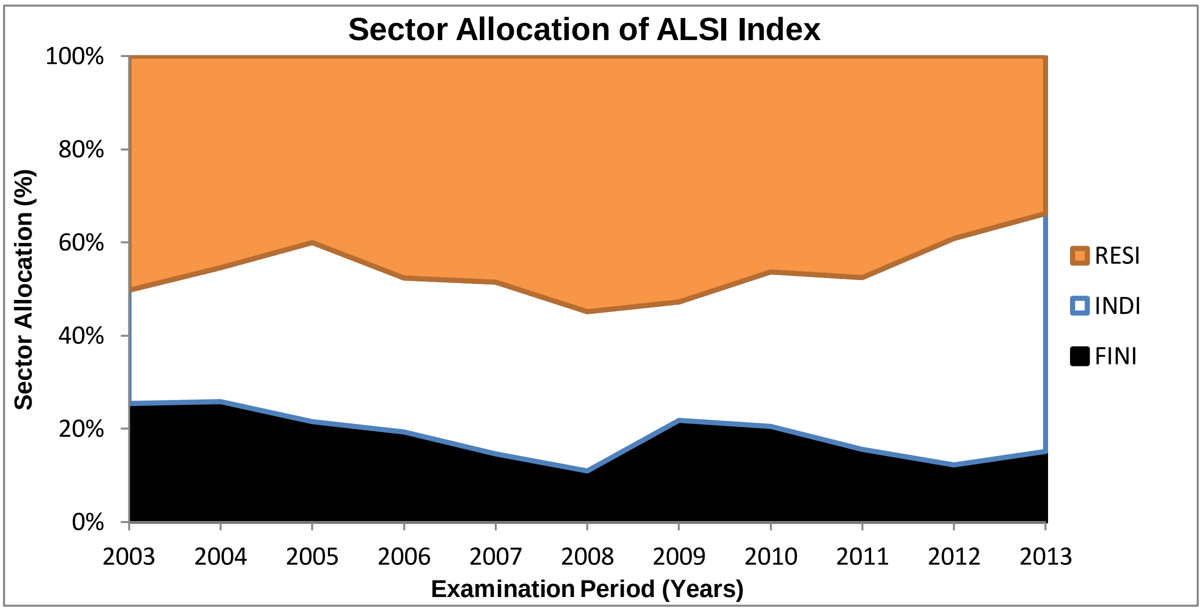


Figure 5.6 illustrates the time-series net sector exposure between the sector allocation of the ALSI index against the optimal sector composition. This represents

the difference between the sector allocation of the ALSI index and the optimal sector composition of the respective constituent sector indices. The sector allocation of the ALSI index represents the effective sector allocation and the optimal sector composition addresses how investors should have allocated their capital and thus, is akin to that of a benchmark. Chart (A) of Figure 5.6 illustrates the net sector exposure of the FINI Top 15 index, Chart (B) illustrates the net sector exposure of the INDI Top 25 index and Chart (C) illustrates the net sector exposure of the RESI Top 10 index. The bar charts in Chart (A), Chart (B) and Chart (C) demonstrates the degree of sector allocation of the respective constituent sector index that is either underweighted or sector allocation of the constituent sector index that is overweighted. A sector allocation above the x-axis indicates that the constituent sector index is overweighted in the ALSI index and a sector allocation below the x-axis suggests that the constituent sector index is underweighted in the optimal sector composition. Alternatively, a sector allocation that plots exactly on the x-axis represents a perfect allocation between the sector allocation of the ALSI index and the optimal sector composition. The results in Chart (A) indicates that the historical sector allocation of the ALSI index is overweighted with substantial weight allocated to the FINI Top 15 index except for 2004, 2005 and 2012. Similarly, the results in Panel (C) indicates that the historical sector allocation of the ALSI is overweighted in favour of the RESI Top 10 index with a substantially higher weight allocation compared to the FINI Top 15 index except for 2005 and 2008. A near perfect allocation is achieved in 2007 with the sector weight exposure in the RESI Top 10 index approximately 1.54% only. On the other hand, the results in Chart (B) indicate that the historical allocation in the INDI Top 25 index is significantly underweighted except for 2005 and 2008 with the sector allocation in the ALSI index overweighted. Overall, the results indicate a significant mismatch in sector exposure between the sector allocation of the ALSI index compared to the optimal sector composition. Investors either overweighted or underweighted their sector exposures except in 2007 when a near perfect allocation is attributed to the RESI Top 10. The results further indicate that the performance of the ALSI index is highly influenced by the return variation attributed to the RESI Top 10 index. Although the INDI Top 25 index represents the best mean-variance efficient allocation, for the most part the sector is underweighted.

Figure 5.6 Comparative Differences in Constituent Sector Allocations between the Sector Allocation of the ALSI INDEX versus Sharpe Ratio Optimal Portfolio Composition

Figure 5.6 presents the time-series sector exposure between the sector allocation of the ALSI index compared to the optimal sector composition over the examination period from 1 January 2003 to 31 December 2013. The bar charts represent the sector allocation of the ALSI index above the optimal sector composition, which is the annual difference between sector allocation of the ALSI index and the optimal sector composition. Chart (A) of Figure 5.6 illustrates the difference in the sector exposure of the FINI Top 15 index, Chart (B) illustrates the difference in the sector exposure of the INDI Top 25 index and Chart (C) illustrates the difference in the sector exposure of the RESI Top 10 index. The results in all three Charts indicate the degree of sector allocation that is either underweighted or sector allocation that is overweighted. A sector allocation above the x-axis suggests that the constituent sector index is overweighted in the ALSI index and a sector allocation below the x-axis suggests that the constituent sector index is underweighted in the optimal sector composition. Alternatively, a sector allocation that matches the x-axis represents a perfect allocation between the sector allocation of the ALSI index and the optimal sector composition.

Chart (A): Difference in Sector Allocation of ALSI and Optimal Sector Composition in FINI Top 15 index

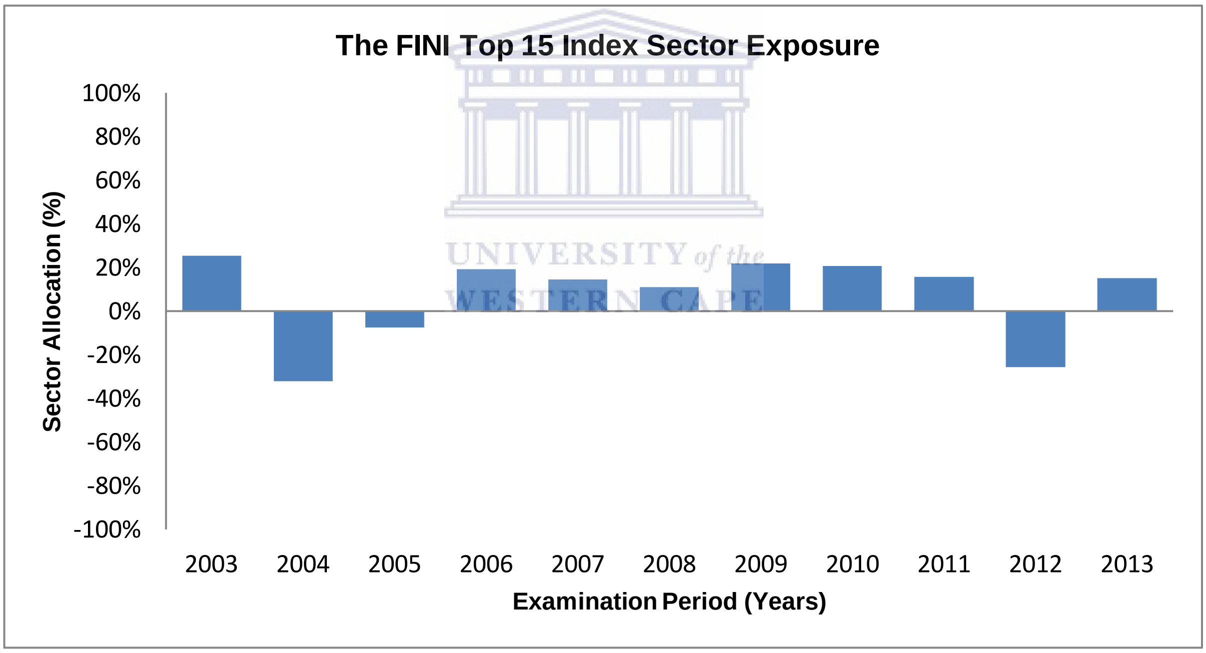


Chart (B): Difference in Sector Allocation of ALSI and Optimal Sector Composition in INDI Top 25 index

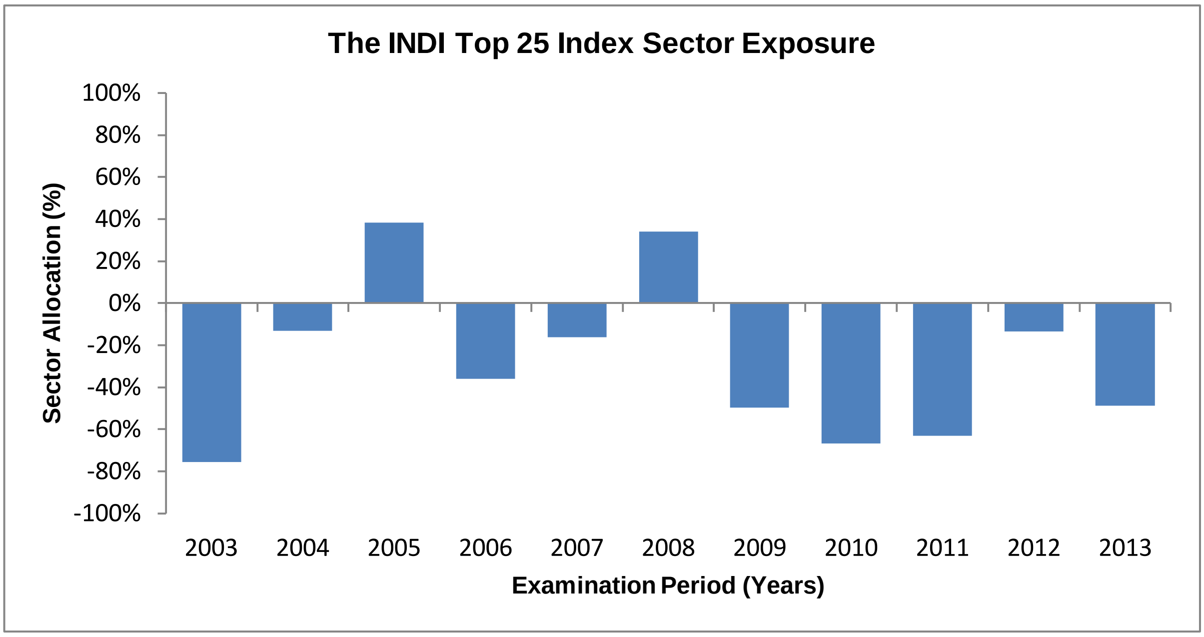
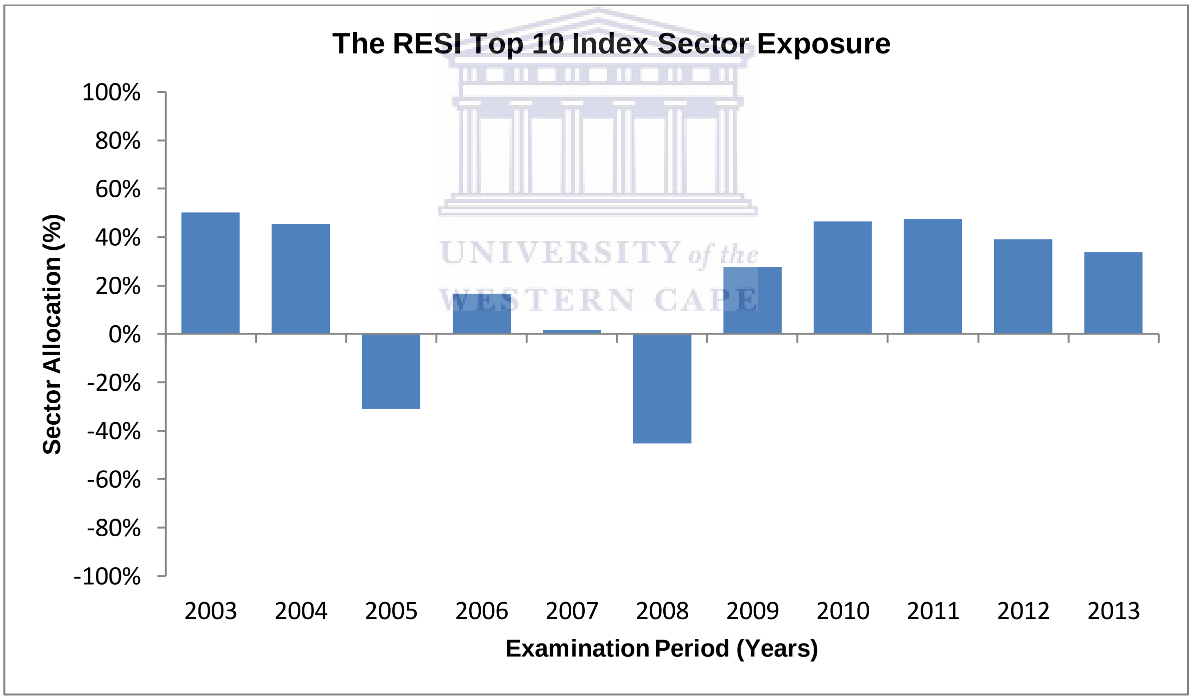


Chart (C): Difference in Sector Allocation of ALSI and Optimal Sector Composition in RESI Top 10 index



5.5 Conclusion

The study set to out to evaluate the mean-variance efficiency of the capitalisation-based sector allocation of the ALSI index. To achieve this objective, the study conducts two tests. In the first test, two optimal long-only portfolios are constructed that maximise the Sharpe ratios over the entire examination period from 1 January 2003 to 31 December 2013 based on the methodology proposed by Hsieh *et al* (2012). The aim of the exercise is to evaluate the performance of the ALSI index against the optimal portfolios. The first optimal long-only portfolio consists of the JSE tradable sector indices with a cash allocation and the second optimal long-only portfolio consists of the JSE tradable sector indices exclusive of a cash allocation. The second test examines the historical comparison between the optimal sector composition and the sector allocation of the ALSI index on an annual basis. The objective of the second test is to analyse the performance attribution of the sector allocation of the ALSI index and to compare the effective sector allocation against the optimal sector composition. Sharpe (1992) return decomposition model is employed to determine the performance attribution of the sector allocation of the ALSI index and Hsieh *et al* (2012) methodology is employed to determine the optimal sector composition.

The risk and return performance statistics reveal that the INDI Top 25 index is the best performing sector over the examination period as it offers the highest annualised arithmetic return and the lowest annualised standard deviation. On the other hand, the RESI Top 10 index offers the lowest annualised arithmetic return and the highest annualised standard deviation compared to the INDI Top 25 index and the FINI Top 15 index. In terms of the risk-adjusted performance measures, the INDI Top 25 index offers the highest Sharpe ratio and is the only index that outperforms the ALSI Top 40 while the Sharpe ratio for the RESI Top 10 index is the most inefficient index. The Treynor ratios also reveal that the INDI Top 25 index and the FINI Top 15 index outperform the ALSI Top 40 index with the INDI Top 25 index the best performing index. Although the regression results reveal that Jensen's alpha across all three sectors is approximately 0.00, the INDI Top 25 index and the RESI Top 10 are the only indexes that achieve statistical significance.

The Sharpe ratios for the long-only portfolio with the cash allocation and the long-only portfolio exclusive of the cash allocation are almost identical at 107.24% and 107.18% respectively. Although the annualised arithmetic return for the portfolio exclusive of the cash allocation is much higher than the annualised arithmetic return for the portfolio with the cash allocation (21.01% vs 16.56% respectively), the portfolio with the cash allocation achieves a much lower standard deviation (8.23% vs 12.39%). This is mainly due to 34.03% of the portfolio composition allocated to the risk-free proxy. These results suggest that the portfolio with the cash allocation offers a more mean-variance efficient allocation than the portfolio exclusive of the cash allocation. Furthermore, the results suggest that the portfolio with the cash allocation is capable of protecting portfolios against economic downswings in financial markets without foregoing its upside risk-adjusted return potential.

