

**UNIVERSITY OF KWAZULU-NATAL**

**THE IMPACT OF INCORPORATING A BOND INDEX  
INTO THE PROXY FOR THE MARKET PORTFOLIO**

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This thesis is submitted in fulfilment of the requirements for the degree of  
**Master of Commerce** by research.

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2011

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## ACKNOWLEDGEMENTS

To begin with I would like to thank my supervisor Barry Strydom, whose advice, support and, most importantly, patience have been of great help to me. Our meetings were always enlightening and offered such great direction. Your guidance during this process was invaluable. To my co-supervisor Andrew Christison, a huge thank you for all of the time and effort that you took out of your hectic work schedule to help with the completion of this thesis. Next I would like to thank Ailie Charteris, who despite her own lecturing and supervising commitments was always willing to offer her time and advice even though she had no obligation to this thesis. Your constant support throughout the past two years is greatly appreciated.

I would also like to thank my girlfriend Kim Thompson, whether it was typing formulas in excel, proof reading, or just helping me through trying times, her love and support was unwavering. Finally I would like to thank my parents, not only have they helped and supported me through these past two years, they have been amazing role models for me my entire life. Words can't express how lucky I am to have them.

## ABSTRACT

The Capital Asset Pricing model (CAPM) is the most widely used equity valuation model in both the United States of America (U.S.) and South Africa, thus its importance in corporate finance cannot be underestimated. The largest criticism of the CAPM lies in the difficulties with estimating its parameters and in particular the return on the market parameter. Roll (1977) believed that it is impossible to estimate the market portfolio let alone find a good proxy for it. The common trend amongst practitioners is to use a broad based stock index such as the S&P 500 or in South Africa's case the All Share Index (ALSI) as a proxy for the market portfolio. However these methods are questionable, as the market portfolio theoretically contains all risky assets held in proportion to their market value, and stock indices ignore large asset classes such as bonds. Furthermore, using a broad based stock index in the South African context ignores South African specific problems such as the supposed segregation of the market to the Resource and Financial and Industrial sectors.

Therefore the purpose of this study was to determine whether simply using the broad based stock index, the ALSI, as a proxy for the market portfolio would suffice or whether the inclusion of debt instruments and the acknowledgement of the segregation on the JSE would enhance the proxy's performances. First a set of theoretical requirements that a proxy must satisfy to be considered a suitable proxy for the market portfolio were derived. Then a review of literature on the matter was undertaken, which showed that studies in both the U.S. and South Africa had had mixed results. Next, the various proxies were formed, and tested using the two-pass regression method.

The two-pass regressions that were run with the model comprising solely of the ALSI as a proxy, produced a negative sloping SML. This result suggested an inverse relationship between risk and return, which is contradictory to the theory set out in chapters two and three. Thus robustness tests were performed on the model, but none solved the problem. Next the proposed multifactor models were tested to see if they would enhance the results of the first model. Although the results improved slightly, they too did not solve the problem. Thus, in conclusion it was found that incorporating a bond index into the proxy for the market portfolio did not significantly enhance the use of the CAPM in South Africa.

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## LIST OF ACRONYMS

AIC	Akaike Information Criterion
ALBI	All Bond Index
ALSI	All Share Index
Alt-X	Alternative Exchange
AMEX	American Stock Exchange
APT	Arbitrage Pricing Theory
ASSA	Actuarial Society of South Africa
BESA	Bond Exchange of South Africa
CAPM	Capital Asset Pricing Model
CFO	Chief Financial Officer
CLRM	Classical Linear Regression Model
CML	Capital Market Line
CRSP	Centre for Research in Security Prices
DDM	Dividend Discount Model
FINDI	Financial and Industrial Index (Financial and Industrial 30)
GLS	Generalised Least Squares
GOLDI	Gold Index
HQIC	Hannan-Quinn Information Criterion
INDI	Industrial Index
JSE	Johannesburg Stock Exchange
LM	Lagrangian Multiplier
MAE	Mean Absolute Error

MAPE	Mean Absolute Percentage Error
MPT	Market Portfolio Theory
MSCI	Morgan Stanley Capital International
MVC	Mean Variance Criterion
NASDAQ	National Association of Securities Dealers Automated Quotations
NCD	Negotiable Certificate of Deposit
NPV	Net Present Value
NYSE	New York Stock Exchange
PWC	PriceWaterhouseCoopers
RESI	Resource Index (Resource 10)
RMSE	Root Mean Squared Error
SA	South Africa
SARB	South African Reserve Bank
SBIC	Schwartz Bayesian Information Criterion
SML	Security Market Line
S&P	Standard and Poor's
T-bill	Treasury Bill
T-bond	Treasury Bond
UK	United Kingdom
U.S.	United States of America
WACC	Weighted Average Cost of Capital
WLS	Weighted Least Squares



## CHAPTER 1

### INTRODUCTION

#### 1.1 Background and Problem Definition

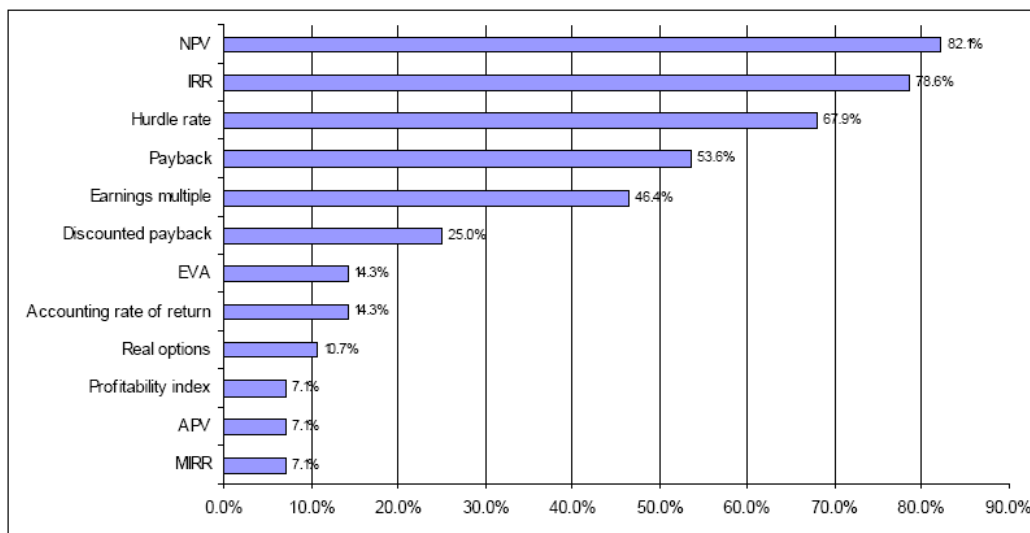
##### 1.1.1 The Valuation of Assets in Financial Management

One of the most difficult facets of financial management is the valuation of various projects and assets (Harrington, 1987: 1; Linley, 1992: 1). The practice of valuing an asset is merely the determination of the fair price that an investor would be willing to pay for the asset. However, this practice has led to much debate in financial circles. According to Graham and Harvey (2001: 197), Correia and Cramer (2008: 36) and PriceWaterhouseCoopers (2009: 21), one of the most popular methods used by Chief Financial Officers (CFO's) when evaluating projects in both the United States (U.S.) and South Africa is the Net Present Value (NPV) model. In Graham and Harvey's (2001: 197) U.S. survey, it was found that 74.9% of CFOs always or almost always apply the NPV model when evaluating a project, while in South Africa, Correia and Cramer (2008: 36) found that 82.1% of CFOs always or almost always apply the NPV model (as shown in figure 1-1). PriceWaterhouseCoopers (PWC) (2009: 21) found that in South Africa amongst 27 financial analysts surveyed, almost all use the NPV approach (income approach). In the PWC survey, not only was it found that the NPV approach was the primary approach in South Africa, but as can be seen from figure 1-2, the method has grown in popularity since 2007.