In comparing the long-only portfolios to the ALSI Top 40 index, the Sharpe ratios of the portfolio with the cash allocation and the portfolio exclusive of the cash allocation is more than double the ALSI index (107.24% and 107.18% vs 52% respectively). In addition, the annualised arithmetic return of the portfolio with the cash allocation is similar to the ALSI index (16.56% vs 17.13% respectively) and the annualised standard deviation of the ALSI index is more than both long-only portfolios (18.06% vs 8.23% and 12.39%). This suggests that the ALSI Top 40 index is mean-variance inefficient compared to the two optimal long-only portfolios. It further suggests that the portfolio with the cash allocation offers the best mean-variance efficient allocation. Comparing the beta coefficients of the long-only portfolios to the ALSI index, both long-only portfolios achieve lower beta coefficients with the beta coefficient of the portfolio with the cash allocation approximately half to that of the ALSI index. Systematic risk is significantly reduced when the risk-free proxy is included in the portfolio composition. Overall, the risk and return characteristics between the long-only portfolios and the ALSI index suggest that the sector-based portfolios offer superior returns at lower risk compared to the ALSI index. Investors would be wise to tilt their portfolios in favour of a sector-based allocation compared to holding the ALSI index.

Based on the comparisons between the CML and EOCAL, the optimal long-only portfolio with the cash allocation is first compared to the ALSI Top 40 index and thereafter, the optimal long-only portfolio exclusive of the cash allocation is compared to the ALSI Top 40 index. In both instances, the long-only portfolios plot above the ALSI index. This indicates that the ALSI index is not representative of the market portfolio. It is also implies that the long-only optimal portfolios are representative of the true optimal risky portfolios. Further, the results show that the RESI Top 10 index is the worst performing index as it plots furthest and well below the CML. This suggests that the cap-weighed sector allocation of the ALSI Top 40 index is overweighted by the resources sector and significantly impacts the performance of the market proxy. This phenomenon is further corroborated with the effective sector allocation of the ALSI index with the FINI Top 15 index providing the lowest sector allocation of 14.86% followed by the INDI Top 25 index that provides a sector allocation of 37.46%. The RESI Top 10 index offers the highest sector allocation of 47.86% which is approximately half the sector allocation of the ALSI index. The insight provided by the sector composition of the ALSI index and the underperformance of the RESI Top 10 index corroborates the criticisms of price-sensitive capitalisation-weighted indices documented by Arnott *et al* (2005).

The evaluation further compares two SMLs. The first SML comprises the ALSI index and the second SML is representative of the two optimal long-only portfolio beta-return characteristics. The results reveal that the SML, representative of the ALSI index beta-return characteristics, is more flat compared to the SML which includes the optimal long-only portfolio with the cash allocation and the optimal long-only portfolio exclusive of the cash allocation. This suggests that the computation of beta coefficients are biased downwards and that investors are not compensated appropriately for bearing more systematic risks. The SML that comprises the long-only portfolios plot above the SML that includes the ALSI index. This implies that the evaluation of stocks on the JSE will be seen to be overvalued. It also indicates that performance measures used to evaluate the performance of portfolio managers will be incorrectly computed as the performance measures are based on an inappropriate benchmark.

The correlation coefficients reveal that the FINI Top 15 index is least sensitive to movements in the ALSI index and the RESI Top 10 index almost mirrors the movements in the ALSI index. This finding corroborates the suggestion that the ALSI index is overweighted and is negatively influenced by the performance of the RESI

Top 10 index. The results further reveal that the correlation between the FINI Top 15 index and the RESI Top 10 index and the correlation between the INDI Top 25 index and the RESI Top 10 index are the lowest on offer. This suggests that the RESI proxy compared to the FINI proxy and the INDI proxy are driven by unique underlying macro-economic influences. The correlations point to diversification benefits on offer to those investors that tilt their portfolios between the resources sector and either of the pre-specified sectors under examination.

The test two results reveal that the optimal portfolio composition over the examination period is generally dominated by the INDI Top 25 index and thus, represents the most mean-variance allocation. Evidence of the steady growth in the financial sector is experienced over the initial phase of the examination period with substantial weight allocated to the FINI Top 15 index. The optimisation model allocates substantial weight to the RESI Top 10 index leading up to the financial crises of 2008. This is indicative strong global economic growth and the subsequent demand for resources over this period. Both the INDI Top 25 index and the FINI Top 15 index experience negative weight allocations leading up to the financial crises of 2008 which suggests that portfolios were repositioned to mitigate global systematic risks.

Using Sharpe (1992) return decomposition model, the sector allocations of the ALSI Top 40 index generally remain stable for the most part over the examination period. Although the sector exposure is dominated by the RESI Top 10 index over the examination period, the sector allocation gradually tilts in favour of the INDI Top 25 index over the latter period of the evaluation. Similar to the optimisation model, both the FINI Top 15 index and the INDI Top 25 index experience negative weight allocations leading up to the financial crises of 2008 with the sector exposure tilting towards the RESI Top 10 index. A period of heavy weight allocation is experienced by the FINI Top 15 index in 2009. This might be due to investors attempting to tilt their portfolios in favour of undervalued stocks after the 2008 financial crises. Overall, the results suggest a mismatch in sector exposure between the sector allocation of the ALSI index compared to the optimal sector composition with investors either overweighting or underweighting their sector exposure. The only time the sector exposure is comparable to the benchmark is achieved in 2007 which is attributed to the RESI Top 10 index. The results further indicate that the performance of the ALSI index is highly influenced by the return variation attributed to the RESI Top 10 index. Although the INDI Top 25 index represents the best mean-variance efficient allocation, for the most part the sector is underweighted.

In summary, the ALSI does not allocate sector-based investment efficiently. Investors would do well to tilt their portfolios away from the market proxy by focusing on sector-based investment.

6

Performance of Sector Styles

6.1 Introduction

The focus in this chapter shifts to determine the primary investment styles that drive the performance of the financial, industrial and resources sectors on the JSE. This study undertakes to evaluate the degree of influence style risks have on the JSE sector returns using the Carhart (1997) four-factor model over the period from 1 January 2003 to 31 December 2013.

The style risks identified for this evaluation include the value, size and momentum effects whereas the indices identified includes the ALSI Top 40 index, the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index. Using the Carhart (1997) four-factor model, time-series regressions are performed to determine whether the aforementioned style risks capture the different dimensions of risk inherent within the pre-specified sector indices. The factors employed by the Carhart (1997) model include the market risk premium (MRP), the value risk premium (HML), the small cap risk premium (SMB) and the momentum risk premium (WML). The proxy for the value risk premium is the return difference between the portfolio of stocks with high B/M ratios and the portfolio of stocks with low B/M ratios. On the other hand, the proxy for the small cap risk premium is the return difference between the small cap portfolio and the large cap portfolio. The proxy for the momentum risk premium is the return difference between the prior 12-month winner portfolio and the prior 12-month loser portfolio.

Section 6.1 presents the descriptive statistics and methodology whereas the results are presented in section 6.2. The chapter concludes by providing a summary of the results in section 6.3.

6.2 Descriptive Statistics

The objective of the evaluation is to infer as much as possible about the influences of the style risks in explaining sector performance. Using the Carhart (1997) four-factor model, the monthly excess returns of each constituent sector index are regressed on the returns of the MRP and the returns on portfolios that mimic the risk factors for SMB, HML and WML over the examination period from 1 January 2003 to 31 December 2013. The time-series regression coefficients are factor loadings that represent the risk factor sensitivities to each of the four risk factors, namely, the MRP, the SMB, the HML and the WML. Furthermore, the monthly excess returns of each constituent sector index represent the dependent variable and the four risk factors represent the explanatory variables. The evaluation is initiated by constructing arithmetic mean returns in the factor mimicking portfolios based on the highest and lowest percentiles capped at 75% and 25% respectively. Equation 6.1 demonstrates the Carhart (1997) regression employed by this research as follows:

$$R_{X,t} - R_{f,t} = \alpha_X + m_X(R_{m,t} - R_{f,t}) + h_X HML_t + s_X SMB_t + w_X WML_t + \varepsilon_{X,t} \qquad \textbf{... 6.1}$$

Where:

$R_{X,t} - R_{f,t}$ represents the monthly excess return on index *X* in month *t;*

α_X represents the regression alpha intercept on index *X*;

$R_{m,t} - R_{f,t}$ represents the market risk premium in month *t;*

m_X represents the sensitivity of index *X's excess* return to movements in the market risk premium (MRP)*;*

h_X represents the sensitivity of index *X's excess* return to movements in the value risk premium (HML)*;*

s_X represents the sensitivity of index *X's excess* return to movements in the small cap risk premium (SMB);

w_X represents the sensitivity of index *X's excess* return to movements in the momentum risk premium (WML); and

$\varepsilon_{X,t}$ represents the undiversifiable risk of index X that is not correlated with returns on the market risk premium, the value risk premium, the small cap risk premium and the momentum risk premium.

The statistical significance of the regression coefficients are evaluated based on the Student *t*-statistic. In addition, the study analyses the signs of the coefficients. A positive coefficient of HML suggests a value bias and a negative coefficient of HML suggests a growth bias. Similarly, a positive coefficient of SMB suggests a small cap bias and a negative coefficient of SMB suggests a large cap bias. Finally, a positive coefficient of WML suggests a momentum bias and a negative coefficient of WML suggests a contrarian (loser) bias. The examination study further evaluates the R-Squared of the Carhart regressions for each sector to determine appropriateness of model fit. The greater the magnitude in R-Squared, the more the factor model explains variability in sector returns.

6.3 Results: Style Analysis of the Major Sectors

The regression results of the Carhart (1997) four-factor model are presented in Table 6.1. The results show that the four-factor model captures much of the variation in sector returns with the R-Squared for the FINI Top 15 index the lowest at 0.482 followed by the INDI Top 25 index at 0.700. The R-Squared for the RESI Top 10 is the highest at 0.853. The R-Squared of 0.853 in favour of the RESI Top 10 index is consistent with the sector allocation of the ALSI index results observed in Chapter 5. The high R-Squared offered by the RESI Top 10 index compared to the FINI Top 15 index and the INDI Top 25 index is mainly due to the sector allocation of the resources sector overweighted in the ALSI index. Another reason for the high R-Squared of the RESI Top 10 index is due to the positively near perfect correlation of 0.92 that exists between the RESI Top 10 index and the ALSI Top 40 index as observed in Chapter 5.

In time-series regressions, the suitability of whether a factor model or asset pricing model is able to explain the cross-section of average returns is dependent upon alpha intercepts that are indistinguishable from zero. The estimated intercepts provided by the time-series regressions offer a formal test as to whether the different combinations of risk factors are able to explain average returns. The alpha intercepts estimated in this evaluation for each of the sector indexes, namely, the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index are all close to 0.0. This suggests that the time-series regression results based on the Carhart (1997) four-factor model is a suitable model to determine the style risks that influence sector performance. This is further corroborated by the statistically high *t*-statistics of the regression coefficients on the MRP risk factor for each sector index. The MRP, predictably, captures a significant amount of common variation in sector returns. The *t*-statistic for the FINI Top 15 index is 9.369 and the *t*-statistic for the INDI Top 25 index is 15.945. On the other hand, the *t*-statistic for the RESI Top 10 index is the highest at 24.213, which is not unexpected as the correlation coefficient between the RESI Top 10 index and the ALSI Top 40 index represents a positively near perfect correlation of 0.92.

Although the time-series regression results based on the Carhart (1997) four-factor model for each sector index show that the regression coefficients are statistically insignificant for the majority of the style risk factors, a certain measure of insight could be inferred from the magnitude of statistical insignificance. Regressing the excess returns of the FINI Top 15 index onto the four risk factors, for instance, exhibits a coefficient of -0.051 and a Student *t*-statistic of -0.562 to the SMB risk factor. Similarly, regressing the excess returns of the RESI Top 10 index onto the four risk factors exhibits a coefficient of -0.010 and a Student *t*-statistic of -0.147 to the SMB risk factor. Despite the regression results for the FINI Top 15 index and the RESI Top 10 index showing weak sensitivities to the SMB risk factor, sector performance for both sectors to some degree have a large cap bias. The regression results further show that the HML and WML risk factor sensitivities to the RESI Top 10 index represent relatively moderate sensitivities. The HML and WML coefficients with the Student *t*-statistics displayed in brackets are -0.090 (-1.125) and -0.081 (-0.588) respectively. The negative coefficient to the HML risk factor suggests that most of the stocks in the resources sector are growth stocks. On the other hand, the negative coefficient to the WML risk factor suggests a contrarian bias.

Lakonishok *et al* (1994) argues that growth stocks are fundamentally riskier than value stocks. The more than high standard deviation for the RESI Top 10 index observed in Chapter 5 coupled with the growth tilt in favour of the resources sector suggest that Lakonishok *et al* (1994) criticisms pertaining to growth stocks are not only exclusive to international markets but to the South African market as well. Regressing the excess returns of the INDI Top 25 index onto the risk factors, the results exhibit coefficients and Student *t*-statistics of 0.091 (1.259), 0.055 (0.852) and 0.056 (1.198) to the HML risk factor, the SMB risk factor and the WML risk factor respectively. Although the coefficients are statistically insignificant and for the most part represent moderate sensitivities to each of the style risk factors, the positive coefficients suggest that the industrial sector, to some degree, has a value bias, a small cap bias and a momentum bias at various times over the sample period. On the other hand, regressing the excess returns of the FINI Top 15 index onto the risk factors, the results show that the HML coefficient offers a high sensitivity and is statistically significant at 2.504. The positive coefficient of 0.257 coupled with the statistically significance to the HML risk factor suggests that the performance of the financial sector, to a large degree, has a value bias.

Table 6.1 Performance Measures of South African based Style Proxies

The following table represents the time-series regression results using the Carhart (1997) four-factor model. The style risks employed include the value, size and momentum effects and the indices include the ALSI Top 40 index, the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index. The risk factors employed by the Carhart four-factor model includes the market risk premium (MRP), the value risk premium (HML), the small cap risk premium (SMB) and the momentum risk premium (WML). The results are significant at the 95% confidence interval. The performance measures are examined over a 132-month period from 1 January 2003 to 31 December 2013.

Constituent Sector Attributes and Descriptive Statistics	**FINI**	**INDI**	**RESI**
R-Square	0.482	0.700	0.853
Alpha	0.000	0.005	-0.003
t-statistic $_{alpha}$	0.066	1.705	-0.894
M $_{MRP}$	0.640	0.773	1.285
t-statistic $_{MRP}$	9.369	15.945	24.213
H $_{HML}$	0.257	0.091	-0.090
t-statistic $_{HML}$	2.504	1.259	-1.125
S $_{SMB}$	-0.051	0.055	-0.010
t-statistic $_{SMB}$	-0.562	0.852	-0.147
W $_{WML}$	0.000	0.056	-0.081
t-statistic $_{WML}$	-0.007	1.198	-1.588

6.4 Conclusion

The time-series regressions using the Carhart (1997) four-factor model is found to comprehensively capture much of the variation in sector returns with the RESI Top 10 index accounting for the highest R-Squared. The power of the factor model to replicate sector returns successfully is further illustrated with the estimated alpha intercepts for each sector index all close to 0.0. This is further corroborated with statistically high Student *t*-statistics to the MRP risk factor for each sector index.

Regressing the excess returns of each sector index onto the risk factors, the results show that the regression coefficients are statistically insignificant for the majority of the style risk factors. Despite the statistical insignificance of the coefficients, a certain degree of insight could be inferred from the magnitude of the Student *t*-statistic results. Although the regression results for both the FINI Top 15 index and the RESI Top 10 index exhibit negative coefficients and show weak sensitivities to the SMB risk factor, the results suggest that sector performance for both sectors to some degree have a large cap bias. On the other hand, the HML and WML risk factor sensitivities to the RESI Top 10 index represent relatively moderate sensitivities. The negative coefficient to the HML risk factor suggests that most of the stocks in the resources sector are growth stocks whereas the negative coefficient to the WML risk factor suggests a contrarian bias.

Lakonishok *et al* (1994) points out that growth stocks are fundamentally riskier than value stocks. The high standard deviation for the RESI Top 10 index compared to the FINI Top 15 index and the INDI Top 25 index observed in Chapter 5 coupled with the growth tilt in favour of the resources sector suggest that Lakonishok *et al* (1994) criticisms have merit. The observations further point out that the phenomenon is not only exclusive to international markets but to the South African market as well. The Student *t*-statistics to the HML risk factor, the SMB risk factor and the WML risk factor for the INDI Top 25 index for the most part provide moderate sensitivities to each of the style risk factors. Furthermore, the positive coefficients to each style risk factor suggest that the INDI Top 25 index, to some degree, has a value bias, a small cap bias and a momentum bias. The HML risk factor for the FINI Top 15 index is the only risk factor that offers a coefficient that is statistically significant. This suggests that the financial sector has a strong value bias.

7

THE MARKET VERSUS THE MAJOR SECTORS

7.1 Introduction

This chapter re-evaluates and updates the evidence of market segmentation phenomenon on the JSE over the extended time period from 1 January 2003 through 31 December 2013. The objective of this chapter is to determine whether sector-based multifactor APT models have greater power compared to the single-factor CAPM in explaining JSE stock returns over the period from 1 January 2003 to 31 December 2013. Two sector-based APT models are constructed: a three-factor APT model using FINI, INDI and RESI tradable sector indices as its explanatory variables; and a two-factor APT model proposed by Van Rensburg (2002) using tradable JSE sector indices FNDI and RESI as its explanatory variables. Due to the growing importance of the financial sector, the three-factor APT model decomposes FNDI into FINI and INDI sector indices. Together with RESI, the financial sector index (FINI) and industrial sector index (INDI) are employed as explanatory variables in the three-factor APT model. A comparison between the explanatory power of the CAPM using the JSE ALSI index as the market proxy and the two sector-based APT models described above is made based on the analysis of the signs and the statistical significance of the models' coefficients.

Section 7.2 provides a summary of the descriptive statistics of the asset pricing models employed in this chapter, whereas Section 7.3 presents the empirical findings for this research. Section 7.4 consolidates and provides a summary of the empirical results conducted for this study.

7.2 Descriptive Statistics and Methodology

The models used to explain the returns of the ALSI constituents are depicted in Equation 7.1, 7.2 and 7.3 below. The time-series excess returns of the ALSI constituents are regressed on the explanatory variables employed by the CAPM and the sector-based multifactor APT models accordingly.

Equation 7.1 demonstrates the CAPM regression employed by this research as follows:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \varepsilon_i \qquad \textbf{... 7.1}$$

Where:

$R_i - R_f$ represents the monthly excess return on the *i*th constituent in ALSI;

α_i represents the regression intercept as a constant deviation from the required rate of return for the *i*th constituent in ALSI, as predicted by the CAPM;

$R_m - R_f$ represents the ALSI market risk premium;

β_i represents the beta coefficient that measures the systematic risk of the *i*th constituent in ALSI;

R_f represents the risk-free rate proxied by the return on the South African 3-month Treasury Bill rate; and

ε_i represents the unsystematic risk of the *i*th constituent in ALSI that is uncorrelated with the returns on the market portfolio.

The sector-based three-factor APT model employed by this research as demonstrated by Equation 7.2 is as follows:

$$R_i - R_f = \alpha_i + \beta_{fini}(R_{fini} - R_f) + \beta_{indi}(R_{indi} - R_f) + \beta_{resi}(R_{resi} - R_f) + \varepsilon_i \qquad \textbf{... 7.2}$$

Where

$R_{fini} - R_f$, represents the risk premium on FINI;

$R_{indi} - R_f$, represents the risk premium on INDI;

$R_{resi} - R_f$ represents the risk premium on RESI;

β_{fini}, β_{indi}, β_{resi} represents the sensitivity of the excess return for the *i*th constituent in ALSI to movements in the FINI, INDI and RESI risk premia respectively;

α_i represents the regression intercept as a constant deviation from the required rate of return as predicted by the APT model for the *i*th constituent in ASLI; and

ε_i represents the unsystematic risk of the *i*th constituent in ALSI that is uncorrelated with returns on FINI, INDI and RESI.

The sector-based two-factor APT model proposed by Van Rensburg (2002) is demonstrated by Equation 7.3 as follows:

$$R_i - R_f = \alpha_i + \beta_{fndi}(R_{findi} - R_f) + \beta_{resi}(R_{resi} - R_f) + \varepsilon_i \qquad \textbf{... 7.3}$$

Where

$R_{findi} - R_f$, represents the risk premium on FNDI;

β_{fndi} represents the sensitivity of the excess return for the *i*th constituent in ALSI to movements in the FNDI risk premium; and

ε_i represents the unsystematic risk of the *i*th constituent in ALSI that is uncorrelated with the returns on FNDI and RESI.

The evaluation is initiated by comparing the coefficients of the CAPM market risk premium to the coefficients of the factor risk premia of the respective APT models. The signs and the statistical significance of the coefficients are evaluated to determine the sensitivity of the ALSI constituent's excess returns to movements in the respective risk factors employed by the CAPM and the APT models respectively. The significance of the regression coefficients are assessed by the Student *t*-statistics at a 1%, 5% and 10% significance levels. In addition, R-Squared and the signs and the statistical significance of the regression intercepts are evaluated to provide an indication of the overall explanatory power of the respective models.

7.3 Results

7.3.1 CAPM versus Sector-Based Three-Factor APT Model

The CAPM and the three-factor APT regression results are presented in Table 7.1 over a 132 month period from 1 January 2003 to 31 December 2013. On the other hand, a complete summary of the ALSI constituents are provided in Appendix A showing the full name of each constituent and the nature of business. In addition, the APT results showing the diverse stock return sensitivities to the sector proxies for each constituent are demonstrated. The regression coefficients that are significant at a 1% level are marked with three asterisks, ***, whereas those at the 5% level are marked with two asterisks, **. Regressions coefficients that are significant at the 10% level are marked with one asterisk, *.

The results show that the CAPM market risk premium explains 73% (146 of 199) of the sample stocks' excess returns statistically significantly, whereas 69% (137 of 199) of sample stock return variations are explained statistically significantly by the sector-based three-factor APT model. The return variations of 34 sample stocks, namely, AIA, BRN, CCO, CIL, CLR, CMP, COH, CRM, CSB, CVH, DCT, ELI, EOH, GPL, HCI, HPA, HSP, HWN, LHG, MDI, MFL, MPT, MVS, NBC, NEP, NT1, OPT, PAN, REB, SCL, TKG, TMG, TON and YRK could not be explained adequately by the CAPM or the three-factor APT models. The statistically insensitivity of these stock returns to the movements of the risk premia on the CAPM and the APT models suggests a natural hedge to those investors looking to mitigate systematic risks.

The observed APT results show that returns on each stock, generally, exhibit significant sensitivity to the dimensions of risk to movements in more than one sector. It is observed that stocks that have sensitivity to RESI excess returns generally exhibit negative sensitivity to either the excess returns of FINI, INDI or RESI. This seemingly negative correlation between FINI, INDI or RESI coefficients provides evidence that resources stocks are exposed to different dimensions of risk compared to stocks in the financial and industrial sectors. These results confirm the market segmentation phenomena presented in prior studies of Van Rensburg and Slaney (1997) and Van Rensburg (2002). Unlike financial and industrial stocks which generate most of their earnings domestically, resources stocks generate a significant portion of their earnings abroad. Firms in the resources sector generally export their products and should therefore benefit from the depreciation of the rand. Thus, these stocks are exposed to and highly influenced by exchange rate movements and global risk factors.

Based on the South African Reserve Bank (SARB) financial year end reports over the period from 2003 to 2013, the resources sector initially benefited from the depreciation of the rand. Towards the end of the first quarter of 2003 the rand started appreciating which muted earnings in the resources sector. In addition, the sector is highly sensitive to political risks as well. To illustrate the sector's sensitivity to political risks, SARB 2002 reports indicated that the government's ambitious empowerment plans introduced during the second half of 2002 caused panic in the resources sector. This resulted in a further decline in their performance. However, earnings in the resources sector was buoyed as the global economic outlook showed signs of improvements during the second half of 2003. This ultimately led to a sustained bull run in international markets which increased demand for resources globally. After the financial crises of 2008, the global economic outlook muted demand for resources as global economic growth slowed down. As the global markets showed signs of improvement towards the end of 2009, demand for resources increased during 2010. Over this same period, earnings were muted due to political unrest as a result of strikes in the mining industry. On the whole, the resources sector is influenced by a weak currency and global demand for commodities and is negatively influenced by political risks.

The diverse economic systematic risks underlying the resources sector is somewhat different to the systematic risks influencing the financial and industrial sectors. The financial and to a lesser extent the industrial sectors benefited from the strong appreciation of the rand. The impact of the strong rand essentially resulted in lower inflation and effectively lower interest rates. The impact of lower interest rates presented the financial sector with opportunities to increase credit extensions and minimise bad debts in South Africa as an emerging economy. The impact of lower interest rates also benefited the real estate market as it increased the viability in the housing market. From 2003, tax rates were lowered which promoted the profitability of the life assurance subsector. The influence of international bull market conditions into South Africa during the latter half of 2003 and the strong local currency further enhanced the earnings of the industrial sector as the sector presents itself as a net importer rather than exporter of goods and services. The earnings prospects of the industrial sector was further enhanced post 2008 due to the bleak economic outlook as the demand for basic commodities increased.

Table 7.1 Regression Results: CAPM versus Three-Factor APT Model

Table 7.1 presents the time-series regression results of the CAPM and the sector-based APT models. The excess returns of ALSI constituents were regressed in CAPM and the sector-based three-factor APT. The regression coefficients, represented by the bold italic, that are statistically significant at the 1% level are marked with three asterisks, ***, whereas those at the 5% level are marked with two asterisks, **. Regression coefficients that are statistically significant at the 10% level are marked with one asterisks, *.

Name of Listed stock	Asset Pricing Model: CAPM			Three-Factor APT				
	R-Squared	Alpha	Constituent Beta Coefficient	R-Squared	Alpha	Constituent Sector Beta Coefficients: FINI	INDI	RESI
ABL	0.095	-0.004	0.554***	0.312	-0.003	1.223***	-0.255	-0.026
ACL	0.307	-0.008	1.186***	0.313	-0.007	0.246	0.336	0.603***
ACP	0.015	0.002	0.127	0.261	0.000	0.623***	-0.035	-0.187***
ADH	0.108	0.010	0.440***	0.192	0.006	0.149	0.566***-	0.052
ADR	0.062	0.002	0.350***	0.128	0.001	0.383**	0.190	-0.011
AEG	0.149	-0.003	0.699***	0.249	-0.009	0.213	0.844***	-0.028
AFE	0.220	0.000	0.568***	0.290	-0.004	0.064	0.633***	0.041
AFR	0.120	-0.009	0.605***	0.163	-0.014	0.097	0.682**	0.024
AFT	0.180	-0.004	0.763***	0.208	-0.009	-0.123	0.795**	0.213
AFX	0.106	-0.008	0.429***	0.192	-0.012**	0.119	0.589***	-0.062
AGL	0.690	-0.012**	1.486***	0.784	-0.007	0.030	0.086	1.084***
AIA	0.043	0.001	-0.155	0.188	0.012	-0.335	-0.431	0.182
AIB	0.029	-0.001	0.144	0.266	-0.002	0.913**	-0.260	-0.037
AIP	0.136	0.000	0.363***	0.178	-0.003	-0.075	0.421	0.100
ALT	0.069	-0.005	0.435***	0.203	0.013	-0.167	1.100***	-0.188
AMS	0.471	-0.012	1.447***	0.607	-0.002	0.438**	-0.620***	1.252***
ANG	0.153	-0.017**	0.750***	0.305	-0.012	-0.367	-0.090	0.838***
APN	0.067	0.017**	0.403***	0.202	0.015**	0.685***	0.115	-0.081
AQP	0.261	-0.010	1.562***	0.359	-0.002	-0.097	0.384	1.467***
ARI	0.467	-0.002	1.400***	0.514	0.002	0.205	0.041	0.962***
ARL	0.097	0.004	0.448***	0.182	0.000	0.264	0.492**	-0.067
ART	0.110	-0.007	0.569***	0.130	-0.005	0.517**	-0.103	0.226
ASR	0.216	0.012	0.982***	0.217	0.013	0.201	0.207	0.532***
ATN	0.147	-0.004	0.563***	0.205	-0.007	0.275	0.453**	0.039
AVI	0.083	0.002	0.379***	0.247	-0.001	0.386**	0.478**	-0.162
AVU	0.066	-0.012	0.376**	0.220	-0.017	0.560**	0.327	-0.159
AWA	0.002	-0.002	0.037	0.321	0.020	0.848**	0.238	-0.352**
AWB	0.007	0.014	-0.093	0.369	0.016	0.989**	0.576	-0.652***
BAT	0.113	0.003	0.539***	0.199	0.002	0.159	0.725***	-0.085
BAW	0.245	-0.010	0.887***	0.310	-0.015	0.285	0.737**	0.103
BCX	0.041	-0.006	0.313**	0.078	-0.008	0.231	0.286	-0.015
BEL	0.100	-0.001	0.796***	0.127	0.003	0.720**	-0.417	0.497***
BGA	0.175	-0.001	0.523***	0.608	-0.001	1.192***	-0.239	-0.043
BIL	0.684	-0.001	1.323***	0.788	0.004	0.084	-0.058	1.006***
BLU	0.114	-0.006	0.645***	0.146	-0.002	0.589**	-0.195	0.279
BRN	0.001	0.020**	0.050	0.044	0.018	0.428	0.079	-0.225

Name of Listed stock	Asset Pricing Model							
	CAPM			Three-Factor APT				
			Constituent			Constituent Sector Beta Coefficients		
	R-Squared	Alpha	Beta Coefficient	R-Squared	Alpha	FINI	INDI	RESI
BSR	0.069	0.008	0.758***	0.118	0.002	0.354	0.815	-0.033
BTI	0.035	0.002	0.202	0.159	-0.006	-0.374	0.815***	-0.086
BVT	0.275	0.001	0.592***	0.501	-0.004	0.301***	0.692***	-0.093
CCO	0.040	0.025***	0.210	0.117	0.020**	-0.563	0.711	0.037
CFR	0.444	0.012	1.112***	0.654	-0.004	-0.564**	1.947***	0.105
CIL	0.043	0.003	0.500	0.059	0.002	-0.383	0.423	0.302
CLH	0.159	0.004	0.433***	0.208	0.003	0.273	0.211	0.083
CLI	0.064	0.007	0.323***	0.063	0.008	0.098	0.038	0.174
CLR	0.017	0.005	0.149	0.045	0.005	0.421	-0.159	0.098
CLS	0.149	0.005	0.518***	0.346	-0.002	0.106	0.911***	-0.164
CMH	0.064	0.005	0.504***	0.133	0.002	0.492	0.365	-0.043
CML	0.136	0.013	0.620***	0.356	0.008	0.814***	0.428	-0.128
CMP	0.023	0.013	0.407	0.035	0.009	-0.049	0.522	0.088
COH	0.018	0.043	0.396	0.056	0.032	-0.963	1.375	-0.057
COM	0.041	0.003	0.481**	0.073	-0.002	0.117	0.696	-0.110
CPI	0.112	0.024***	0.596***	0.296	0.023***	1.072***	-0.082	-0.021
CPL	0.030	0.003	0.206**	0.276	0.002	0.739***	-0.052	-0.179**
CRM	0.010	-0.013	0.219	0.028	-0.012	0.445	-0.190	0.082
CSB	0.021	0.014	0.248	0.074	0.011	0.316	0.300	-0.145
CVH	0.029	0.020	-0.153	0.084	0.017	0.371	-0.161	-0.175
CZA	0.140	-0.004	1.461***	0.176	0.004	0.061	-0.225	1.246***
DAW	0.054	0.014	0.487***	0.102	0.013	0.655**	0.051	0.003
DCT	0.020	0.002	0.262	0.054	-0.001	0.247	0.320	-0.103
DLT	0.036	-0.010	0.125	0.474	-0.028**	0.596*	0.530	-0.356*
DRD	0.062	-0.020	0.759***	0.198	-0.013	-0.740	-0.186	1.078***
DSY	0.109	0.007	0.395***	0.283	0.001	-0.046	0.867***	-0.167**
DTC	0.347	0.003	1.327***	0.416	-0.001	0.646***	0.713**	0.301**
EHS	0.109	-0.007	0.850***	0.127	-0.003	0.663	-0.323	0.503***
ELI	0.047	0.009	0.488	0.054	0.008	0.027	0.386	0.140
EMI	0.012	-0.002	0.114	0.251	-0.005	0.508***	0.134	-0.227***
EOH	0.022	0.021***	0.219	0.095	0.018***	0.293	0.305	-0.147
EQS	0.129	-0.015	0.618***	0.202	-0.024**	0.025	0.912**	-0.062
EXX	0.323	0.003	1.130***	0.422	0.008	-0.168	0.043	0.962***
FBR	0.105	0.022***	0.570***	0.276	0.014	0.201	1.022***	-0.244**
FFA	0.001	-0.001	-0.014	0.142	-0.002	0.481**	-0.214	-0.126
FPT	0.045	-0.002	0.237**	0.353	-0.003	0.808***	-0.090	-0.164**
FSR	0.209	0.000	0.615***	0.744	0.000	1.412***	-0.259**	-0.070
FWD	0.184	-0.005	0.819***	0.368	-0.012	0.598**	0.801**	-0.153
GFI	0.140	-0.020**	0.752***	0.297	-0.012	-0.074	-0.487	0.924***
GND	0.249	0.011	0.902***	0.290	0.005	-0.176	1.023***	0.188
GPL	0.054	-0.004	0.384	0.042	-0.006	-0.043	0.292	0.096
GRF	0.197	0.002	0.863***	0.283	-0.005	0.210	0.947***	0.026
GRT	0.035	0.002	0.215**	0.268	0.001	0.750***	-0.133	-0.132
HAR	0.135	- 0.021	0.946***	0.284	-0.013	-0.318	-0.376	1.133***
HCI	0.008	0.030	0.344	0.037	0.032	1.042	-0.431	-0.018
HDC	0.141	0.003	0.558***	0.213	0.001	0.329	0.438	0.022