In order to apply the NPV model, various inputs are required, these inputs include estimates of the investment's future cash inflows and costs, as well as an estimate of the company's discount rate which is used to calculate the present value of the forecasted cash inflows (Firer, Ross, Westerfield and Jordan, 2004: 250-251; Brown and Reilly, 2009: 327). The future cash inflows and costs are usually forecasts, whilst the most common discount rate used for the NPV method is the Weighted Average Cost of Capital (WACC) (Firer, 1993: 23; Brown and Reilly, 2009: 327). Along with the after-tax cost of debt, one of the required inputs for the WACC is a cost of equity for the project (Brigham and Ehrhardt, 2005: 307). The cost of debt is not difficult to

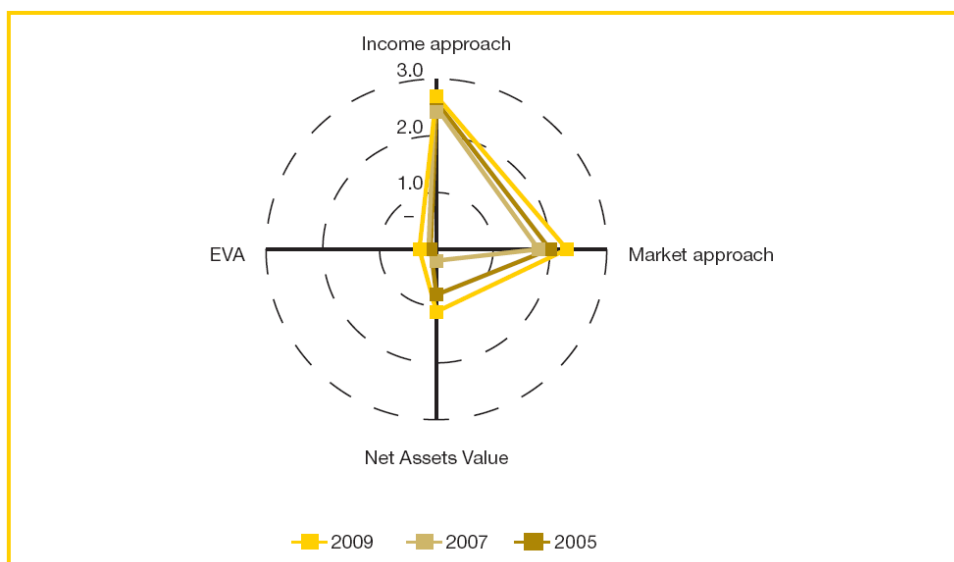
attain as it is a market-related value. However, calculating the cost of equity is a complex process as it is a theoretical concept representing the relative risk of a company, and thus is not directly observable (Firer, 1993: 24).

**Figure 1- 1 Project valuation methods used in practice in South Africa**



(Source: Correia and Cramer 2008: 36)

**Figure 1- 2 Valuation approaches used in practice in South Africa**

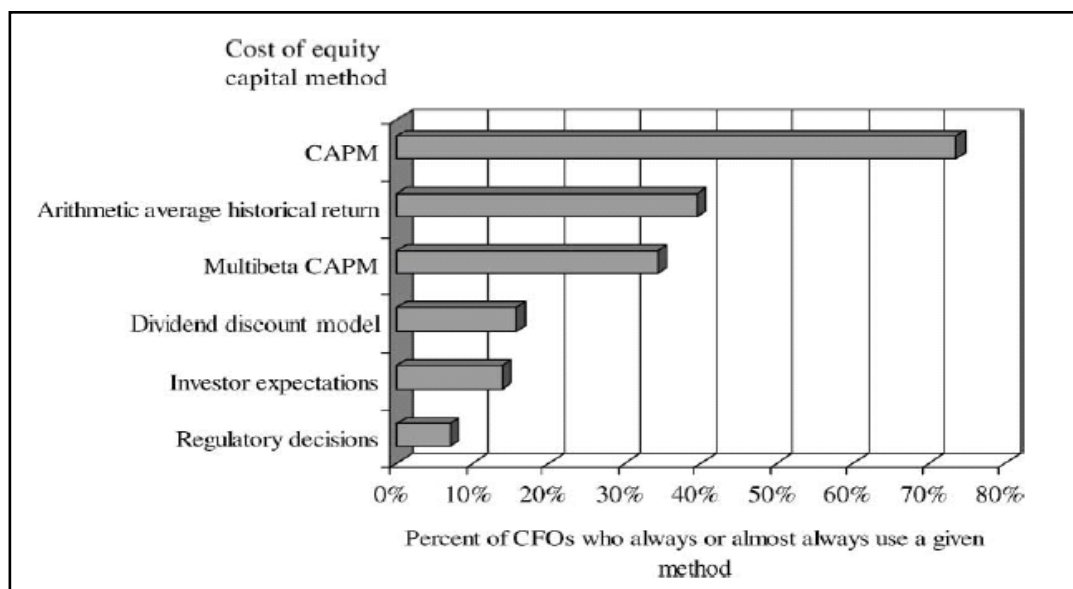


(Source: PriceWaterhouseCoopers, 2009: 21)

There are various methods by which the cost of equity can be calculated, such as the Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), Bond-Yield-Plus-Risk-Premium and Dividend Discount Model (DDM) (Bodie, Kane and Marcus, 2007: 227, 390-414; Firer *et al*, 2008: 411, 466-470). The DDM has serious limitations in that it can only be used by companies that pay dividends on a regular basis, and furthermore it assumes that the dividend growth rate is constant. Whilst the Bond-Yield-Plus-Risk-Premium method is often ignored due to the difficulties inherent in attempting to get accurate estimates for the risk premium (Firer, 1993: 25). Further, Bodie *et al* (2007: 229) point out the APT model only applies to well diversified portfolios, and although it can be used for individual assets, this will involve a considerable amount of additional effort.

From a practical point of view, the survey carried out by Graham and Harvey (2001: 203) in the U.S. found that although a number of techniques are used, the Capital Asset Pricing Model (CAPM) is the most popular model when evaluating the cost of equity. Graham and Harvey (2001: 201) found that 73.5 percent of respondents surveyed always, or almost always used the CAPM. This is depicted in figure 1-3 below.

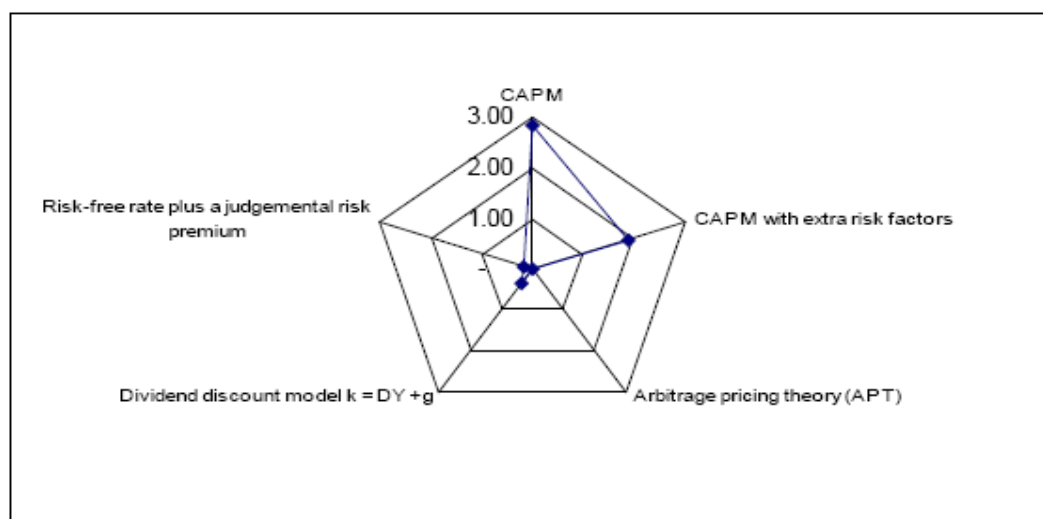
**Figure 1-3 Cost of equity methods used in practice in the U.S.**



(Source: Graham and Harvey, 2001: 203)

It was also found by Correia and Cramer (2008: 41) that in South Africa, all the CFOs that took part in the survey used the CAPM or some variant of it to determine the cost of equity. The CAPM is so popular that Correia and Cramer (2008:41) point out that practitioners do not use the DDM, the Bond-Yield-Plus-Risk-Premium approach or the Arbitrage Pricing Theory (APT) in practice. These results are shown in figure 1-4 below, the diagram illustrates the relative weights associated with the different approaches based on the respondents of the survey. As can clearly be seen, the CAPM is the most popular model. The 2009 survey of PriceWaterhouseCoopers (2009: 26) also found that “the CAPM is the primary methodology used to estimate the cost of equity, with all respondents stating that they either always or frequently use it”.