Name of Listed stock	Asset Pricing Model: CAPM			Three-Factor APT				
	R-Squared	Alpha	Constituent Beta Coefficient	R-Squared	Alpha	Constituent Sector Beta Coefficients: FINI	INDI	RESI
HLM	0.123	***-0.029*****	***0.749******	0.136	***-0.030*****	0.276	0.394	0.199
HPA	0.003	-0.007	0.053	0.018	-0.008	0.024	0.147	-0.060
HPB	0.048	-0.016	***0.438*****	0.092	-0.015	0.518	0.059	0.085
HSP	0.023	0.002	0.166	0.089	-0.007	0.531	0.216	-0.152
HWN	0.017	***0.026*****	0.293	0.019	***0.027*****	-0.121	0.118	0.207
HYP	0.005	0.005	0.080	0.269	0.004	***0.698******	-0.067	***-0.247******
ILA	0.106	-0.002	***0.692******	0.146	-0.006	0.363	0.525	0.045
ILV	0.166	-0.002	***0.586******	0.188	0.000	0.100	-0.062	***0.437******
IMP	0.467	-0.010	***1.368******	0.575	-0.001	***0.495******	***-0.555*****	***1.123******
INL	0.344	-0.004	***0.903******	0.536	-0.009	***0.642******	***0.633******	0.015
INP	0.366	-0.005	***0.946******	0.521	-0.008	***0.662******	***0.549******	0.084
IPF	0.066	0.005	-0.322	0.257	-0.009	***0.984*****	-0.117	***-0.633*****
IPL	0.189	-0.002	***0.709******	0.353	-0.008	***0.437*****	***0.770******	-0.120
ITU	0.204	***-0.015*****	***0.658******	0.238	***-0.015*****	***0.457*****	0.158	0.180
IVT	0.084	***0.013*****	***0.379******	0.129	0.010	-0.009	***0.555******	-0.028
JDG	0.100	-0.008	***0.531******	0.398	***-0.013*****	***0.841******	***0.512*****	***-0.294******
JSE	0.141	0.008	***0.726******	0.197	0.002	0.087	***0.842*****	0.073
KAP	0.036	-0.005	***0.371*****	0.089	-0.010	0.033	***0.717*****	-0.121
KGM	0.053	0.007	***0.307******	0.069	0.005	0.177	0.226	0.001
KIO	0.379	0.007	***1.160******	0.462	0.015	0.307	-0.341	***0.955******
LBH	0.120	-0.005	***0.363******	0.223	-0.009	0.011	***0.598******	-0.069
LEW	0.088	-0.004	***0.427******	0.412	-0.005	***0.947******	0.102	***-0.197*****
LHC	0.050	***0.020*****	-0.220	0.175	0.016	0.572	-0.212	***-0.364*****
LHG	0.007	0.007	0.192	0.019	0.003	-0.043	0.425	-0.054
LON	0.366	-0.018	***1.549******	0.456	-0.011	0.004	-0.101	***1.265******
MDC	0.130	0.006	***0.369******	0.176	0.003	0.042	***0.409*****	0.035
MDI	0.023	0.001	-0.153	0.035	0.006	-0.162	-0.245	0.053
MFL	0.016	0.016	0.593	0.030	0.018	-0.408	0.175	0.597
MIX	0.108	0.016	***0.940******	0.140	0.010	0.234	0.835	0.113
MMI	0.205	-0.001	***0.572******	0.381	-0.003	***0.672******	0.183	-0.002
MML	0.081	-0.009	***0.557******	0.100	-0.013	-0.240	0.642	0.208
MND	0.308	0.007	***1.089******	0.358	0.003	0.240	***0.818*****	0.245
MNP	0.362	0.007	***1.233******	0.415	0.001	0.024	***1.139******	0.274
MPC	0.070	***0.015*****	***0.404******	0.382	0.008	***0.559******	***0.717******	***-0.362******
MPT	0.003	0.014	-0.054	0.039	0.009	0.360	-0.001	-0.163
MRF	0.292	-0.011	***1.474******	0.298	-0.013	-0.291	***0.929*****	***0.726******
MSM	0.075	0.005	***0.395******	0.296	-0.003	0.159	***0.911******	***-0.271******
MTA	0.098	0.006	***0.581******	0.124	0.001	-0.192	***0.771*****	0.098
MTN	0.271	0.009	***0.739******	0.445	0.003	0.268	***0.875******	-0.069
MTX	0.093	-0.006	***0.940******	0.106	-0.011	-0.113	***1.004*****	0.191
MUR	0.129	-0.005	***0.664******	0.190	-0.007	0.472	0.363	0.089
MVS	0.007	-0.018	0.088	0.053	-0.013	0.409	-0.384	0.163
NBC	0.011	-0.037	-0.334	0.028	-0.050	-0.489	0.727	-0.542
NED	0.122	-0.006	***0.454******	0.567	***-0.009*****	***1.012******	0.139	***-0.229******
NEP	0.000	***0.016*****	-0.016	0.032	0.011	0.096	0.194	-0.176
NHM	0.330	-0.006	***1.417******	0.336	-0.004	0.104	0.319	***0.847******

Name of Listed stock	Asset Pricing Model: CAPM			Three-Factor APT				
	R-Squared	Alpha	Constituent Beta Coefficient	R-Squared	Alpha	Constituent Sector Beta Coefficients: FINI	INDI	RESI
NIV	0.223	0.026	***0.966****	0.383	0.024	-1.378	1.473	0.543
NPK	0.105	-0.003	***0.327*****	0.202	-0.006	0.236	***0.322*****	-0.048
NPN	0.394	***0.016*****	***0.940*****	0.573	0.008	0.044	***1.217*****	0.010
NT1	0.004	-0.006	0.193	0.021	-0.013	-0.428	0.826	-0.064
NTC	0.144	0.005	***0.490*****	0.248	0.001	0.208	***0.558*****	-0.034
OCE	0.011	0.004	0.147	0.070	0.001	***-0.496*****	***0.597*****	0.026
OCT	0.001	0.008	0.041	0.110	0.006	***0.548*****	-0.020	***-0.236*****
OML	0.382	-0.006	***0.924*****	0.553	-0.008	***0.884*****	0.217	0.140
OMN	0.192	0.007	***0.637*****	0.210	0.004	0.246	0.424	0.097
OPT	0.000	-0.007	-0.019	0.046	0.003	0.334	-0.698	0.217
PAM	0.117	-0.004	***0.877*****	0.123	-0.002	0.097	0.082	***0.574*****
PAN	0.046	0.001	0.595	0.084	0.001	-0.524	0.408	0.482
PAP	0.046	-0.002	***0.215*****	0.199	-0.001	***0.604*****	-0.233	0.017
PET	0.094	0.000	***0.838*****	0.093	-0.001	0.101	0.399	0.361
PFG	0.104	0.007	***0.380*****	0.146	0.002	0.050	0.488	-0.019
PGL	0.170	-0.024	***0.950*****	0.254	***-0.035*****	0.782	0.811	-0.156
PGR	0.236	0.003	***0.884*****	0.329	-0.001	***0.535*****	***0.587*****	0.080
PHM	0.043	0.005	***0.337*****	0.058	0.003	-0.250	0.450	0.128
PIK	0.127	-0.001	***0.374*****	0.216	-0.004	0.127	***0.443*****	-0.014
PMM	0.006	0.009	0.109	0.176	0.007	***0.678*****	0.024	***-0.266*****
PNC	0.142	0.035	***1.610*****	0.150	0.033	0.113	0.851	***0.719*****
PPC	0.085	-0.002	***0.422*****	0.220	-0.005	***0.537*****	0.285	-0.091
PSG	0.094	0.017	***0.626*****	0.215	0.010	0.515	***0.723*****	-0.159
RBP	0.175	-0.016	***0.533*****	0.319	-0.003	0.614	-0.630	***0.670*****
RBX	0.093	-0.004	***0.633*****	0.201	-0.012	0.070	***1.080*****	-0.137
RCL	0.063	0.003	***0.343*****	0.112	-0.001	-0.046	***0.580*****	-0.039
RDF	0.014	0.000	0.145	0.181	-0.002	***0.505*****	0.140	***-0.218*****
REB	0.013	-0.002	-0.091	0.091	-0.010	0.290	0.130	-0.268
REI	0.128	-0.003	***0.400*****	0.432	***-0.016*****	***-0.431*****	***1.322*****	-0.179
REM	0.392	0.004	***0.500*****	0.597	-0.001	***0.364*****	***0.511*****	-0.108
RES	0.004	0.009	0.073	0.193	0.008	***0.587*****	-0.079	***-0.191*****
RLO	0.102	-0.001	***0.411*****	0.334	-0.006	***0.484*****	***0.488*****	***-0.198*****
RMH	0.199	0.000	***0.608*****	0.655	0.000	***1.310*****	-0.196	-0.063
RMI	0.134	0.013	***0.330*****	0.158	0.013	0.388	0.045	0.145
RPL	0.145	-0.003	***0.526*****	0.249	-0.014	-0.684	***1.317*****	-0.002
SAB	0.353	0.003	***0.648*****	0.504	-0.003	***-0.314*****	***1.044*****	0.048
SAC	0.053	-0.004	***0.262*****	0.197	-0.006	***0.528*****	0.048	-0.083
SAP	0.262	***-0.021*****	***1.014*****	0.300	***-0.026*****	0.027	***0.971*****	0.206
SBK	0.225	-0.001	***0.586*****	0.812	0.000	***1.422*****	***-0.385*****	-0.034
SCL	0.005	-0.002	0.341	0.016	0.007	0.941	-0.864	0.345
SFN	0.061	0.007	***0.455*****	0.140	0.002	0.313	0.564	-0.116
SGL	0.252	-0.017	1.858	0.534	0.075	2.217	-3.538	***2.341****
SHF	0.331	0.001	***0.980*****	0.489	-0.008	-0.130	***1.407*****	0.023
SHP	0.035	***0.014*****	***0.250*****	0.217	0.007	-0.015	***0.856*****	***-0.280*****
SIM	0.031	0.014	***1.073*****	0.049	0.024	0.608	-0.834	***1.042*****
SLM	0.268	0.002	***0.589*****	0.535	0.000	***0.726*****	0.207	-0.030

Name of Listed stock	Asset Pricing Model: CAPM			Three-Factor APT				
	R-Squared	Alpha	Constituent Beta Coefficient	R-Squared	Alpha	Constituent Sector Beta Coefficients: FINI	INDI	RESI
SNT	0.088	0.003	***0.401****	0.160	0.000	0.290	0.357	-0.032
SNU	0.065	-0.006	***0.705****	0.079	-0.009	0.281	0.501	0.112
SOL	0.580	-0.003	***1.084****	0.626	-0.001	-0.107	***0.301***	***0.709****
SPG	0.110	-0.014	***0.742****	0.145	-0.015	***0.635***	0.235	0.087
SPP	0.081	0.006	***0.302****	0.219	0.001	-0.007	***0.640****	-0.107
SSK	0.115	-0.010	***0.777****	0.180	-0.013	0.477	0.526	0.076
SUI	0.142	-0.002	***0.503****	0.248	-0.005	***0.490****	0.250	0.007
SUR	0.086	0.006	***0.372****	0.124	0.003	0.031	***0.462***	0.011
SYC	0.022	-0.002	0.167	0.307	-0.005	***0.588****	0.196	***-0.271****
TBS	0.195	0.000	***0.444****	0.332	-0.008	0.044	***0.767****	-0.114
TCP	0.033	-0.004	-0.163	0.271	-0.002	***0.883****	-0.666	-0.097
TFG	0.129	0.005	***0.562****	0.482	0.000	***0.948****	***0.400***	***-0.251****
TKG	0.068	-0.017	0.410	0.080	-0.016	0.033	0.224	0.252
TMG	0.005	0.014	0.072	0.226	-0.002	0.513	0.645	-0.420
TON	0.033	-0.006	0.258	0.054	-0.007	0.138	0.247	-0.017
TRE	0.113	0.005	***0.420****	0.121	0.003	0.015	0.353	0.108
TRU	0.083	0.008	***0.419****	0.344	0.003	***0.637****	***0.467***	***-0.242****
TSH	0.040	0.008	***0.265***	0.141	0.004	0.336	0.316	-0.144
VKE	0.065	0.000	***0.306****	0.258	-0.002	***0.586****	0.139	-0.132
VOD	0.119	0.003	***0.381****	0.194	-0.006	-0.084	***0.846***	-0.112
WBO	0.120	0.009	***0.488****	0.264	0.005	***0.398***	***0.511***	-0.104
WEZ	0.068	-0.010	***1.042***	0.090	-0.003	0.515	-0.430	***0.854***
WHL	0.153	0.009	***0.550****	0.440	0.002	***0.487****	***0.737****	***-0.230****
YRK	0.004	0.007	-0.179	0.006	0.004	-0.185	0.247	-0.165
ZED	0.150	-0.003	***0.440****	0.174	-0.006	-0.015	***0.460***	0.084

Table 7.2 presents a summary of the performance statistics between the CAPM and the sector-based three-factor APT model. Panel (A) presents the regression results of average R-Squared and alpha intercepts between the two models. Panel (B) presents the regression results of the number of stocks that exhibit statistically significant positive factor loadings versus the number of stocks that exhibit statistically significant negative factor loadings for the CAPM and the three-factor APT model. The prominent sector proxies used as explanatory variables in the APT model includes FINI, INDI and RESI tradable sector indices. The performance

measures are examined over a 132-month period from 1 January 2003 to 31 December 2013.

Table 7.2 Performance Summary: CAPM versus Three-Factor APT Model

Table 7.2 presents a summary of the performance statistics between the CAPM and the sector-based three-factor APT model. Panel (A) presents the regression results of average R-Squared and alpha intercepts between the two models. Panel (B) presents the regression results of the number of stocks that exhibit statistically significant positive factor loadings versus the number of stocks that exhibit statistically significant negative factor loadings for the CAPM and the APT model. The prominent sector proxies used as explanatory variables in the APT model includes FINI, INDI and RESI sector indices. The performance measures are examined over a 132-month period from 1 January 2003 to 31 December 2013.

Panel (A): Summary of Regression Results between CAPM and Sector-Based Three-Factor APT Asset Pricing Models

Asset Pricing Model	CAPM	Three-Factor APT
Mean R-Square (R^2)	13.02%	24.32%
Mean Alpha of Regression	0.001	-0.001

Panel (B): Stocks Displaying a Significant Factor Loading to Market Proxy and Sector Exposures

Market Proxy and Sector Exposures	Number of Significantly Positive Factor Loadings	Number of Significantly Negative Factor Loadings	Total
MRP	146	0	146
FINI	62	4	66
INDI	67	4	71
RESI	29	27	56

Panel (A) shows that the mean R-Squared for the CAPM regressions is 13.02%. On the other hand, the three-factor APT regression on average explains 24.32% variations in the sample stocks' excess returns. The mean R-Squared provided by the APT model captures 11.3% more excess return variation compared to that of the CAPM model. Although the mean alpha for both the CAPM and three-factor APT asset pricing models are almost identical at 0.001 and –0.001 respectively, the three-factor APT has greater explanatory power in explaining ALSI constituents' excess return variations compared to that of the CAPM.

In Panel (B), a total of 146 factor loadings of sample stocks' excess returns are positively correlated to the CAPM market risk premium. This suggests that the market risk is the most important determinant in explaining stock returns on the JSE. However, when risks are decomposed into distinctive sector risks in the APT model, FINI, INDI and RESI risk premia collectively provide superior power compared to the CAPM in explaining stock returns on the JSE. As demonstrated earlier, the sector-based APT model produces much higher R-Squared compared to the single-factor CAPM.

A total of 66 stocks are influenced by risks in the financial sector as 62 of the factor loadings exhibit positive sensitivity compared to 4 of the factor loadings that exhibit negative sensitivity to the FINI risk premium. On the other hand, 71 stocks are influenced by risks in the industrial sector with 67 of the factor loading exhibiting a positive sensitivity relative to 4 that exhibit a negative sensitivity to the INDI risk premium. Of significance in Panel (B) is the number of negative factor loadings compared to the number of positive factor loadings on the RESI risk premium. A total of 56 of the factor loadings exhibit sensitivity to the RESI risk premia with 27 of the factor loadings exhibiting negative sensitivity compared to 29 of the factor loadings exhibiting positive sensitivity to the RESI risk premium. If one considers the beta-return relationship depicted by the security market line (SML), the CAPM postulates that all assets are influenced by similar macro-economic influences. However, the superior explanatory power of the sector-based APT model pertaining to the diverse resources sector exposures of ALSI constituents point to stock returns being influenced by more than one SML on the JSE. Similar to the findings of Van Rensburg and Slaney (1997) and Van Rensburg (2002) prior to the completion of the restructuring of the JSE, the results concur with their findings. The market segmentation phenomenon on the JSE continues to exist over the extended examination period from 1 January 2003 through 31 December 2013.

The rationale of decomposing FNDI into FINI and INDI in the APT model is validated as approximately a third (66 of 199) of sample stocks have statistically significant factor loadings to the FINI risk premia. The significant growth in the financial sector as highlighted in Chapter 4, Section 4.3, indicates that the sector has a distinctive influence on the South African stock market. The 29 positive factor loadings on RESI risk premiums also point to the overwhelming influence the sector has on the JSE. It alludes to the fact that the ALSI, to a large degree, is driven by resources stocks. However, with 66 and 67 of stocks that show significant factor loadings to the FINI and INDI risk premia respectively, the results highlight the dominance of the two sectors in the South African economy.

7.3.2 Two-Factor APT Model versus Three-Factor APT Model

The regression results of the two-factor APT model and the three-factor APT model are presented in Table 7.3. The results for the two-factor APT model show that 78% (155 of 199) of the excess return variations of sample stocks are explained statistically significantly, in contrast to the 3-factor APT that only explains 69% (137 of 199) of sample stocks' excess return variations. It is also observed that the identities of the 35 stocks whose excess return variations are not adequately explained by the two-factor APT models are similar to those not adequately explained by the CAPM and the three-factor APT model.

Table 7.3 Regression Results: Two-Factor APT Model versus Three-Factor APT Model

Table 7.3 presents the time-series regression results of sector-based two-factor APT and three-factor APT models. The sector-based two-factor APT proxies consist of FNDI and RESI whereas the sector-based three-Factor APT proxies consist of FINI, INDI and RESI. The excess returns of ALSI constituents were regressed in both the sector-based APT models. The regression coefficients, represented by the bold italic, that are statistically significant at the 1% level are marked with three asterisks, ***, whereas those at the 5% level are marked with two asterisks, **. Regression coefficients that are statistically significant at the 10% level are marked with one asterisks, *.

Name of Listed stock	Asset Pricing Model: Two-Factor APT				Three-Factor APT				
			Constituent Sector Beta Coefficients				Constituent Sector Beta Coefficients		
	R-Squared	Alpha	FNDI	RESI	R-Squared	Alpha	FINI	INDI	RESI
ABL	0.190	-0.009	0.986***	-0.121	0.312	-0.003	1.223***	-0.255	-0.026
ACL	0.310	-0.007	0.563***	0.601***	0.313	-0.007	0.246	0.336	0.603***
ACP	0.176	-0.002	0.598***	-0.233***	0.261	0.000	0.623***	-0.035	-0.187***
ADH	0.173	0.007	0.660***	-0.029	0.192	0.006	0.149	0.566***	-0.052
ADR	0.115	0.000	0.574***	-0.033	0.128	0.001	0.383**	0.190	-0.011
AEG	0.225	-0.008	0.975***	0.007	0.249	-0.009	0.213	0.844***	-0.028
AFE	0.271	-0.003	0.654***	0.067	0.290	-0.004	0.064	0.633***	0.041
AFR	0.153	-0.012	0.733***	0.051	0.163	-0.014	0.097	0.682**	0.024
AFT	0.183	-0.005	0.565***	0.269	0.208	-0.009	-0.123	0.795**	0.213
AFX	0.183	-0.011	0.679***	-0.046	0.192	-0.012**	0.119	0.589***	-0.062
AGL	0.784	-0.007	0.117	1.084***	0.784	-0.007	0.030	0.086	1.084***
AIA	0.176	0.013	-0.704	0.193	0.188	0.012	-0.335	-0.431	0.182
AIB	0.041	-0.005	0.334	-0.029	0.266	-0.002	0.913**	-0.26	-0.037
AIP	0.151	-0.001	0.283	0.125	0.178	-0.003	-0.075	0.421	0.100
ALT	0.168	-0.009	0.873***	0.129	0.203	0.013	-0.167	1.100***	-0.188
AMS	0.586	-0.006	-0.132	1.190***	0.607	-0.002	0.438**	-0.620***	1.252***
ANG	0.305	-0.012	-0.367	-0.090	0.305	-0.012	-0.367	-0.090	0.838***
APN	0.163	0.013	0.811***	-0.128	0.202	0.015**	0.685***	0.115	-0.081
AQP	0.356	-0.002	-0.430	1.449***	0.359	-0.002	-0.097	0.384	1.467***
ARI	0.514	0.001	0.285	0.936***	0.514	0.002	0.205	0.041	0.962***
ARL	0.164	0.000	0.709***	-0.057	0.182	0.000	0.264	0.492**	-0.067
ART	0.110	-0.008	0.445**	0.178	0.130	-0.005	0.517**	-0.103	0.226
ASR	0.221	0.013	0.457**	0.507***	0.217	0.013	0.201	0.207	0.532***
ATN	0.204	-0.007	0.728***	0.032	0.205	-0.007	0.275	0.453**	0.039
AVI	0.221	-0.002	0.826***	-0.168	0.247	-0.001	0.386**	0.478**	-0.162
AVU	0.196	-0.020**	0.910***	-0.214	0.220	-0.017	0.560**	0.327	-0.159
AWA	0.197	-0.019	0.839***	-0.347	0.321	0.020	0.848**	0.238	-0.352**

Name of Listed stock	Asset Pricing Model: Two-Factor APT R-Squared	Alpha	Constituent Sector Beta Coefficients FNDI	RESI	Three-Factor APT R-Squared	Alpha	Constituent Sector Beta Coefficients FINI	INDI	RESI
AWB	0.298	-0.016	1.299**	-0.652***	0.369	0.016	0.989**	0.576	-0.652***
BAT	0.187	-0.001	0.841***	-0.063	0.199	0.002	0.159	0.725***	-0.085
BAW	0.308	-0.014	0.995** *	0.099	0.310	-0.015	0.285	0.737**	0.103
BCX	0.073	-0.008	0.502**	-0.021	0.078	-0.008	0.231	0.286	-0.015
BEL	0.101	-0.001	0.323	0.423***	0.127	0.003	0.720**	-0.417	0.497***
BGA	0.409	-0.007	1.028***	-0.155**	0.608	-0.001	1.192***	-0.239	-0.043
BIL	0.787	0.004	0.043	0.993***	0.788	0.004	0.084	-0.058	1.006***
BLU	0.117	-0.117	0.481	0.197	0.146	-0.002	0.589**	-0.195	0.279
BRN	0.035	-0.016	0.513***	-0.254	0.044	0.018	0.428	0.079	-0.225
BSR	0.107	0.003	1.087***	-0.008	0.118	0.002	0.354	0.815	-0.033
BTI	0.072	-0.002	0.451	-0.114	0.159	-0.006	-0.374	0.815***	-0.086
BVT	0.492	-0.004	0.977***	-0.091	0.501	-0.004	0.301***	0.692***	-0.093
CCO	0.038	0.025**	0.195	0.074	0.117	0.020**	-0.563	0.711	0.037
CFR	0.520	0.004	1.405***	0.038	0.654	-0.004	-0.564**	1.947***	0.105
CIL	0.045	0.006	-0.052	0.372	0.059	0.002	-0.383	0.423	0.302
CLH	0.185	0.003	0.448***	0.082	0.208	0.003	0.273	0.211	0.083
CLI	0.062	0.008	0.139	0.167	0.063	0.008	0.098	0.038	0.174
CLR	0.023	0.005	0.091	0.116	0.045	0.005	0.421	-0.159	0.098
CLS	0.304	0.000	0.937***	-0.120	0.346	-0.002	0.106	0.911***	-0.164
CMH	0.118	0.001	0.830***	-0.058	0.133	0.002	0.492	0.365	-0.043
CML	0.328	0.005	1.277***	-0.183	0.356	0.008	0.814***	0.428	-0.128
CMP	0.029	0.011	0.384	0.130	0.035	0.009	-0.049	0.522	0.088
COH	0.024	0.033	0.839	-0.101	0.056	0.032	-0.963	1.375	-0.057
COM	0.070	-0.001	0.791	-0.093	0.073	-0.002	0.117	0.696	-0.110
CPI	0.221	0.018**	1.042**	-0.114	0.296	0.023***	1.072***	-0.082	-0.021
CPL	0.188	-0.001	0.707***	-0.237***	0.276	0.002	0.739***	-0.052	-0.179**
CRM	0.015	-0.014	0.250	0.049	0.028	-0.012	0.445	-0.190	0.082
CSB	0.065	0.010	0.592***	-0.151	0.074	0.011	0.316	0.300	-0.145
CVH	0.043	0.016	0.058	-0.166	0.084	0.017	0.371	-0.161	-0.175
CZA	0.176	0.003	-0.017	1.241***	0.176	0.004	0.061	-0.225	1.246***
DAW	0.083	0.011	0.729***	-0.048	0.102	0.013	0.655**	0.051	0.003
DCT	0.049	-0.001	0.545**	-0.104	0.054	-0.001	0.247	0.320	-0.103
DLT	0.376	-0.030**	1.012**	-0.373*	0.474	-0.028*	0.596*	0.530	-0.356*
DRD	0.193	-0.10	-0.994***	1.147***	0.198	-0.013	-0.740	-0.186	1.078***
DSY	0.229	0.004	0.738***	-0.114	0.283	0.001	-0.046	0.867***	-0.167**
DTC	0.415	-0.002	1.379***	0.268**	0.416	-0.001	0.646***	0.713**	0.301**
EHS	0.108	-0.007	0.385	0.434***	0.127	-0.003	0.663	-0.323	0.503***
ELI	0.052	0.009	0.377	0.155	0.054	0.008	0.027	0.386	0.140
EMI	0.196	-0.006	0.637***	-0.255***	0.251	-0.005	0.508***	0.134	-0.227***
EOH	0.089	0.018***	0.592***	-0.158	0.095	0.018**	0.293	0.305	-0.147
EQS	0.178	-0.021	0.842***	-0.014	0.202	-0.024*	0.025	0.912**	-0.062
EXX	0.422	0.009	-0.140	0.981***	0.422	0.008	-0.168	0.043	0.962***
FBR	0.261	0.015**	1.176***	-0.216	0.276	0.014	0.201	1.022***	-0.244**
FFA	0.038	-0.004	0.210	-0.145	0.142	-0.002	0.481**	-0.214	-0.126
FPT	0.236	-0.006	0.747***	-0.231***	0.353	-0.003	0.808***	-0.090	-0.164**

Name of Listed stock	Asset Pricing Model								
	Two-Factor APT				Three-Factor APT				
			Constituent Sector Beta Coefficients				Constituent Sector Beta Coefficients		
	R-Squared	Alpha	FNDI	RESI	R-Squared	Alpha	FINI	INDI	RESI
FSR	0.507	-0.007	1.241***	-0.202***	0.744	0.000	1.412***	-0.259**	-0.070
FWD	0.367	-0.013	1.412***	-0.198	0.368	-0.012	0.598**	0.801**	-0.153
GFI	0.301	-0.013	-0.585***	0.925***	0.297	-0.012	-0.074	-0.487	0.924***
GND	0.258	0.009	0.768***	0.253***	0.290	0.005	-0.176	1.023***	0.188
GPL	0.043	-0.005	0.275	0.092	0.042	-0.006	-0.043	0.292	0.096
GRF	0.265	-0.003	1.089***	0.059	0.283	-0.005	0.210	0.947***	0.026
GRT	0.161	-0.002	0.633***	-0.192**	0.268	0.001	0.750***	-0.133	-0.132
HAR	0.289	-0.012	-0.752***	1.166***	0.284	-0.013	-0.318	-0.376	1.133***
HCI	0.020	0.026	0.705	-0.131	0.037	0.032	1.042	-0.431	-0.018
HDC	0.204	-0.001	0.751***	0.017	0.213	0.001	0.329	0.438	0.022
HLM	0.135	-0.030**	0.668**	0.183	0.136	-0.030**	0.276	0.394	0.199
HPA	0.014	-0.008	0.150	-0.053	0.018	-0.008	0.024	0.147	-0.060
HPB	0.074	-0.018	0.588**	0.043	0.092	-0.015	0.518	0.059	0.085
HSP	0.058	-0.006	0.564	-0.135	0.089	-0.007	0.531	0.216	-0.152
HWN	0.018	0.028**	-0.018	0.223	0.019	0.027**	-0.121	0.118	0.207
HYP	0.179	0.001	0.643***	-0.300***	0.269	0.004	0.698***	-0.067	-0.247***
ILA	0.138	-0.006	0.861***	0.043	0.146	-0.006	0.363	0.525	0.045
ILV	0.187	0.000	0.049	0.425***	0.188	0.000	0.100	-0.062	0.437***
IMP	0.549	-0.004	-0.023	1.063***	0.575	-0.001	0.495***	-0.555**	1.123***
INL	0.532	-0.010**	1.300***	-0.022	0.536	-0.009	0.642***	0.633***	0.015
INP	0.515	-0.010	1.244***	0.042	0.521	-0.008	0.662***	0.549***	0.084
IPF	0.165	-0.010	0.488	-0.590**	0.257	-0.009	0.984**	-0.117	-0.633**
IPL	0.341	-0.007	1.183***	-0.122	0.353	-0.008	0.437**	0.770***	-0.120
ITU	0.238	-0.017** *	0.673***	0.133	0.238	-0.015**	0.457**	0.158	0.180
IVT	0.121	0.011	0.527***	-0.007	0.129	0.010	-0.009	0.555***	-0.028
JDG	0.354	-0.015**	1.344***	-0.335***	0.398	-0.013**	0.841***	0.512**	-0.294***
JSE	0.184	0.005	0.854***	0.102	0.197	0.002	0.087	0.842**	0.073
KAP	0.078	-0.008	0.686***	-0088	0.089	-0.010	0.033	0.717**	-0.121
KGM	0.064	0.005	0.387**	0.000	0.069	0.005	0.177	0.226	0.001
KIO	0.448	0.012	0.017	0.909***	0.462	0.015	0.307	-0.341	0.955***
LBH	0.202	-0.007	0.574***	-0.043	0.223	-0.009	0.011	0.598***	-0.069
LEW	0.325	-0.010	1.093***	-0.275***	0.412	-0.005	0.947***	0.102	-0.197**
LHC	0.113	0.013	0.253	-0.377**	0.175	0.016	0.572	-0.212	-0.364**
LHG	0.012	0.006	0.291	-0.014	0.019	0.003	-0.043	0.425	-0.054
LON	0.456	-0.011	-0080	1.256***	0.456	-0.011	0.004	-0.101	1.265***
MDC	0.160	0.004	0.416***	0.055	0.176	0.003	0.042	0.409**	0.035
MDI	0.036	0.007	-0.426	0.076	0.035	0.006	-0.162	-0.245	0.053
MFL	0.029	0.021	-0.358	0.672	0.030	0.018	-0.408	0.175	0.597
MIX	0.142	0.011	1.059**	0.107	0.140	0.010	0.234	0.835	0.113
MMI	0.337	-0.006	0.880***	-0.052	0.381	-0.003	0.672***	0.183	-0.002
MML	0.080	-0.009	0.316	0.264	0.100	-0.013	-0.240	0.642	0.208
MND	0.356	0.004	1.024***	0.248	0.358	0.003	0.240	0.818**	0.245
MNP	0.401	0.004	1.090***	0.312***	0.415	0.001	0.024	1.139***	0.274
MPC	0.339	0.008	1.217***	-0.362***	0.382	0.008	0.559***	0.717***	-0.362***
MPT	0.016	0.009	0.210	-0.145	0.039	0.009	0.360	-0.001	-0.163