**Figure 1- 4 Cost of equity methods used in practice in South Africa**



(Source: Correia and Cramer, 2008: 41)

## 1.2 The Capital Asset Pricing Model

The surveys conducted by Graham and Harvey (2001: 203), Correia and Cramer (2008: 41) and PriceWaterhouseCoopers (2009: 26) illustrate that the CAPM is a very important model in the world of finance. The CAPM represents an equilibrium risk – return relationship, where the expected return on a risky asset or portfolio of assets is equivalent to the sum of the return on a risk-free asset and a premium awarded for bearing risk (Pike and Neale, 2006: 249). Sharpe (1964: 436) describes the risk associated with this model as systematic or non-diversifiable risk,

as an investor cannot be rewarded for bearing risk that can be diversified away. Reilly and Brown (2006: 240) echo these sentiments and describe the CAPM as a model that depicts the equilibrium risk-return relationship, showing that the expected return on a risky security or portfolio of securities is linearly related to non-diversifiable risk, as it is assumed that any firm-specific risk can be diversified away by the investor. As Firer *et al* (2008: 411) point out, the relationship between risk and return displayed in the CAPM can be depicted graphically by the Security Market Line (SML). If the CAPM provides an accurate description of capital markets, it is a simple matter to establish the risk/return relationship for efficient market strategies (Laubscher, 2002: 133). The SML is set out in the following formula:

$$E(R_i) = R_f + \beta_i [E(R_m) - R_f] \quad (1.1)$$

Where:

$E(R_i)$  is the expected return on security i

$R_f$  is the return on the risk-free asset

$\beta_i$  is asset i's beta (volatility of the share relative to the market portfolio)

$E(R_m)$  is the expected return on the market portfolio

The model was developed under several assumptions, of which one assumption is that there exists an “optimally efficient market portfolio” (Laubscher, 2002: 134). Theoretically the market portfolio contains all the risky assets in the market held in their respective proportions. The portfolio is theoretically the most diversified portfolio possible and should have the same return as the actual market (Harrington 1987: 166; Laubscher, 2002: 134; Reilly and Brown 2006: 231). Conceptually the CAPM is a very simple model, however, a number of problems are faced due to the crude assumptions underlying it. As a result of these simplistic assumptions, one of the largest problems that most of its users face, is in estimating the variables of the model. Firer (1993: 23) emphasizes this point when he states “very little help is offered to the practitioner in the selection of appropriate values for the parameters of this model, in particular the risk-free rate and the market risk premium”. It is because of these underlying assumptions that the application of the CAPM is not as simple as it may seem.

### 1.3 The Application of the CAPM

As has been pointed out in the afore mentioned surveys, the CAPM is a very popular model, suggesting that the concern for practitioners when calculating the cost of equity is not which model to use, but rather the complication lies in the estimation of the parameters of the CAPM. Due to the popularity of the CAPM it is crucial that the parameters of the model are estimated accurately (Harrington, 1983: 4; Laubscher, 2002: 133; Bowie and Bradfield, 1993: 6). Here-in lies the problem associated with the CAPM. As researchers such as Bowie and Bradfield (1993: 6) have mentioned... “since the development of modern portfolio theory and the consequent emergence of asset pricing models, much effort in the finance literature has focused on the accurate estimation of the parameters underpinning these models”. This was reiterated by Correia and Uliana (2004: 66), as they stated “in practice the application of the CAPM has been hampered by difficulty in determining every one of its variables”. Thus it can be seen that despite the importance and apparent usefulness of the CAPM, there is debate on how to estimate its separate parameters. The reason for the difficulty in estimating the parameters is that the variables outlined in equation 1.1 are all theoretical values and thus proxies for these parameters must be identified (Firer, 1993: 25)

To emphasise the importance of selecting appropriate proxies for the parameters in the CAPM, Bruner, Eades, Harris and Higgins (1998: 22-23) conducted a study in which they measured the effect of the erroneous estimation of the CAPM parameters. Bruner et al (1998: 22-23) conducted their study on two companies and found that for the first company (Black & Decker) the WACC could vary from a maximum of 12.8% to a minimum of 8.5%, the second company (MacDonald's) could vary from 11.6% to 9.30% depending on the proxies that were used. To illustrate the impact these variations could have on either company, if it is assumed that there is a perpetual flow of income of \$10 million for both companies the present value for Black & Decker would range from \$78 million to \$118 million, whilst the present value of MacDonald's would range from \$86 million to \$108 million (Bruner et al, 1998: 23). The difference in these values is, as can be seen, very large and the erroneous values can have large influence on a firm's profitability.

Thus this example shows that it is very important to estimate the CAPM's parameters as accurately as possible, because the CAPM will have a direct impact on whether the NPV is positive or negative. Incorrect NPV values could ultimately result in projects that will be either

accepted when they should not, or projects that will be rejected when they should be accepted, both scenarios will have massive repercussions for a firm. As shown in equation 1.1, the three parameters that need to be estimated are the return on a risk-free asset, a beta ( $\beta$ ), and the return on the market portfolio.

Sharpe (1964: 431-433) describes a riskless asset as an asset with which its returns have zero variance and zero covariance with any other asset – basically an asset with no risk. However there are questions amongst academics as to which is the most appropriate proxy for the risk-free asset as well as whether such an asset even exists. Despite these questions, authors such as Harrington (1983: 149), Carleton and Lakonishok (1985: 39) and Laubscher (2002: 134) believe suitable proxies can be found for the risk-free asset. A study carried out in the U.S. by Bruner et al (1998: 16) illustrated that the majority of corporate firms in the U.S. surveyed used returns on government securities as a proxy for the risk-free rate. Whilst in South Africa, Correia and Uliana (2004: 71) explain that the surrogates that are usually used for the risk-free rate are also government securities. Strydom and Charteris (2009: 2) point out that the debate is not whether or not to employ a government security but rather the term of the government security. However, Affleck-Graves *et al* (1998: 11), Harrington (1987: 149) and Firer (1993: 26), found that the T-bill would be an appropriate proxy for the risk-free asset, and thus for the purpose of this study T-bills will suffice.

The second parameter that needs to be calculated in order to use the CAPM is beta ( $\beta$ ). Laubscher (2002: 134) describes beta as a parameter that “measures the volatility (i.e. the fluctuations in price) of a share or share portfolio and estimates how the expected returns on a share or share portfolio will move relative to the movement in the returns in the market portfolio”. Both Laubscher (2002: 134) and Correia and Uliana (2004: 73), state that betas are often obtained from historical betas, and these historical betas are normally obtained by regressing the particular share returns to the market portfolio returns (Van Rensburg 1995; Bodie *et al* 2007: 205). This shows that the market proxy plays an instrumental role in calculating the beta for the model. Thus this point illustrates that not only is it important to find an appropriate proxy for the parameter return on the market, the proxy will also play a vital role in another parameter of the model – beta.

Despite the difficulty in estimating all the parameters of the CAPM, it is believed that a suitable proxy can be found for the risk-free rate parameter, and as can be seen, the beta parameter for the model is highly dependent on an accurate estimation of the market portfolio. Thus the importance of an accurate estimate for the return on the market portfolio is evident. Numerous studies in the U.S. have been conducted on the most suitable proxy for the market portfolio (Roll, 1977; Brigham and Shome, 1981; Amihud and Mendelson, 1991; Stambaugh, 1982; Vandell and Stevens, 1982; Carleton and Lakonishok, 1985; Roll and Ross, 1994; Levy and Roll, 2009). The results of these studies have been mixed, and although the conclusions may be inappropriate in a South African context because of how different the two markets are, lessons can be learnt from these studies and their results. Due to the importance of the CAPM in the South African financial world, it is vital that the lessons learnt are applied so that a parameter, like the return on the market, is estimated accurately.

### **1.3.1 Estimation of the Return on the Market**

One underlying assumption of the CAPM is that all investors will choose to hold the market portfolio (Bodie *et al* 2007: 205) as it minimizes risk and is the optimal portfolio. Firer (1993: 31) describes the market portfolio as a portfolio that... “should contain *all* risky assets in the economy in proportion to their market value”, reiterating this point Laubscher (2002: 134) defines the market portfolio as a portfolio that... “consists of all risky assets and is the most broadly diversified portfolio available”. These definitions imply that assets such as art work, real estate, debt instruments and all other investable assets make up the portfolio. Laubscher (2002: 134) goes on to state “the market return is not easy to estimate” and adds that there is doubt as to whether there is an index on the stock exchange that can accurately depict the market portfolio.

Roll (1977) was one of the first academics to criticise the CAPM, and in particular the proxy for the market portfolio, saying that it was not possible to estimate the market portfolio let alone find a good proxy for it. Roll (1977: 131) stated that “the market portfolio identification problem constitutes a severe limitation”. Despite Roll’s criticisms the common trend in modern finance is to use a broad-based index of common stocks such as the S&P 500 in the U.S., and the All Share Index (ALSI) in South Africa (Harrington 1987: 167; Firer 1993: 31) as proxies for their respective markets. However, as many academics such as Stambaugh (1982), Shanken (1987), Firer (1993), Goltz and Le Sourd (2010) point out, these market indices are only equity



indices and make up a small proportion of the total market and ignore large asset classes such as bonds and real estate. Aside from bonds and real estate, the proxy also ignores other risky assets such as art, stamps, human capital, etc (Jagannathan and Wang, 1996: 5). Thus theoretically, the proxies used in practice are very far from the true market portfolio.

To further complicate the issue, a problem which is particularly relevant in South Africa, is that of market segmentation. Academics such as Van Rensburg and Slaney (1997: 1) and Correia and Uliana (2004: 65) suggest that due to the segmentation between the Resources and the Financial and Industrial sectors, along with the historical dominance of the Mining sector on the Johannesburg Stock Exchange (JSE), there is a need to question the trend of using the ALSI as a proxy for the market, as there may be a need to incorporate Resource, Financial and Industrial information. Bowie and Bradfield (1993: 13) highlight this point when they state “the choice of which market index to use... on the JSE raises the question of whether there is self imposed segmentation occurring between the Mining and Industrial sectors on the JSE”. This point of market segmentation could prove to be valid as Firer (1993:31-32) believed that the market for a certain investor is characterized by the investment options available to him or her, and because of this, investors should choose a market proxy that is similar to his or her own investment strategy. Firer (1993: 31-32) believed that such a strategy would almost, if not completely eliminate firm specific risk.

Bowie and Bradfield (1993: 13-14) expand on these points, as they argue that numerous investors believe mining shares represent a different type of risk and thus mining shares form a different market. They go on to mention that the market corresponds to the “universe of shares available to an investor”, thus if there is evidence of segmentation on the JSE, say between Resource, Financial and Industrial sectors, it could be argued that shares would be priced to compensate investors for bearing the risk of these market sectors separately. Basically, each of these sectors have different risk premia that is not captured by a single factor CAPM. Thus if a significant amount of investors separate their capital by investing in Financial and Industrial rather than resources or vice versa, then the segmentation between the sectors should have an effect on the beta coefficients related to the sectors. It can therefore be argued that the... “estimation of systematic risk must take account of the segmentation by using appropriate (different) market proxies for the securities...” in the relevant sectors. These points are backed up by the findings of Venter, Bradfield and Bowie (1992: 14) where they found that outputs of the CAPM were “dramatically” improved when sector specific indices were used.

Following Roll's critique (1977) and because of the issue of segmentation in South Africa, the question has to be asked if the ALSI is an appropriate proxy for the market portfolio? These discussions illustrate that, according to theory, practitioners are far from using an accurate proxy for the market portfolio. It is generally accepted by academics like Roll (1977), Harrington (1983), Firer (1993) and Laubscher (2002) that the market portfolio cannot be mimicked, and that accurate proxies will be hard to find, however the above arguments suggest that there could be possible room for improvement from the current method of using a broad-based index of common stock.

What is worth noting in the definition of the market portfolio is that firstly the portfolio is mean-variance efficient and secondly, the portfolio contains *all* risky assets. When concerned with mean-variance, broad based indices of common stock have been found wanting in the past (Roll, 1977; Kandel and Stambaugh, 1987). This is where the addition of debt instruments could play a role. Not only will it add a very large asset class to the proxy, thus getting closer to conforming with the definition of the portfolio containing all risky assets, it could help to attain mean-variance efficiency of the proxy too. With the fairly recent formation of the All Bond Index (ALBI), which is an index that consists of the top 20 listed bonds, ranked by market capitalisation and liquidity (BESA/ASSA 2000: 5), there could be a simple method to adding bonds to the proxy and thus to get a step closer to an accurate proxy for the market portfolio.

Aside from the addition of a bond index to the proxy for the market portfolio, the study will also aim to examine whether segmentation on the JSE will influence the use of the proxy for the market portfolio. Thus investigating whether or not there is a need to take into consideration Resource, Financial and Industrial data. The ultimate goal of the study is to obtain findings that can improve the capacity of corporate management to apply the CAPM in calculating the cost of equity, which is one of the major stepping-stones to correctly evaluating a project.

## **1.4 Research Problem and Objectives**

### **1.4.1 Research Problem**

Thus the research problem, which is the focus of this study, is summarised in the following question:

*Will the incorporation of a bond index into the proxy for the market portfolio whilst also allowing for market segmentation enhance the use of the CAPM in South Africa?*

### **1.4.2 Research Objectives**

The purpose of this study is therefore to identify whether the performance of the CAPM can be improved by adding a bond index to the proxy for the market portfolio, and if so, in what combinations? Specifically the three primary objectives of this study are:

- Does the common trend of using the ALSI as a market portfolio suffice in the South African context?
- To test whether a portfolio synthesized from the market and bond indices will enhance the proxy i.e. are bonds priced as a risk factor?
- Does the existence of market segmentation on the JSE allow for further enhancements of the proxy? i.e. are the separate indices priced as separate risk factors?

## **1.5 The Scope and Method of the Study**

### **1.5.1 Scope of the Study**

The establishment of the correct parameters to use in the CAPM is crucial given the popularity and thus importance of the model in capital budgeting decisions. The centre of attention for this study, however, is the estimation of the return on the market portfolio and not the other variables. This is because firstly, the estimation of the market portfolio plays such a vital role in the estimation of beta, and secondly, it is believed that adequate proxies are available for the

risk-free rate as well as the fact that there is a relative amount of consensus amongst academics on the matter as explained in section 1.3 (Harrington, 1983: 149; Carleton and Lakonishok, 1985: 39; Firer, 1993: 26; Affleck-Graves *et al*, 1998: 11; Laubscher, 2002: 134). The research problem implicitly assumes that the CAPM relationship holds. This assumption appears plausible given the empirical results of Bradfield, Barr and Affleck-Graves (1988), Bradfield and Barr (1989) and Ward (1994). Ward (1994: 100) went on to mention that the CAPM withstood the tests of the JSE. Not all academics however agree on this point (for example Van Rensburg and Slaney (1997) and Van Rensburg (2002) found evidence questioning the validity of the model), the purpose of this study however is to examine whether adding a bond index to the market proxy improves the results of the CAPM and not the validity of the CAPM in SA.

The performance of various proxies, namely, one of the ALSI alone, the ALSI and ALBI, the RESI and FINDI, and a proxy consisting of the RESI, FINDI and ALBI, are examined and compared for the period January 2000 to December 2010. Data for the period January 1997 to December 1999 is used as the out-of-sample data for the initial estimation period known as beta sorting. The time period of the study was constrained by the availability of data on the ALBI, as it was only formed in July 2000 (Bond Exchange of South Africa, 2000: 4), and therefore the period could not be extended further back than 2000. Monthly prices and dividend yields were obtained, in accordance with the studies of Black *et al* (1972) and Fama and MacBeth (1973) who all used monthly returns in tests of the CAPM. This data was collected from the JSE statistics and records department, the South African Reserve Bank (SARB) and McGregor BFA. However, shares listed on the venture capital market, the alternative exchange (Alt-X) and the development capital market were not considered due to the affect of thin trading. In addition to ordinary shares, data was also collected from the JSE on preference shares. This was done to increase the number of assets included in the assessment of the proxies for the market portfolio.

### **1.5.2 Methodology**

This study is made up of both a literature review and an empirical analysis. In the first part of the paper, the literature review, a set of theoretical criteria for the proxy for the market portfolio are developed and discussed. In the literature review the mean-variance efficiency of various market proxies are examined, and the most commonly employed proxies in both the U.S. and South Africa are discussed at length, comparing them to the theoretical criteria that was set out.

The literature review also looks at the addition of bonds to the market proxy. Finally, the South African specific problem of market segmentation is theoretically discussed.