Name of Listed stock	Asset Pricing Model: Two-Factor APT				Three-Factor APT				
			Constituent Sector Beta Coefficients				Constituent Sector Beta Coefficients		
	R-Squared	Alpha	FNDI	RESI	R-Squared	Alpha	FINI	INDI	RESI
MRF	0.282	-0.009	0.555	0.797***	0.298	-0.013	-0.291	0.929**	0.726***
MSM	0.255	-0.001	0.981***	-0.229**	0.296	-0.003	0.159	0.911***	-0.271***
MTA	0.103	0.004	0.511***	0.154	0.124	0.001	-0.192	0.771**	0.098
MTN	0.448	0.004	1.138***	-0.063	0.445	0.003	0.268	0.875***	-0.069
MTX	0.100	-0.009	0.860**	0.234	0.106	-0.011	-0.113	1.004**	0.191
MUR	0.170	-0..008	0.791***	0.081	0.190	-0.007	0.472	0.363	0.089
MVS	0.022	-0.014	-0.152	0.181	0.053	-0.013	0.409	-0.384	0.163
NBC	0.019	-0.046	0.293	-0.501	0.028	-0.050	-0.489	0.727	-0.542
NED	0.472	-0.014***	1.209***	-0.313***	0.567	-0.009**	1.012***	0.139	-0.229***
NEP	0.032	0.011	0.283	-0.178	0.032	0.011	0.096	0.194	-0.176
NHM	0.338	-0.004	0.445	0.840	0.336	-0.004	0.104	0.319	0.847***
NIV	0.226	0.031	0.522	0.565	0.383	0.024	-1.378	1.473	0.543
NPK	0.189	-0.006	0.540***	-0.050	0.202	-0.006	0.236	0.322**	-0.048
NPN	0.541	0.010**	1.205***	0.056	0.573	0.008	0.044	1.217***	0.010
NT1	0.010	-0.010	0.460	-0.115	0.021	-0.013	-0.428	0.826	-0.064
NTC	0.232	0.001	0.727***	-0.020	0.248	0.001	0.208	0.558***	-0.034
OCE	0.012	0.005	0.025	0.100	0.070	0.001	-0.496**	0.597**	0.026
OCT	0.071	0.004	0.509***	-0.267**	0.110	0.006	0.548***	-0.020	-0.236**
OML	0.519	-0.011**	1.175***	0.060	0.553	-0.008	0.884***	0.217	0.140
OMN	0.213	0.004	0.679***	0.088	0.210	0.004	0.246	0.424	0.097
OPT	0.017	-0.002	-0.339	0.179	0.046	0.003	0.334	-0.698	0.217
PAM	0.122	-0.002	0.153	0.578***	0.123	-0.002	0.097	0.082	0.574***
PAN	0.068	0.006	0.217	0.565***	0.084	0.001	-0.524	0.408	0.482
PAP	0.100	-0.004	0.393***	-0.038	0.199	-0.001	0.604***	-0.233	0.017
PET	0.093	-0.001	0.483	0.370	0.093	-0.001	0.101	0.399	0.361
PFG	0.135	0.004	0.494***	0.002	0.146	0.002	0.050	0.488	-0.019
PGL	0.258	-0.037**	1.604***	-0.196	0.254	-0.035**	0.782	0.811	-0.156
PGR	0.308	-0.002	1.087***	0.070	0.329	-0.001	0.535**	0.587**	0.080
PHM	0.042	0.006	0.141	0.177	0.058	0.003	-0.250	0.450	0.128
PIK	0.189	-0.003	0.513***	0.008	0.216	-0.004	0.127	0.443***	-0.014
PMM	0.128	0.005	0.710***	-0.314***	0.176	0.007	0.678***	0.024	-0.266**
PNC	0.143	0.036	0.819	0.782***	0.150	0.033	0.113	0.851	0.719**
PPC	0.184	-0.006	0.790***	-0.109	0.220	-0.005	0.537***	0.285	-0.091
PSG	0.206	0.010	1.221***	-0.177	0.215	0.010	0.515	0.723**	-0.159
RBP	0.268	-0.005	-0.238	0.680***	0.319	-0.003	0.614	-0.630	0.670***
RBX	0.187	-0.009	1.071***	-0.102	0.201	-0.012	0.070	1.080***	-0.137
RCL	0.093	0.001	0.478***	-0.003	0.112	-0.001	-0.046	0.580***	-0.039
RDF	0.145	-0.004	0.639***	-0.247***	0.181	-0.002	0.505***	0.140	-0.218**
REB	0.069	-0.009	0.303	-0.251	0.091	-0.010	0.290	0.130	-0.268
REI	0.262	-0.011	0.875***	-0.209	0.432	-0.016**	-0.431**	1.322***	-0.179
REM	0.569	-0.002	0.830***	-0.105	0.597	-0.001	0.364***	0.511***	-0.108
RES	0.120	0.006	0.512***	-0.234***	0.193	0.008	0.587***	-0.079	-0.191**
RLO	0.313	-0.007	0.962***	-0.215***	0.334	-0.006	0.484***	0.488***	-0.198**
RMH	0.464	-0.007	1.197***	-0.185**	0.655	0.000	1.310***	-0.196	-0.063
RMI	0.138	0.012	0.326	0.147	0.158	0.013	0.388	0.045	0.145

Name of Listed stock	Two-Factor APT				Three-Factor APT				
			Constituent Sector Beta Coefficients				Constituent Sector Beta Coefficients		
	R-Squared	Alpha	FNDI	RESI	R-Squared	Alpha	FINI	INDI	RESI
RPL	0.177	-0.011	0.899**	0.010	0.249	-0.014	-0.684	1.317***	-0.002
SAB	0.405	0.001	0.675***	0.115	0.504	-0.003	-0.314***	1.044***	0.048
SAC	0.148	-0.008	0.579***	-0.119	0.197	-0.006	0.528***	0.048	-0.083
SAP	0.289	-0.024***	0.957***	0.243	0.300	-0.026***	0.027	0.971***	0.206
SBK	0.520	-0.007	1.147***	0.178***	0.812	0.000	1.422***	-0.385***	-0.034
SCL	0.006	0.000	0.070	0.286	0.016	0.007	0.941	-0.864	0.345
SFN	0.130	0.002	0.838***	-0.109	0.140	0.002	0.313	0.564	-0.116
SGL	0.384	0.044	-1.751	2.110	0.534	0.075	2.217	-3.538	2.341*
SHF	0.441	-0.004	1.202***	0.093	0.489	-0.008	-0.130	1.407***	0.023
SHP	0.175	0.010	0.762***	-0.231**	0.217	0.007	-0.015	0.856***	-0.280***
SIM	0.044	0.019	-0.175	0.962**	0.049	0.024	0.608	-0.834	1.042**
SLM	0.487	-0.003	0.978***	-0.089	0.535	0.000	0.726***	0.207	-0.030
SNT	0.146	0.000	0.620***	-0.034	0.160	0.000	0.290	0.357	-0.032
SNU	0.075	-0.009	0.745**	0.119	0.079	-0.009	0.281	0.501	0.112
SOL	0.620	0.000	0.179	0.729***	0.626	-0.001	-0.107	0.301**	0.709***
SPG	0.134	-0.017	0.895***	0.041	0.145	-0.015	0.635**	0.235	0.087
SPP	0.176	0.003	0.559***	-0.072	0.219	0.001	-0.007	0.640***	-0.107
SSK	0.168	-0.014	0.971***	0.057	0.180	-0.013	0.477	0.526	0.076
SUI	0.219	-0.006	0.726***	-0.015	0.248	-0.005	0.490***	0.250	0.007
SUR	0.117	0.004	0.469***	0.029	0.124	0.003	0.031	0.462**	0.011
SYC	0.253	-0.007	0.782***	-0.305***	0.307	-0.005	0.588***	0.196	-0.271***
TBS	0.311	-0.007	0.789***	-0.115	0.332	-0.008	0.044	0.767***	-0.114
TCP	0.033	-0.004	-0.182	-0.063	0.271	-0.002	0.883*	-0.666	-0.097
TFG	0.407	-0.002	1.335***	-0.301***	0.482	0.000	0.948***	0.400**	-0.251***
TKG	0.081	-0.016	0.262	0.253	0.080	-0.016	0.033	0.224	0.252
TMG	0.193	-0.003	1.034	-0.428	0.226	-0.002	0.513	0.645	-0.420
TON	0.051	-0.007	0.365	-0.018	0.054	-0.007	0.138	0.247	-0.017
TRE	0.117	0.004	0.351**	0.122	0.121	0.003	0.015	0.353	0.108
TRU	0.296	0.002	1.067***	-0.260***	0.344	0.003	0.637***	0.467**	-0.242***
TSH	0.127	0.004	0.636***	-0.153	0.141	0.004	0.336	0.316	-0.144
VKE	0.199	-0.004	0.720***	-0.167	0.258	-0.002	0.586***	0.139	-0.132
VOD	0.188	-0.004	0.770***	-0.083	0.194	-0.006	-0.084	0.846**	-0.112
WBO	0.240	0.005	0.871***	-0.105	0.264	0.005	0.398**	0.511**	-0.104
WEZ	0.084	-0.007	0.146	0.794**	0.090	-0.003	0.515	-0.430	0.854**
WHL	0.419	0.002	1.198***	-0.236***	0.440	0.002	0.487***	0.737***	-0.230***
YRK	0.004	0.006	-0.003	-0.123	0.006	0.004	-0.185	0.247	-0.165
ZED	0.164	-0.004	0.411***	0.103	0.174	-0.006	-0.015	0.460**	0.084

Table 7.4 provides a summary of the performance statistics between the two-factor APT model and the three-factor APT model. Panel (A) shows the regression results of the average R-Squared and alpha intercepts between the two models; and Panel

(B) shows the regression results of the stocks that exhibit statistically significant positive (negative) factor loadings for the risk premia in the respective models.

Table 7.4 Performance Summary: Two-Factor APT Model versus Three-Factor APT Model

Table 7.4 presents a summary of the performance statistics between the sector-based two-factor APT and sector-based three-factor APT models. Panel (A) presents the regression results of average R-Squared and alpha intercepts between the two models. Panel (B) presents the regression results of the number of stocks that exhibit statistically significant positive factor loadings versus the number of stocks that exhibit statistically significant negative factor loadings for both APT models. The prominent sector proxies used as explanatory variables in the two-factor APT model includes FNDI and RESI sector indices and the three-factor APT model includes FINI, INDI and RESI sector indices. The performance measures are examined over a 132-month period from 1 January 2003 to 31 December 2013.

Panel (A): Summary of Regression Results Between Sector-Based Two-Factor APT and Sector-Based Three-Factor APT Asset Pricing Models

Asset Pricing Model	Two-Factor APT	Three-Factor APT
Mean R-Square (R^2)	20.90%	24.32%
Mean Alpha of Regression	-0.001	-0.001

Panel (B): Stocks Displaying a Significant Factor Loading to Sector Exposures on Both APT Models

Sector Exposures on APT models	Number of Significantly Positive Factor Loadings	Number of Significantly Negative Factor Loadings	Total
FINDI	128	3	131
RESI	30	29	59
FINI	62	4	66
INDI	67	4	71
RESI	29	27	56

Overall, there is no distinctive improvement in the explanatory power for the two factor APT models. The mean R-Squared between the two models are almost identical at 20.90% and 24.32% for the two-factor APT and the three-factor APT models respectively whereas the mean alpha is almost identical. Similarly, the number of positive factor loadings versus the number of negative factor loadings to either model is almost identical. The appealing quality of the three-factor model compared to the two-factor APT model is that the underlying systematic risks of the sample stocks are clearly distinguished between the financial and industrial sectors. Alternatively, FNDI employed by the two-factor APT model represents a composite risk factor for the financial and industrial sectors. Thus, the three-factor APT model presents investors with an opportunity to more closely examine the underlying risks that drive their investment returns and tailor their portfolios accordingly to mitigate systematic risks and meet their investment objectives.

7.4 Conclusion

The examination extends the observations of the market segmentation phenomena documented prior to the JSE restructuring by Van Rensburg and Slaney (1997) and Van Rensburg (2002). Whereas Van Rensburg (2002) proposes a sector-based two-factor APT model with RESI and FNDI as explanatory variables to explain JSE stock returns, this research explores the application of a sector-based three-factor APT model on the JSE by decomposing FNDI into FINI and INDI to better track sample stock returns. This exercise is motivated by the significant growth exhibited by the financial sector over the examination period from 1 January 2003 to 31 December 2013.

The time-series regression results reveal that the CAPM market risk premium adequately explain 73% of the sample stocks' excess return variations whereas the sector-based three-factor APT model explains 69% of the sample stocks' excess return variations. The results further reveal that the excess return variations of approximately 34 stocks could not be explained adequately by both the CAPM and the two APT models. This suggests that these stocks could provide a natural hedge to those investors looking to counter market risks.

The observations on the three-factor APT regressions show that the sample stock returns, generally, exhibit significant sensitivity to dimensions of risk to movements in more than one sector. Stocks that exhibit sensitivity to the movements in the RESI risk premia generally exhibit negative sensitivity to movements in either the FINI, INDI or RESI risk premia. The apparently negative correlation between FINI, INDI or

RESI coefficients suggests that resources stocks are exposed to different dimensions of risk compared to stocks in the financial and industrial sectors. Resources stocks, unlike stocks in the financial and industrial sectors that generate a significant portion of their earnings domestically, derive a significant portion of the earnings in international markets through exports. Therefore, firms in the resources sector are highly exposed and influenced by exchange rate movements and global economic risk factors. Resources stocks are net exporters and, thus, the weakness of the rand coupled with the demand for their commodities are highly beneficial to their earnings. However, resources stocks are highly sensitive to political risks. The government's ambitious empowerment plans or labour unrest, for example, over the examination period have been shown to have a negative impact on their performance. The financial and industrial sectors, on the other hand, are positively influenced by low interest rates, strong currency and robust economic growth domestically in general. Low interest rates over the examination period, for example, increased the viability of the banking subsector to offer favourable credit extensions and the real estate subsector benefited with investors increasing their appetite in the housing market. Retail firms in the industrial sector are generally net importers and thus benefited through the lower cost of import goods when the rand strengthened.

The results also revealed that the sector-based APT model captures more average excess return variations of sample stocks compared to that of the CAPM. Study results also reveal that the number of stocks that are influenced negatively by movements in the resources sector is close to the number of stocks that are positively influenced by the movements in the resource sector. This finding support the use of a sector-based multifactor APT model on the JSE as South African stocks seem to exhibit different sector exposures on the JSE. Similar to the findings of Van

Rensburg and Slaney (1997) and Van Rensburg (2002) prior to the completion of the restructuring of the JSE, the results concur with their findings in identifying significant market segmentation phenomenon on the JSE for the extended examination period from 1 January 2003 through 31 December 2013.

The beta-return relationship captured by the SML is dis-proportional as more than one SML exists on the JSE. The economic systematic risks underlying the sector proxies are driven by distinctive macro-variable influences. This phenomenon is contrary to the SML relationship highlighted by the CAPM theory as all assets are expected to behave linearly to the benchmark portfolio. The diverse stock return sensitivities to the sector proxies show a non-linear relationship which further suggests that the CAPM is an inappropriate model to measure systematic risks.

The justification for decomposing FNDI into FINI and INDI in the three-factor APT model is validated as sample stocks have significantly positive factor loadings to the FINI risk premium. This phenomenon is attributed to the growing importance of the financial sector, which indicates that the sector has a distinctive influence in the South African stock market.

In comparing the two-factor APT model, with FNDI and RESI as the explanatory variables, to the three-factor APT model, the results reveal that no distinctive advantage exist between the two models in explaining stock returns on the JSE. The regression results for both models are almost identical. However, the unique characteristic that makes the three-factor APT model more appealing is that the systematic risks inherent in the distinctive sectors that impact individual stock's returns could be observed more closely by separating FINI and INDI in the asset pricing model.. As a result, investors could more easily tailor their portfolios to mitigate the pervasive macro-variable influences inherent in these sectors. To conclude, this study proposes the application of the sector-based three-factor APT model on the JSE.