The second part of the study involves estimating the proxies for the market portfolio, then testing these proxies in a CAPM framework and comparing them to determine the most suitable proxy for the market portfolio. The first step in the empirical analysis is the selection and definition of parameters. The first parameter to be formed was the portfolios, as grouped data allows for the effects of non-independence (Black *et al* 1972: 8). The formation of the portfolios is done by allocating the ordinary and preference shares obtained from the JSE into portfolios in accordance with the studies conducted by Black *et al* (1972) and Fama and MacBeth (1973). As mentioned in section 1.5.1, the shares will be sorted based on the beta sorting procedure. The use of portfolios help to minimise the presence of non-systematic risk, meaning the portfolios are more efficient than a single security, which will ultimately allow for more accurate betas to be formed as they measure systematic risk.

Next, the choice and estimation of the risk-free asset was performed, the three-month Treasury bill (T-bill) was deemed an appropriate proxy for the purpose of this study (Carleton and Lakonishok, 1985: 41; Brigham and Ehrhardt, 2005: 311). With regards to the estimation of the risk-free asset, yields on the T-bill were annualised and since the frequency of the study is monthly, monthly yields were required. Botha (2006: 240) proposed the following method to obtain monthly yields from annual yields.

$$\text{Price of T - bill: } P_t = 100\,000 - (\text{Quoted Yield} \times 91/360 \times 100\,000) \quad (1.2)$$

$$\text{Compound Return} = 100\,000 / P_t \quad (1.3)$$

$$\text{Monthly IRR} = \text{Compound Return}^{1/3} - 1 \quad (1.4)$$

(Botha 2006: 240)

Following the establishment of the first two parameters, the proxies, as the final parameter, are developed. The conventional CAPM uses the returns of the market index as a proxy for the return on the market (Harrington 1983: 87; Fifer 1993: 31; Correia and Cramer 2008: 45), and

thus the ALSI was used as the first proxy and, in a sense, as a control for the study. The total returns of the ALSI were used as the market index. The second proxy to be developed was the two factor CAPM. The proxy was specified using both the ALSI and ALBI returns as explanatory variables. This approach has the advantage that the weightings need not be pre-specified for the market portfolio proxy. The weightings were incorporated into the estimated sensitivities. The next step in the investigation was to test the impact of the apparent market segmentation on the JSE. This was carried out by using a two factor CAPM with the RESI and FINDI as the explanatory variables in the proxy. The fourth and final proxy to be formed was a combination of proxy two and three. The proxy brings together the two aspects of the study, the addition of debt instruments and the segmentation of the market. The proxy was a three factor model with the RESI, FINDI and ALBI as the variables. This proxy helped test if there is presence of segmentation, whether the addition of bonds will further enhance the proxy, and the use of the CAPM.

Following the selection of parameters, the tests on the various proxies were run. The first test that was carried out on the proposed proxies was the two-pass regression method (Black, Jensen and Scholes 1972; Fama and MacBeth 1973). Once the outputs of the two pass regression were examined, their significance was also scrutinised, which was done by comparing each proxy's t-statistic. The "t-stats" were evaluated according to whether they were significant at the 5% level of significance. The purpose of this was to find if once the ALBI (debt instruments) had been added to the proxy, whether or not its coefficient was found to be positive and significant, as this would illustrate that the market prices the risk associated with debt instruments and is therefore a relevant addition to the proxy.

The final tests of the paper involved testing the explanatory and forecasting abilities of each of the proxies. In order to test the explanatory power of a proxy, two information criteria were used, namely, Akaike's (1974) information criterion (AIC) and the Schwarz (1978) Bayesian information criterion (SBIC). In order to test the forecasting ability of the proxies, the in-sample out of sample test was used. The results from the tests were then ranked and compared according to three criteria, the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). These tests helped to determine whether the addition of bonds to the market proxy, and the acknowledgement of segmentation on the JSE, enhanced the performance of the CAPM.

## 1.6 Structure of the Study

This study consists of six chapters:

- **Chapter 1** provides a background to the study, highlighting the issues faced by practitioners when employing the CAPM and in particular the return on the market portfolio. This is followed by a definition of the research problem and objectives. Following this, the scope of the study is outlined and the research methodology of the study briefly explained. The chapter is completed with a short outline of the subsequent chapters.
- **Chapter 2** highlights the role of the market portfolio in both the derivation and applications of the CAPM. The theoretical background of the market portfolio is discussed with particular attention being paid to three points, firstly, that the estimation of the market portfolio can be very intricate, secondly, that the proxy for the market portfolio needs to be mean-variance efficient, and finally, that the market portfolio by definition contains *all* risky assets. Lastly, the intricacies involved in estimating the market portfolio are examined in depth.
- **Chapter 3** focuses on the importance of choosing an appropriate proxy for the market portfolio. The fact that the proxy for the market portfolio needs to be mean-variance efficient is explored in greater detail and a number of studies that have explored the matter, as well as test proxies are reviewed. Following this the more specific choice of market proxy in the U.S. is explored, and the feasibility of adding a bond index to the proxy for the market portfolio explored. A number of papers on the topic are discussed. Finally, the choice of market proxy in South Africa is discussed, with the issue of market segmentation being examined.
- **Chapter 4** describes the methodology that is used in this study with respect to the determination of whether the addition of a bond index to the market index, as well as the recognition of market segmentation, will enhance the market proxy in South Africa. The justification for the methodologies employed are also provided.
- **Chapter 5** presents the results obtained from the various tests described in chapter 4. These results are then discussed in conjunction with the theory from chapters 2 and 3, as well as international empirical evidence.
- **Chapter 6** provides the conclusions and implications that can be drawn from the study, as well as recommendations for future studies.

## CHAPTER 2

### THE SIGNIFICANCE OF THE MARKET PORTFOLIO

#### 2.1 Overview

In this chapter, the role of the market portfolio in applications of the CAPM is highlighted, illustrating that the parameter plays a vital role in not only the calculation of the market risk premium, but also in the calculation of any asset's beta. Next, the part that the market portfolio plays in the derivation of the Capital Asset Pricing Model is discussed briefly. Then the CAPM is developed from modern portfolio theory, and it is shown how the market portfolio, with special attention being paid to mean-variance efficiency, is established. Following this, the market portfolio is defined, after which this definition is scrutinised from a practical stand point. It is then established that as the theoretical market portfolio is practically impossible, and an adequate proxy is required to represent it. Finally, the first steps of estimating the proxy for the market portfolio are considered including the use of historical data, geometric vs. arithmetic returns, value- vs. equal weighted portfolios and time period. It is shown that all of these issues are important to the establishment of the market proxy and thus should not be ignored.

#### 2.2 The Role of the Market Portfolio in Applications of the CAPM

The studies carried out by Graham and Harvey (2001: 203), Correia and Cramer (2008: 41) and recently, the survey conducted by PriceWaterhouseCoopers (2009: 26) prove that the CAPM is a crucial model in corporate finance not only in the U.S. but in South Africa too. The model displays the equilibrium risk – return relationship, although Sharpe (1964) is usually credited with the development of the CAPM, academics such as Treynor (1961), Lintner (1965) and Mossin (1966) have all made small but crucial contributions to the model (Barr, Bradfield & Affleck-Graves 1988: 1). The model was developed under several assumptions, of which one assumption is that there exists an “optimally efficient market portfolio” (Laubscher, 2002: 134). The CAPM is illustrated in the following formula:



$$E(R_i) = R_f + \beta_i [E(R_m) - R_f] \quad (2.1)$$

Where:

$E(R_i)$	- is the expected return on a share/portfolio
$R_f$	- is the risk-free rate of return
$\beta_i$	- beta of asset i (volatility of the share i relative to the market portfolio)
$E(R_m)$	- expected return on the market portfolio
$E(R_m) - R_f$	- market risk premium

(Laubscher, 2002: 133)

The CAPM formula can be broken down into two components, firstly the compensation for the pure time value of money ( the return on the risk-free asset) and secondly, a risk premium. The risk premium is a function of the difference between the expected return of the market portfolio and the risk-free rate, multiplied by the assets unique beta (Pike and Neale, 2006: 249). Thus, conceptually the CAPM is a very simple model, however, a number of problems are faced due to the crude assumptions underlying it. As result of these simplistic assumptions, one of the largest problems that most of its users face is estimating the variables of the model (Corriea and Uliana, 2004: 66). Firer (1993: 23) emphasizes this point when he states “very little help is offered to the practitioner in the selection of appropriate values for the parameters of this model”. This poses a severe problem for the users of the CAPM, as a model is only as good as it’s inputs. The three inputs of the CAPM as can be seen from the equation are the risk-free rate of return, the beta and the return on the market. It is crucial that these parameters are estimated accurately.

In the CAPM, the return on the market portfolio appears once, when calculating the risk premium. However, the return on the market portfolio plays a vital role in the estimation of another parameter of the model, beta (Firer, 1993: 25; Laubscher, 2002: 134; Goltz and Le Sourd, 2010: 15). As Laubscher (2002: 134) describes, beta is an estimate of the risk of an asset *relative to the market portfolio*. Cuthbertson (1996: 41) illustrates that the beta of asset i is calculated as follows:

$$\beta_i = \frac{cov(R_i, R^m)}{var(R^m)} \quad (2.2)$$

Thus it can be seen that besides the fact that the market portfolio is itself one of the parameters of the CAPM, it plays a pivotal role in estimating the beta parameter. It is therefore important that the return on the market portfolio is obtained for the success of this model. The market portfolio is just as important as the other two parameters of the model in obtaining accurate cost of equity estimates for any firm, but as Fifer (1993: 29) stated, “the expected future return on the market,  $E(R_m)$ , is somewhat more difficult to estimate than  $R_f$ ”. Goltz and Le Sourd (2010: 15) also emphasize the importance of the market portfolio stating that it is “*The central prediction of the CAPM*”. Gilbertson (1979) (cited in Fifer, 1993: 33) explains that in South Africa in particular estimating the return on the market portfolio is “fraught with problems” and that there is “little guidance if any” that assist in this matter. Further to this Corriea and Uliana (2004: 65) cite that due to the apparent segmented nature of the JSE, the estimation of the market portfolio in South Africa becomes far more complicated. This study will therefore focus on the estimation of the market portfolio. While the importance of the risk-free asset and beta is noted, their estimation falls outside the scope of this study.

The quality of the results of any model, process, or system is reliant on the quality of inputs, and the CAPM is no exception; erroneous parameter values will lead to incorrect cost of equity estimates and possibly wrong decisions concerning the allocation of scarce resources in the economy. It is thus very important to assess the validity of the processes used to estimate the market portfolio in South Africa to make sure that the values used for this parameter are both appropriate and accurate. In order to fully understand the market portfolio and the controversies surrounding it as well as to understand the significance of the market portfolio within the CAPM framework it is important to understand how the idea and theories behind it were established.

### **2.3 The Market Portfolio and its Role in the Development of the CAPM**

The CAPM of Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966) is one of the most significant tools in the world of finance and its development, in combination with Markowitz’s modern portfolio theory (Markowitz, 1952 and 1959), has transformed the field of finance. Many academics admit that without the CAPM life would be hard (Lakonishok, 1993: 38; Laubscher, 2002: 143). Central to the development of the CAPM was the idea of modern portfolio theory (MPT). MPT as a valuation model had immense appeal, it pioneered the

evaluation of assets on the dual basis of risk and return. Prior to MPT assets were evaluated solely on their returns; whilst if risk was considered it was done so intuitively or subjectively (Harrington, 1997: 5; Linley, 1992: 2). Another reason for the popularity of MPT was that assets were evaluated according to their impact on the risk and return of an investor's whole portfolio, as compared to earlier models which evaluated assets individually (Harrington, 1987: 5-6). These evaluation techniques revolutionised the field of finance and played a pivotal role in the development of the CAPM and in particular one of its parameters – the return on the market portfolio.

The Markowitz model (1952) was the first model to deal clearly with the risk of a portfolio. It was built upon two key objectives of the investor; to maximise expected return whilst minimising the risk (variance) of that return (Markowitz, 1952: 77). This criteria in selecting portfolios is known as the mean-variance criterion, and is central to the establishment of the market portfolio (Fama, 1976: 258; Cuthbertson, 1996: 26; Bodie *et al*, 2007: 171; Brown and Reilly, 2009: 228; Goltz and Le Sourd, 2010: 15). The mean-variance criterion, and in particular the mean-variance efficiency of the market portfolio, is a vital concept in the framework of the CAPM. Bodie *et al* (2007: 212) support this by stating that there is “one central prediction of the CAPM: The market portfolio is mean-variance efficient”. Ross (1977: 177) goes as far as to describe the CAPM as the “mean variance capital asset pricing model” being a “focal point for finance”.

In order to obtain mean-variance efficiency Markowitz (1952: 77) assumed that an investor would rather have a higher expected return (ER) than a lower expected return, but at the same time dislike risk. Therefore, if an investor is faced with a choice between portfolio ‚A’ (of  $n$  securities) and portfolio ‚B’ (of a different set of  $n$  securities) then according to the mean-variance criterion (MVC), portfolio A is preferable to portfolio B if the following applies:

1.  $E_A(R) \geq E_B(R)$  and
2.  $\text{var}_A(R) \leq \text{var}_B(R)$  or  $SD_A(R) \leq SD_B(R)$

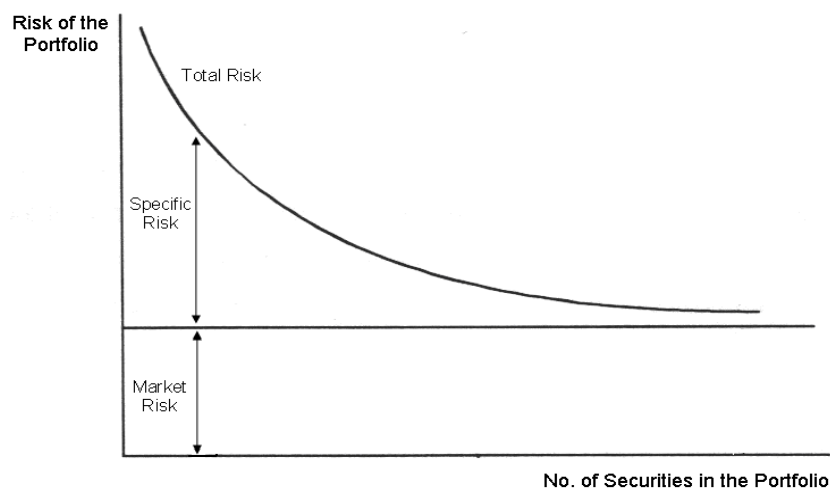
(Markowitz, 1952; Fama, 1976: 258-260; Kandel, 1984: 66; Cuthbertson, 1996: 26)

If for example an investor finds the situation where  $E_A(R) > E_B(R)$  and  $\text{var}_A(R) > \text{var}_B(R)$ , then based on MVC a decision cannot be reached (Cuthbertson, 1996: 26). By joining these

objectives Markowitz was able to create a model which provides a framework for investors in making capital market decisions, such that they select portfolios that have the lowest possible risk for a given return, or the highest possible return for a given risk (Harrington, 1987: 6; Adams, Booth and Bowie, 2003: 229; Brown and Reilly, 2009: 182).

The goal of maximising the expected level of return whilst minimising the level of risk, can be attained via effective diversification of the risk in their portfolios. There are two forms of risk. Firstly there is risk related to firm-specific influences known as non-systematic or firm-specific risk and secondly there is risk related to general economic conditions known as systematic or market risk (Fuller and Farrell, 1987: 456; Bodie *et al*, 2007: 163; Brown and Reilly, 2009: 211). Diversification serves to minimize the former as shown by figure 2-1 below.