8

CONCLUSION

Capital market theories and the development of financial asset pricing models such as modern portfolio theory (MPT), the separation theorem, the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) provide potential solutions to asset allocation decisions in efficient capital markets. The MPT suggest methods to manage risk and the separation theorem proposes that investors identify the optimal risky portfolio, namely the market portfolio. In addition, the separation theorem proposes that investors choose an asset mix which is based on a risk-free asset and the market portfolio subject to their degree of risk appetite. The basic premise underlying capital market theories presupposes that investors are risk-averse, behave rationally and have homogeneous expectations regarding the mean, variance and covariance of returns.

The CAPM, a single factor linear model, is an extension of the MPT and the separation theorem. It is the first asset pricing model developed to assist investors in determining the equilibrium rate of return on assets in an efficient capital market. Due to the fact that firm-specific risks can be diversified away, the only relevant risk is systematic risk. These are risks which are influenced by macro-economic events. Sharpe (1965) points out that individual assets are expected to be influenced by the same macro-economic risks which implies that all assets are expected to move in tandem to any increase (decrease) when the market portfolio increases (decreases). The beta coefficient of the CAPM is used to compute systematic risk and measures the sensitivity of an asset's returns to movements in the market portfolio. In addition, it is the only relevant risk parameter employed by the CAPM.

Ross (1976) introduces a multifactor asset pricing model under APT, an alternative to the single-factor CAPM, based on less stringent assumptions. Roll's (1977; 1978) critique pertaining to the unobservable nature of a true market portfolio suggests that the beta coefficient is a biased estimate. Unlike the beta coefficient which is the only relevant risk parameter used by the CAPM, the distinct advantage of the APT is that it is able to accommodate multiple sources of risk.

An alternative school of thought to capital market theories, behavioural finance, focus on how investors actually make decisions. Kahneman and Tversky (1979), and many other empiricists thereafter, argue that investors' behave irrationally as they are influenced by psychological biases in their investment decision making. This behaviour lead investors to make sub-optimal economic and financial decisions.

Prospect theory, developed by Kahneman and Tversky (1979), examines various behavioural biases associated with how investors actually behave. The psychological biases highlighted by prospect theory such as loss aversion and the certainty effect, for example, suggest that investors prefer to gamble as a result of incurring losses. Kahneman and Tversky (1979) point out that these behavioural biases lead investors to violate the assumptions of traditional finance and are inconsistent with most common utility functions. They further point out this behaviour has pervasive implications on asset prices which are in direct contradiction to efficient capital market theories.

The well-documented anomalies such as the size effect, the value effect, the short-term momentum effect and long-term price reversals have spawned significant debate related to the joint hypothesis problem of the efficient market hypothesis (EMH). The well-documented anomalies suggest that asset pricing models based on investor rationality are subject to pricing irregularities and have prompted many observers to argue that the anomalies provide evidence against the EMH.

In defence of EMH, Fama and French (1992; 1993) introduce a rational multifactor model which attempts to explain the anomalies. The rational multifactor model they introduce is a three-factor model which is an extension of the CAPM and includes the value style risk and the size style risk as additional risk factors. Their three-factor model captures most of the empirical anomalies unexplained by the CAPM and point out that the anomalies should only be considered evidence against the CAPM. Carhart (1997), on the other hand, extends Fama and French (1993) three-factor model and includes the momentum effect of Jegadeesh and Titman (1993) as the third style risk in his four-factor model. Carhart's (1997) four-factor model is able to explain a greater degree of variation in return and manages to explain abnormal return in the momentum portfolio. In addition to the well-documented anomalies, Arnott, Hsu and Moore (2005) argue that cap-weighted indices are price-sensitive and are likely to be mean-variance inefficient due to investor irrationality. They show that price-insensitive indices, formed on the basis of fundamental values, are able to outperform cap-weighted indices. Optimisation-weighted portfolios are also found to be a superior alternative to cap-weighted indices.

The South African stock market is unique for a number of reasons. The performance of the ALSI index is highly influenced by the performances of three sectors, namely, the financial sector, the industrial sector and the resources sector. In addition, a minority of stocks have an overriding influence to the performance of the ALSI index. The top 10 constituents, for example, account for roughly 57% of ALSI index ranked by market cap. The most prominent index on the JSE is the ALSI Top 40 index and is also seen as the barometer for the wider market. Over the sample period from 1 January 2003 to 31 December 2013, the ALSI Top 40 index mirrors the performance and at time outperforms the ALSI index. The ALSI Top 40 index is a tradable index and consists of the sum of the constituents that comprises the JSE tradable sector indices, namely the FINI Top 15 index, the INDI Top 25 index and the RESI Top 10 index. The many practical applications of the aforementioned tradable indices, together with the constituents that comprise the ALSI index, are included in the sample for this research.

Another unique underlying characteristic on the South African stock market is that more than one security market line exist the JSE. This is due to stocks in the resources sector being influenced by a different set of macro-economic factors compared to stocks in the financial sector and industrial sector. Motivated by the market segmentation phenomena on the JSE, Van Rensburg and Slaney (1997) employ a two-factor APT asset pricing model with the JSE Actuaries All-Gold and industrial indices as explanatory variables. Their two-factor APT model is found to provide a superior account in asset pricing applications relative to employing the CAPM. In lieu of the sector reclassification programme undertaken on the JSE in 2000, Van Rensburg (2002), using an examination period prior to the sector reclassification date of 2000, re-examines the market segmentation on the JSE. Employing a two-factor APT model with RESI and FNDI as sector proxies, Van Rensburg (2002) shows that a sector-based APT model has greater explanatory power to that of the CAPM.

Since 2000, the JSE has undertaken many restructuring initiatives and has made strides, including the amalgamation with FTSE to form the FTSE/JSE to align the South African stock market to international competitiveness standards. In addition, the financial sector has become an important sector in terms of its contribution to GDP. This research is motivated by the aforementioned influences coupled with the criticisms of price-sensitive cap-weighted indices documented by Arnott *et al* (2005) to examine the application of sector-based investment influences over the period from 1 January 2003 to 31 December 2013.

Motivated by the criticisms of Arnott *et al* (2005) that the cap-weighted ALSI index is potentially mean-variance inefficient, two long-only portfolios that maximises the Sharpe ratio are constructed over the entire sample period and compared to the ALSI Top 40 index. The first optimal portfolio consists of the JSE tradable sector indices with a cash allocation and the second optimal portfolio consists of the JSE tradable sector indices exclusive of a cash allocation. The results indicate that the optimal portfolio with the cash allocation offers the best mean-variance efficient allocation. The ALSI index is the worst performing portfolio as it offers a Sharpe ratio of less than half to that of the two optimal long-only portfolios. Although the Sharpe ratios for both long-only portfolios are almost identical, the results reveal that the portfolio with the cash allocation offers the lowest standard deviation. This is mainly due to a significant share of the capital allocated to the risk-free proxy. In addition, both long-only portfolios offer beta coefficients which are lower than the ALSI Top 40 index with the beta coefficient of the portfolio with the cash allocation approximately half to that of the ALSI Top 40 index. The results suggest that the portfolio with the cash allocation is capable of protecting portfolios against economic downswings in financial markets without foregoing its upside risk-adjusted return potential. Overall, the risk and return characteristics between the two long-only portfolios and the ALSI index suggest that the sector-based portfolios offer superior returns at lower risk compared to the ALSI index.

Of the three sector indices under examination, the risk and return performance statistics reveal that the INDI Top 25 index is the most consistent performer as it offers the highest risk-adjusted returns. It is the only sector index that offers a Sharpe ratio that outperforms the ALSI Top 40 index. The INDI Top 25 index offers the highest annualised arithmetic return and the lowest annualised standard deviation over the entire sample period. The Treynor ratios also reveal that the INDI Top 25 index and the FINI Top 15 index outperform the ALSI Top 40 index. On the other hand, the RESI Top 10 index is the worst performer of the three sector indices. It offers the lowest risk-adjusted returns, lowest annualised arithmetic return and the highest annualised standard deviation over the entire sample period. In addition, the RESI Top 10 index is the only sector index with a beta coefficient above the ALSI Top 40 index.

In examining the effective sector allocation of the cap-weighted ALSI Top 40 index, the results indicate that the ALSI index is overweighted by the resources sector over the entire sample period. The sector allocation of the RESI Top 10 index is approximately half the entire sector allocation of the ALSI index.

In examining the capital market line (CML), both long-only portfolios plot above the CML. This indicates that both long-only portfolios are representative of the true optimal risky portfolios and further suggests that the ALSI index is unrepresentative of the market portfolio. The observations further reveal that the RESI Top 10 index plots furthest and well below the CML. Based on the insight provided by the sector composition of the ALSI index over the entire sample period and the underperformance of the RESI Top 10 index, the results corroborates the criticisms of price-sensitive cap-weighted indices documented by Arnott *et al* (2005). The above results are further corroborated by the correlation coefficient between the RESI Top 10 and ALSI index. The RESI Top 10 index is almost a mirror image of the ALSI index.

Further insight is provided by the beta-return characteristics between a security market line (SML) that comprises the ALSI index and a SML that is representative of the two long-only portfolios. The results show that the SML that comprises the ALSI index is more flat than the SML that comprises the two optimal long-only portfolios. This is indicative of the underperformance of the ALSI index. This further suggests that the estimation of beta coefficients are potentially biased downwards and that investors are not compensated appropriately for bearing more risk. Stocks that plot along the SML are potentially overvalued and that performance measures employed to evaluate the performance of portfolio managers will be incorrectly computed as a result of the inappropriate benchmark.

Sharpe (1992) return decomposition model is employed to examine the performance attribution of the sector allocation of the ALSI index and the results thereof are compared against the optimal sector composition on an annual basis. The optimal sector composition, for the most part, is dominated by the industrial sector. On the other hand, the sector allocation of the ALSI index remains stable over the examination period with the sector composition dominated by the resources sector. Similar to the results above, the results suggest that the ALSI index is highly influenced by the return variation of the RESI Top 10 index. Although the INDI Top 25 index offers the best mean-variance allocation compared to the FINI Top 15 index and the RESI Top 10 index, the results suggest that the INDI Top 25 index is highly underweighted in the ALSI index. Overall, the outcomes of the results suggest that ALSI does not allocate sector-based investment efficiently. Cavaglia, Melas, and Tsouderos (2000) and Cavaglia and Morez (2002) argue that a sector allocation strategy may be a superior alternative to those investors that index a market portfolio. The outcomes of these results suggest that investors would do well to tilt their portfolios away from the market proxy by focusing on sector-based investment.

Based on Vardharaj and Fabozzi (2007) arguments that investment styles and sectors are intercorrelated, the research examines the primary investment styles that drive the performance of the financial, industrial and resources sectors on the JSE. The value effect, the size effect and the momentum effect represent the major style risks on the South African market and are employed in the Carhart (1997) four-factor model to determine the correlation between the investment styles and the sectors. Regressing the excess returns of each sector index onto the style risk factors, the time-series regression results indicate that the financial sector is highly influenced by the value style risk which suggests a strong value bias in favour of the financial sector over the entire examination period. The industrial sector, on the other hand, is moderately influenced by all three style risks which suggest a value bias, a small cap bias and a momentum bias. The resources sector, for the most part, is influenced by growth stocks and has a contrarian bias. The fact that the RESI Top 10 index offers the highest standard deviation compared to the FINI Top 15 index and the INDI Top 25 index, the growth tilt in favour of the resources sector supports Lakonishok *et al* (1994) claims that growth stocks are fundamentally more riskier. Although the examination provides insight to the influence of the various style risks on sector performance, a limitation of the examination is that the style risk influence was evaluated over the entire examination period. Further tests should be conducted to determine the influence of the style risks on sector performance over bullish market conditions such as the market conditions prior to the market crash of 2008 and bearish market conditions post 2008.

Given the market segmentation phenomena documented prior to the sector reclassification of the JSE, sector-based APT asset pricing models are re-evaluated and compared to the single-factor CAPM over an extended examination period from 1 January 2003 to 31 December 2013. A sector-based two-factor APT model proposed by Van Rensburg (2002) with the JSE tradable sector indices, FNDI and RESI employed as the sector proxies is re-examined. In addition, the application of a sector-based three-factor APT model with the JSE tradable sector indices, FINI, INDI and RESI employed as the sector proxies is explored.

In comparing the three-factor APT model to the single-factor CAPM, the time-series regression results indicate that the three-factor APT model captures a greater degree of average excess return variations of sample stocks. Furthermore, the results seem to suggest that South African stocks exhibit different sector exposures on the JSE. The number of stocks that are influenced negatively by the movement in the resources sector is close to the number of stocks that are positively influenced by the movements in the resources sector. Stocks that exhibit sensitivity to movements in the RESI risk premia generally exhibit negative sensitivity to movements in either the FINI, INDI or RESI risk premia. As a result of the negative correlation between the FINI, INDI or RESI coefficients, stocks in the resources sector are exposed to different dimensions of risk compared to stocks in the financial and industrial sectors.

The risks experienced by stocks in the resources sector compared to stocks in the financial and industrial sectors are attributed to the fact that firms in the resources sector are net exporters. A significant portion of their earnings are generated in international markets. This suggests that firms in the resources sector are highly exposed and influenced by movements in exchange rates and global economic risk factors. The weakness of the rand coupled with the demand for their commodities are highly beneficial to their earnings. On the other hand, resources stocks are highly sensitive to political risks. Labour unrest, for example, has been shown to dampen the earnings potential of resources stocks. Firms in the financial sector and industrial sector, on the other hand, generate most of their earnings in the South African market. These sectors are highly influenced by low interest rates, a strong currency and robust economic growth.

The results suggest that the market segmentation phenomenon continues to exist over the extended examination period from 1 January 2003 to 31 December 2013. The beta-return relationship captured by the SML suggests that more than one SML exists on the JSE. The economic systematic risks underlying the sector proxies are driven by distinctive macro-variable influences which are contrary to the SML relationship highlighted by the CAPM theory. All assets are expected to behave linearly to the benchmark portfolio. The non-linear relationship exhibited by the diverse stock return sensitivities to the sector proxies suggest that the CAPM is an inappropriate model to measure systematic risks.

The regression results further reveal that the justification for decomposing FNDI into FINI and INDI in the three-factor APT model is validated as sample stocks have significantly positive factor loadings to the FINI risk premium which is indicative of the distinctive influence the sector has on the South African market. Comparing the three-factor APT model to the two-factor APT model, the results reveal that no distinct advantage exists between the two models. The regression results between the two APT models are almost identical. The unique characteristic underlying the three-factor APT model is that it is a more appealing model to the two-factor APT model. Systematic risks inherent in the distinctive sectors that impact individual stock returns are more easily identifiable by separating FINI and INDI in the asset pricing model. As result, investors could more easily tailor their portfolios to mitigate the pervasive macro-variable influences in these sectors. In conclusion, this study proposes the application of a sector-based three-factor APT model on the JSE.

The application of sector proxies in APT asset pricing models on the South African stock market suggests that macro-economic variables are an important determinant that influence asset returns. Further research is thus suggested based on the pervasive influence of macro-economic variables to determine to what degree they explain equilibrium returns similar to the research undertaken by Chen, Roll and Ross (1986). Further tests for macro-economic predictability could potentially lead to additional tests for market timing on the South African stock market.

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APPENDIX A

Summary of ALSI Constituents and Three-factor APT Results

(2003 to 2013)

The summary provides a breakdown of the JSE code for each constituent on ALSI, the full name of the company and the nature of business of the company. In addition, time-series regression results for the sector-based three-factor APT model are shown for ease of reference. The regression coefficients, represented by the bold italic, that are statistically significant at the 1% level are marked with three asterisks, ***, whereas those at the 5% level are marked with two asterisks, **. Regression coefficients that are statistically significant at the 10% level are marked with one asterisks, *.