**Figure 2-1 Risk reduction through diversification**



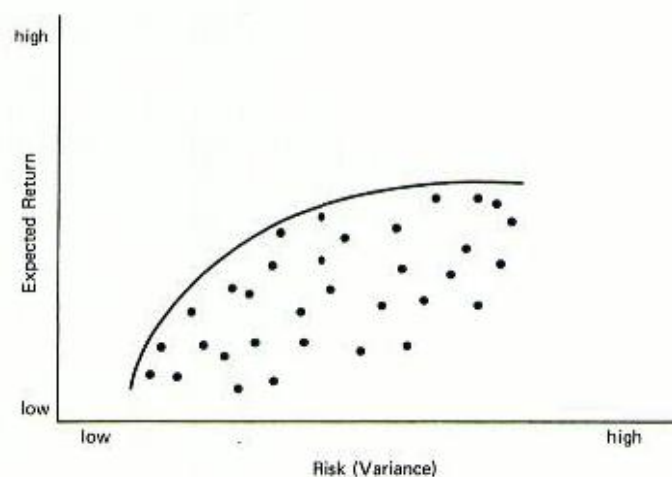
(Source: Pike and Neale, 2006: 241)

It is a commonly acknowledged point that the larger the number of assets in a portfolio the lower the risk of the portfolio (Cuthbertson, 1996: 25; Neu-Ner and Firer, 1997: 44; Luenberger, 1998: 151; Bodie *et al*, 2007: 163; Brown and Reilly, 2009: 211). However, in a study conducted on the JSE by Neu-Ner and Firer (1997: 57), it was found that nearly 90% of the benefits of diversification could be obtained by holding a random portfolio of only 30 shares. This illustrates that although the risk of a portfolio may continue to drop the more shares are added, after 30 shares any further addition results in minimal diversification. An interesting

point found by Neu-Ner and Firer (1997: 57) was that the impact of diversification was far more effective in South Africa when compared with other countries such as the U.S., France, Germany and Italy. Despite this, not all risk can be completely diversified as virtually all securities are affected by systematic risk. Systematic or market risk is defined as “the variability in all risky assets caused by macroeconomic variables” (Brown and Reilly, 2009: 211). Due to the fact that this risk affects all risky assets it cannot be eliminated no matter how many assets are held in the portfolio as shown by figure 2-1.

The fundamental revelation of Markowitz’s (1952) model is that investors choose among all possible portfolios on the basis of both of the mean-variance criterion (Markowitz, 1952: 82; Cuthbertson, 1996: 26; Adams, 2003: 233). A graph can be plotted of the expected returns and risk of all attainable investments and portfolios, which is known as the opportunity set or feasible set (Harrington, 1987: 11; Luenberger, 1998: 155; Van Horne, 2002: 59; Bodie *et al*, 2007:P 171). This can be illustrated graphically for a group of investments, and is shown in figure 2-2.

**Figure 2- 2 The efficient frontier**



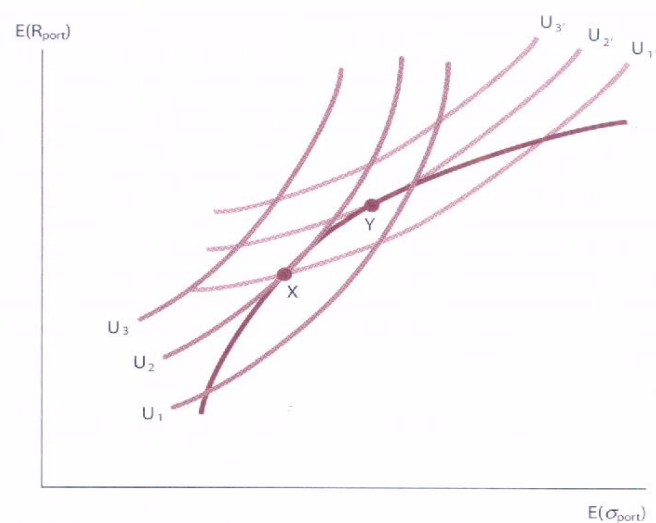
(Source: Harrington, 1987: 10)

Each investor wants to select an optimal portfolio, known as an efficient portfolio i.e. a portfolio that has the lowest possible risk for a given return, or the highest possible return for a given risk (a mean-variance efficient portfolio). The curved line in figure 2-2 illustrates and links all the efficient portfolios, the line is known as the efficient frontier (Luenberger, 1998:

156-157; Adams *et al*, 2003: 236; Reilly and Brown, 2006: 221; Bodie *et al*, 2007: 180). What is worth noting and can be seen on figure 2-2, is that the slope of the efficient frontier decreases steadily the further upward and to the right of the line an investor moves. This means that moving up the frontier by adding equal amounts of risk gives decreasing amounts of expected return. Although all the efficient portfolios have been identified, the question to be asked is which portfolio will each investor choose? The answer to this is dependent on each individual investor's appetite for risk (Harrington, 1987: 11; Luenberger, 1998: 157; Brown and Reilly, 2009: 199). The more risk averse an investor is the further down the left of the efficient frontier, whilst the more risk seeking the investor the further up the right of the line. The portfolio on the efficient frontier that the investor chooses to invest in will be the one that maximises his or her utility (Brown and Reilly, 2009: 199).

An investor's utility curve is representative of the trade-off he or she is willing to make between risk and expected return. In combination with the efficient frontier, the utility curve helps determine which portfolio along the efficient frontier a particular investor will choose. This process is displayed in figure 2-3, the optimal portfolio or the mean-variance efficient portfolio has the highest utility for a given investor and is at the point of tangency between the investor's utility curves and the efficient frontier. In figure 2-3, the more risk averse investor would choose portfolio X, whilst a more risk seeking investor would prefer portfolio Y (Harrington, 1987: 11-12; Luenberger, 1998: 157; Brown and Reilly, 2009: 199).

**Figure 2-3** Selecting an optimal risky portfolio



(Source: Brown and Reilly, 2009: 199)

Despite the fact that the Markowitz model is theoretically simple, it does have a number of shortcomings. One of the largest problems faced when using the model is the number and complexity of calculations required to implement the model (Harrington, 1987: 12; Luenberger, 1998: 158; Reilly and Brown, 2006: 219). Whilst the calculation of the portfolio's return is fairly simple, the complexity lies in the calculation of the portfolio's risk (variance). The variance of a basic two-asset portfolio is calculated as follows:

$$\sigma_{port} = \sqrt{w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1 w_2 r_{1,2} \sigma_1 \sigma_2} \quad (2.3)$$

Where:

- $w_1$  is the weighting of asset 1 in the portfolio
- $w_2$  is the weighting of asset 2
- $\sigma_1$  is the standard deviation of asset 1
- $\sigma_2$  is the standard deviation of asset 2
- $r_{1,2}$  is the correlation coefficient of asset 1 and asset 2

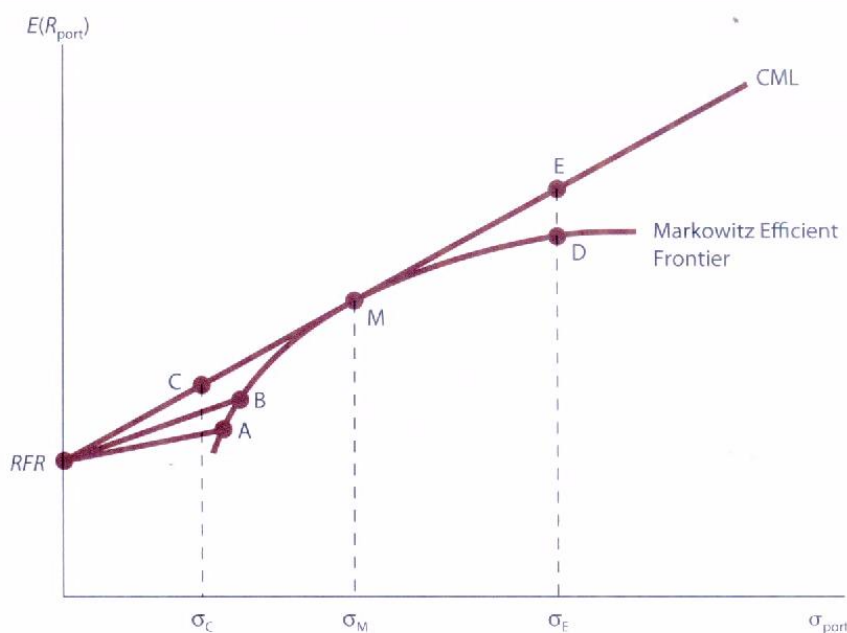
(Brown and Reilly, 2009: 191)

As can be seen from equation 2.3, the calculation is complex for a simple two-asset portfolio, and the larger the portfolio the larger the number of correlations that need to be calculated to assess the portfolio's variance. For a portfolio containing N assets, the amount of correlations that have to be calculated is  $N(N - 1)/2$ . As an example, if a portfolio contained the 30 assets needed to eliminate 90% of the diversifiable risk a practitioner would have to calculate 435 correlations to estimate the portfolio's variance, illustrating that this process can become very burdensome (Harrington, 1987: 12; Reilly and Brown, 2006: 219). A second issue faced by the Markowitz model is the inherent difficulty of forecasting future returns. The process of forecasting one asset's return is challenging enough, but forecasts must be made for every asset in the portfolio and under an array of circumstances (Harrington, 1987: 13). Due to the complexity of the Markowitz model, practitioners and academics did not adopt the concept. However, due to its logic many academics tried to modify and develop new models based on

the concept, the most popular of which is the CAPM (Firer, 1993: 4; Farrell, 1997: 59; Reilly and Brown, 2006: 232).