Name of listed stock (Code)	**Summary of ALSI Constituents**				
	Name of Company	**Nature of Business**	**Constituent beta coefficients**		
			FINI	**INDI**	**RESI**
ABL	African Bank	Consumer Finance	***1.223****	-0.255	-0.026
ACL	ArcelorMital	Steel Producer	0.246	0.336	***0.603****
ACP	Acucap Properties Limited	Property Development and Management	***0.623****	-0.035	***-0.187****
ADH	Advtech	Specialised Consumer Services	0.149	***0.566****-	0.052
ADR	Adcorp Holdings	Education, Business Training and Employment	***0.383***	0.190	-0.011
AEG	Aveng	Heavy Construction	0.213	***0.844****	-0.028
AFE	AECI	Chemicals - Speciality	0.064	***0.633****	0.041
AFR	Afgri	Farming and Fishing	0.097	***0.682***	0.024
AFT	Afrimat	Construction Equipment	-0.123	***0.795***	0.213
AFX	African Oxygen	Chemicals - Speciality	0.119	***0.589****	-0.062
AGL	Anglo American	Mining	0.030	0.086	***1.084****
AIA	Ascension Properties A	REITs Diversified	-0.335	-0.431	0.182
AIB	Ascension Properties B	REITs Diversified	***0.913***	-0.260	-0.037
AIP	Adcock Ingram	Pharmaceuticals	-0.075	0.421	0.100
ALT	Allied Technologies	Electrical Equipment	-0.167	***1.100****	-0.188
AMS	Anglo American Platinum	Mining	***0.438***	***-0.620****	***1.252****
ANG	Anglogold Ashanti	Mining	-0.367	-0.090	***0.838****
APN	Aspen Pharmacare	Pharmaceuticals	***0.685****	0.115	-0.081
AQP	Aquarius Platinum	Mining	-0.097	0.384	***1.467****
ARI	African Rainbow Metals	Mining	0.205	0.041	***0.962****
ARL	Astral Foods	Agricultural Suppliers and Animal Feed	0.264	***0.492***	-0.067
ART	Argent Industrial	Steel	***0.517***	-0.103	0.226
ASR	Assore	Mining	0.201	0.207	***0.532****
ATN	Allied Electronics	Electrical Equipment	0.275	***0.453***	0.039
AVI	Avi	Food Processors	***0.386***	***0.478***	-0.162
AVU	Avusa	Media and Entertainment	***0.560***	0.327	-0.159

Name of listed stock (Code)	Summary of ALSI Constituents				
	Name of Company	Nature of Business	Constituent beta coefficients		
			FINI	INDI	RESI
AWA	Arrowhead Properties A	REITs Industrial and Office	***0.848*****	0.238	***-0.352*****
AWB	Arrowhead Properties B	REITs Industrial and Office	***0.989*****	0.576	***-0.652******
BAT	Brait	Investment Services	0.159	***0.725******	-0.085
BAW	Barloworld	Diversified Industrials	0.285	***0.737*****	0.103
BCX	Business Connexion	Industrial Consulting and Information	0.231	0.286	-0.015
BEL	Bell Equipment	Technology	***0.720*****	-0.417	***0.497******
BGA	Barclays Africa	Agricultural Equipment	***1.192******	-0.239	-0.043
BIL	BHP Billiton	Banks	0.084	-0.058	***1.006******
BLU	Blue Label	Mining	***0.589*****	-0.195	0.279
BRN	Brimstone Investment	Wireless Telecom Services	0.428	0.079	-0.225
BSR	Basil Read	Investment Companies	0.354	0.815	-0.033
BTI	British American Tobacco	Heavy Construction	-0.374	***0.815******	-0.086
BVT	Bidvest	Tobacco	***0.301******	***0.692******	-0.093
CCO	Capital and Counties	Diversified Industrials	-0.563	0.711	0.037
CFR	Richemont	Real Estate and Asset Management	***-0.564*****	***1.947******	0.105
CIL	Consolidated Infrastructure	Luxury Goods	-0.383	0.423	0.302
CLH	City Lodge Hotels	Electrical Equipment	0.273	0.211	0.083
CLI	Clientele	Hotels	0.098	0.038	0.174
CLR	Clover	Life Assurance	0.421	-0.159	0.098
CLS	Clicks	Food Processors	0.106	***0.911******	-0.164
CMH	Combined Motors	Food and Drug Retailers	0.492	0.365	-0.043
CML	Coronation	Vehicle Sales	***0.814******	0.428	-0.128
CMP	Cipla Medpro	Asset Managers	-0.049	0.522	0.088
COH	Curro Holdings	Pharmaceuticals	-0.963	1.375	-0.057
COM	Comair	Specialised Consumer Services	0.117	0.696	-0.110
CPI	Capitec	Airlines and Airports	***1.072******	-0.082	-0.021
CPL	Capital Property	Banks	***0.739******	-0.052	***-0.179*****
CRM	Ceramic Industries	Financial Services	0.445	-0.190	0.082
CSB	Cashbuild	Tiles and Sanitaryware	0.316	0.300	-0.145
CVH	Capevin Holdings	Retailers - Hardlines	0.371	-0.161	-0.175
CZA	Coal of Africa	Beverages – Distillers and Vintners	0.061	-0.225	***1.246******
DAW	Distribution and	Metals and Minerals			
	Warehousing Network	Building and Construction Materials	***0.655*****	0.051	0.003
DCT	Datacentrix	Computer Services	0.247	0.320	-0.103
DLT	Delta Property Fund	Real Estate Holdings and Development	***0.596****	0.530	***-0.356****
DRD	DRDGold	Mining	-0.740	-0.186	***1.078******
DSY	Discovery	Life Assurance	-0.046	***0.867******	***-0.167*****
DTC	Datatec	Computer Services	***0.646******	***0.713*****	***0.301*****
EHS	Efraz Highveld Steel & Van	Steel	0.663	-0.323	***0.503******
ELI	Ellies	Electrical Equipment	0.027	0.386	0.140
EMI	Emira Property	Property Management	***0.508******	0.134	***-0.227******
EOH	EOH Holdings	Computer Services	0.293	0.305	-0.147
EQS	Eqstra Holdings	Diversified Industrials	0.025	***0.912*****	-0.062

Name of listed stock (Code)	Summary of ALSI Constituents				
	Name of Company	Nature of Business	Constituent beta coefficients		
			FINI	INDI	RESI
EXX	Exxaro Resources	Mining	-0.168	0.043	0.962***
FBR	Famous Brands	Restaurant and Pub Franchises	0.201	1.022***	-0.244**
FFA	Fortress Income Fund	REITs Diversified	0.481**	-0.214	-0.126
FPT	Fountainhead Property	Real Estate Investment Trust	0.808***	-0.090	-0.164**
FSR	Firstrand	Banks	1.412***	-0.259**	-0.070
FWD	Freeworld Coatings	Speciality Industrial	0.598**	0.801**	-0.153
GFI	Goldfields	Mining	-0.074	-0.487	0.924***
GND	Grindrod	Marine Transportation	-0.176	1.023***	0.188
GPL	Grand Parade	Speciality Finance	-0.043	0.292	0.096
GRF	Group Five	Heavy Construction	0.210	0.947***	0.026
GRT	Growthpoint Properties	Property Management	0.750***	-0.133	-0.132
HAR	Harmony Gold	Mining	-0.318	-0.376	1.133***
HCI	Hosken Holdings	Investment Companies	1.042	-0.431	-0.018
HDC	Hudaco	Industrial Supplier – Engineering	0.329	0.438	0.022
HLM	Hulamin	Steel	0.276	0.394	0.199
HPA	Hospitality Property Fund A	Hotel and Resort Property Fund	0.024	0.147	-0.060
HPB	Hospitality Property Fund B	Hotel and Resort Property Fund	0.518	0.059	0.085
HSP	Holdsport	Retailers – Multi Department	0.531	0.216	-0.152
HWN	Howden Africa	Industrial Machinery	-0.121	0.118	0.207
HYP	Hyprop	REITs Retail	0.698***	-0.067	-0.247***
ILA	Iliad Africa	Building Material Supplier	0.363	0.525	0.045
ILV	Illovo Sugar	Food Processors	0.100	-0.062	0.437***
IMP	Impala Platinum	Mining	0.495***	-0.555**	1.123***
INL	Investec Limited	Investment Services	0.642***	0.633***	0.015
INP	Investec PLC	Investment Services	0.662***	0.549***	0.084
IPF	Investec Property Fund	REITS Diversified	0.984**	-0.117	-0.633**
IPL	Imperial Holdings	Transportation Services	0.437**	0.770***	-0.120
ITU	Intuprop	Real Estate Investments Trust	0.457**	0.158	0.180
IVT	Invicta Holdings	Industrial Supplier - Engineering	-0.009	0.555***	-0.028
JDG	JD Group	Retailers - Hardlines	0.841***	0.512**	-0.294***
JSE	JSE Limited	Johannesburg Stock Exchange	0.087	0.842**	0.073
KAP	Kap International	Diversified Industrials	0.033	0.717**	-0.121
KGM	Kagiso Media	Media	0.177	0.226	0.001
KIO	Kumba Iron Ore	Mining	0.307	-0.341	0.955***
LBH	Liberty Holdings	Insurance	0.011	0.598***	-0.069
LEW	Lewis Group	Furniture and Home Retailer	0.947***	0.102	-0.197**
LHC	Life Healthcare Group	Healthcare	0.572	-0.212	-0.364**
LHG	Litha Healthcare	Pharmaceuticals	-0.043	0.425	-0.054
LON	Lonmin	Mining	0.004	-0.101	1.265***
MDC	Medi-Clinic	Healthcare	0.042	0.409**	0.035
MDI	Master Drilling	Industrial Suppliers	-0.162	-0.245	0.053
MFL	Metrofile	Information Management	-0.408	0.175	0.597
MIX	Mix Telematics	Business Support Services	0.234	0.835	0.113

Name of listed stock (Code)	Summary of ALSI Constituents				
	Name of Company	Nature of Business	Constituent beta coefficients		
			FINI	INDI	RESI
MMI	MMI Holdings	Life Assurance	***0.672****	0.183	-0.002
MML	Metmar	Nonferrous Metals	-0.240	0.642	0.208
MND	Mondi Limited	Paper	0.240	***0.818***	0.245
MNP	Mondi Plc	Paper	0.024	***1.139****	0.274
MPC	Mr Price Group	Retailers – Soft Goods	***0.559****	***0.717****	***-0.362****
MPT	Mpact	Containers and Packaging	0.360	-0.001	-0.163
MRF	Merafe Resources	Mining	-0.291	***0.929***	***0.726****
MSM	Massmart	Retailers – Multi Department	0.159	***0.911****	***-0.271****
MTA	Metair Investments	Auto Parts	-0.192	***0.771***	0.098
MTN	MTN Group	Wireless Telecom Services	0.268	***0.875****	-0.069
MTX	Metorex	Mining Supplier	-0.113	***1.004***	0.191
MUR	Murray and Roberts	Heavy Construction	0.472	0.363	0.089
MVS	Mvelaphanda	Mining	0.409	-0.384	0.163
NBC	Newbond	Investment Companies	-0.489	0.727	-0.542
NED	Nedbank	Banks	***1.012****	0.139	***-0.229****
NEP	New Europe Property	Real Estate Holdings and Development	0.096	0.194	-0.176
NHM	Northam Platinum	Mining	0.104	0.319	***0.847****
NIV	Niveus Investments	Investment Companies	-1.378	1.473	0.543
NPK	Nampak	Containers and Packaging	0.236	***0.322***	-0.048
NPN	Naspers	Broadcasting Contractors	0.044	***1.217****	0.010
NT1	Net 1 Ueps Tech	Financial Administration	-0.428	0.826	-0.064
NTC	Netcare	Healthcare	0.208	***0.558****	-0.034
OCE	Oceana Group	Farming and Fishing	***-0.496***	***0.597***	0.026
OCT	Octodec	Real Estate Holdings and Development	***0.548****	-0.020	***-0.236***
OML	Old Mutual	Life Assurance	***0.884****	0.217	0.140
OMN	Omnia Holdings	Speciality Chemicals	0.246	0.424	0.097
OPT	Optimum Coal	Mining	0.334	-0.698	0.217
PAM	Palabora Mining	Mining	0.097	0.082	***0.574****
PAN	Pan African Resource	Mining	-0.524	0.408	0.482
PAP	Pangbourne Properties	Property Management	***0.604****	-0.233	0.017
PET	Petmin	Mining and Industrial Services	0.101	0.399	0.361
PFG	Pioneer Foods	Food Processors	0.050	0.488	-0.019
PGL	Pallinghurst Resources	Investment Companies	0.782	0.811	-0.156
PGR	Peregrine Holdings	Investment Services	***0.535***	***0.587***	0.080
PHM	Phumelela	Gaming and Leisure	-0.250	0.450	0.128
PIK	Pick ‘n Pay	Food and Drug Retailers	0.127	***0.443****	-0.014
PMM	Premium Properties	Real Estate Holdings and Development	***0.678****	0.024	***-0.266***
PNC	Pinnacle Technology	Computer Hardware	0.113	0.851	***0.719***
PPC	Pretoria Portland Cement	Building and Construction Materials	***0.537****	0.285	-0.091
PSG	PSG Group	Investment Services	0.515	***0.723***	-0.159
RBP	Royal Bafokeng Platinum	Mining	0.614	-0.630	***0.670****
RBX	Raubex Group	Heavy Construction	0.070	***1.080****	-0.137
RCL	RCL Foods	Farming and Fishing	-0.046	***0.580***	-0.039

Name of listed stock (Code)	Summary of ALSI Constituents				
	Name of Company	Nature of Business	Constituent beta coefficients		
			FINI	INDI	RESI
RDF	Redefine	REITs Diversified	0.505***	0.140	-0.218**
REB	Rebosis Property	REITs Diversified	0.290	0.130	-0.268
REI	Reinet Investments	Investment Companies	-0.431**	1.322***	-0.179
REM	Remgro	Diversified Industrials	0.364***	0.511***	-0.108
RES	Resilient Property	REITs Retail	0.587***	-0.079	-0.191**
RLO	Reunert	Electrical Equipment	0.484***	0.488***	-0.198**
RMH	RMB Holdings	Banks	1.310***	-0.196	-0.063
RMI	Rand Merchant Insurance	Investment Companies	0.388	0.045	0.145
RPL	Redefine International	Real Estate Holdings and Development	-0.684	1.317***	-0.002
SAB	SABMiller	Beverages - Brewers	-0.314***	1.044***	0.048
SAC	SA Corporate Real Estate	REITs Diversified	0.528***	0.048	-0.083
SAP	Sappi	Paper and Pulp	0.027	0.971***	0.206
SBK	Standard Bank Group	Banks	1.422***	-0.385***	-0.034
SCL	Sacoil Holdings	Oil - Integrated	0.941	-0.864	0.345
SFN	Sasfin	Investment Services	0.313	0.564	-0.116
SGL	Sibanye Gold	Mining	2.217	-3.538	2.341*
SHF	Steinhoff	Furnishings and Floor Coverings	-0.130	1.407***	0.023
SHP	Shoprite	Food and Drug Retailers	-0.015	0.856***	-0.280***
SIM	Simmer and Jacks Mines	Mining	0.608	-0.834	1.042**
SLM	Sanlam	Life Assurance	0.726***	0.207	-0.030
SNT	Santam	Insurance – Non-Life	0.290	0.357	-0.032
SNU	Sentula	Mining	0.281	0.501	0.112
SOL	Sasol	Chemicals - Speciality	-0.107	0.301**	0.709***
SPG	Super Group	Business Support Services	0.635**	0.235	0.087
SPP	The Spar Group	Food and Drug Retailers	-0.007	0.640***	-0.107
SSK	Stefanutti Stocks Holdings	Heavy Construction	0.477	0.526	0.076
SUI	Sun International	Gaming and Leisure	0.490***	0.250	0.007
SUR	Spur Corporation	Restaurants and Pubs	0.031	0.462**	0.011
SYC	Sycom Property	Real Estate Investments Trust	0.588***	0.196	-0.271***
TBS	Tiger Brands	Food Processors	0.044	0.767***	-0.114
TCP	Transaction Capital	Speciality Finance	0.883*	-0.666	-0.097
TFG	The Foschini Group	Retailers –Soft Goods	0.948***	0.400**	-0.251***
TKG	Telkom	Fixed Line Telecom Services	0.033	0.224	0.252
TMG	Times Media Group	Media Agencies	0.513	0.645	-0.420
TON	Tongaat	Food Processors	0.138	0.247	-0.017
TRE	Trencore	Transport Services	0.015	0.353	0.108
TRU	Truworths	Retailers –Soft Goods	0.637***	0.467**	-0.242***
TSH	Tsogo Sun	Gaming and Leisure	0.336	0.316	-0.144
VKE	Vukile Property	Real Estate Holdings and Development	0.586***	0.139	-0.132
VOD	Vodacom	Wireless Telecom Services	-0.084	0.846**	-0.112
WBO	WBHO	Heavy Construction	0.398**	0.511**	-0.104
WEZ	Wesizwe	Mining	0.515	-0.430	0.854**
WHL	Woolworths	Retailers – Multi Department	0.487***	0.737***	-0.230***

Name of listed stock (Code)	Summary of ALSI Constituents				
	Name of Company	Nature of Business	Constituent beta coefficients		
			FINI	INDI	RESI
YRK	York Timber	Forestry	-0.185	0.247	-0.165
ZED	Zeder Investments	Speciality Finance	-0.015	***0.460****	0.084