The CAPM's first development of the Markowitz model was the addition of a risk-free asset (Sharpe, 1964: 426). This allowed investors to hold the risk-free asset and a portfolio of risky assets in desired combinations of the two, known as the two-fund separation theory (Brown and Reilly, 2009: 212; Goltz and Le Sourd, 2010: 14). The risk-free asset has zero variance (zero risk) (Firer, 1993: 26; Cuthbertson, 1996: 34; Bodie *et al*, 2007: 133; Brown and Reilly, 2009: 206), and any possible combinations of the risk-free asset and a portfolio of risky assets results in a linear function (Cuthbertson, 1996: 34; Luenberger, 1998: 153; Adams *et al*, 2003: 247; Goltz and Le Sourd, 2010: 14), which is displayed in figure 2-4 below.

**Figure 2-4 The capital market line**



(Source: Brown and Reilly, 2009: 209)

As can be seen from the diagram, the risk-free asset can be combined with any portfolio (i.e. portfolio A, B and M), however due to the mean-variance criterion any investor wants to obtain the most efficient portfolio available, hence for example, any rational investor would not choose portfolio A over portfolio B as the combination of risk-free asset and portfolio B offers an equal



return for less risk or vice versa, a higher return for equal risk when compared to the combination of the risk-free asset and portfolio A. Following this principle, the combination of risk-free asset and risky portfolio which will provide the most superior outcome will be the combination where the line from the risk-free return is tangential to the efficient frontier (Sharpe, 1964: 432). In figure 2-4, this is shown by point M, and because all rational investors want to maximise their utilities, all investors will hold combinations of the risk-free asset and portfolio M. Any point along the line  $R_fM$ , i.e. any combination of the risk-free asset and portfolio M is superior to any other portfolio (for example point C is more efficient than A or B as it offers a higher return for less risk than both A and B), and thus forms the a new efficient frontier, known as the Capital Market Line (CML) (Sharpe, 1964: 442). Point M - the optimal portfolio, is known as the Market Portfolio (Harrington, 1987: 14; Fifer, 1993: 29; Brigham and Ehrhardt, 2005: 184; Brown and Reilly, 2009: 208; Goltz and Le Sourd, 2010: 14-15).

## 2.4 The Market Portfolio

According to Laubscher (2002: 134) “the existence of an optimally efficient market portfolio is one of the single most important implications of the CAPM”. The market portfolio was not only pivotal to the development of the CAPM, it is central to the use of the CAPM. Fifer (1993: 31), Campbell, Lo and MacKinlay (1997: 213), Bodie *et al* (2007: 205) and Brown and Reilly (2009: 228) define the market portfolio as a portfolio that contains all risky assets in the economy in proportion to their market value, Fuller and Farrell (1987: 494) state that the portfolio should be an *ex ante* efficient portfolio, i.e., a portfolio that offers the highest expected return for a given level of risk, whilst Goltz and Le Sourd (2010: 15) describe the market portfolio as the portfolio with “the highest Sharpe Ratio among all possible portfolios. This market portfolio is an asset portfolio that mimics the market: it is made of all assets in the economy and the assets are capital weighted; that is, each asset is weighted by its percentage of the total value of the entire market for assets”. Ward (1994: 100), and Laubscher (2002: 134) describe the market portfolio as the most broadly diversified portfolio available to investors. Reilly and Brown (2006: 236) describe the market portfolio from an American point of view and state that “it includes not only U.S. common stocks but *all* risky assets, such as non-U.S. stocks, U.S. and non-U.S. bonds, options, real estate, coins, stamps, art, or antiques”. Consequently, Radcliffe (1997: 259) concludes that if this portfolio is held it is not possible to diversify risk any further. Goltz and Le Sourd (2010: 15) believe the theory behind the market portfolio is “elegant”, however as Brown and Reilly (2009: 228) point out, theory is often very different from reality.

### **2.4.1 The Market Portfolio: Theory versus Practice**

Although the idea of the market portfolio has been described as “elegant” (Goltz and Le Sourd, 2010: 15) and despite the concept being acknowledged as reasonable in theory, one thing numerous academics agree on is that it is very difficult, if not impossible to implement in practice (Gibbons and Ferson, 1985: 217; Fifer, 1993: 29-31; Laubscher, 2002: 134; Cuthbertson and Nitzsche, 2005: 194; Brown and Reilly, 2009: 228; Goltz and Le Sourd, 2010: 26). According to Jagannathan and Wang (1996: 6), the CAPM and thus the market portfolio were developed in a hypothetical framework, and as a result it is very different and difficult for practitioners to implement accurately. Laubscher (2002: 134) put it bluntly, stating that “the market return is not easy to estimate”, Fifer (1993:31) and Rees (1995:171) elaborated mentioning that the market portfolio is not an easy parameter to estimate as it is doubtful whether a portfolio comprising of all risky assets such as the one described above, does or will ever exist. Trying to estimate such a portfolio would be computationally arduous and because of this fact, a proxy for the market portfolio is employed when using the CAPM (Fifer 1993: 31; Ward 1994: 100; Bruner *et al*, 1998: 20; Laubscher 2002: 134; Bodie *et al*, 2007: 205). Further complicating the issue, Carleton and Lakonishok (1985: 38), Harrington (1987: 167) and Fifer (1993: 30) highlight that although using a proxy for the market portfolio may appear simple, underlying complexities may trip up a practitioner. Such complexities include how the return should be calculated, if an index is used as a proxy should it be value- or equal-weighted and over what time span should the return be calculated? All these issues illustrate that in practice estimating the market portfolio is not straight forward.

## **2.5 Estimating the Market Return**

In order to find the return on the market portfolio it would involve finding the return of every risky asset class, which includes not only stocks but bonds, real estate, art, stamps and even human capital (Jagannathan and Wang, 1996: 5; Reilly and Brown, 2006: 236). As stated, not only is this near impossible but it is highly doubtful that a portfolio of this nature even exists (Fifer, 1993: 31; Rees, 1995: 171; Laubscher, 2002: 134). The estimation of the return on the market is thus a complex process that should not be taken lightly (Carleton and Lakonishok, 1985: 38; Athanasoulis and Shiller, 2000: 301-302).

In the absence of a true market portfolio it becomes very important that an adequate proxy is found. Despite the numerous ways in which to describe and define the market portfolio two points appear constant, the market portfolio contains all risky assets and is mean-variance efficient (Cuthbertson, 1996: 26; Luenberger, 1998: 174; Adams *et al*, 2003: 247; Reilly and Brown, 2006: 236; Goltz and Le Sourd, 2010: 15). Thus based on this, when attempting to mimic the theoretical market portfolio these two characteristics of the market portfolio are critical to the success of the proxy.

However, before deciding on a proxy for the market portfolio the “underlying complexities” alluded to by Carleton and Lakonishok (1985: 38) need to be addressed. These issues are very important to the success of the proxy, as they play a vital role in the actual selection of the proxy. For example, the question, if an index is used should it be equal- or value-weighted and the question of over what time period should the return be calculated - both need to be answered before any proxy is chosen, as is the case with the issue of how the return should be calculated. Thus these issues, the first steps towards estimating the market return are discussed in the following sections.

### **2.5.1 The use of Historical Data as a Predictor of the Market Return**

The most common method used by practitioners to forecast the future market return is through the use of historical figures (Bruner *et al*, 1998: 20; PriceWaterhouseCoopers Corporate Finance, 2009: 32). Historical figures are viewed as fairly stable, and the future is not expected to change too drastically from the past. As a result, practitioners assume that the past is an adequate “mirror of the investor’s expected market premium” (Harrington, 1987: 167). Carleton and Lakonishok (1985: 38) however warn that the consequences of ignoring the complexity of this method can be substantial in monetary terms. As an example, assume a large company, (company A) with a book value of common equity amounting to R5 billion. Every percentage point in estimating its cost of equity translates into R50 million of earnings per year, when applied as an earnings rate on book value. Thus the discrepancies between the estimates of cost of equity produced by various “readings” of historical returns could very easily add up to 3, 4, 5 or more percentage points a year. This translates into discrepancies of anywhere between R150 million to R250 million and upwards in required earnings for company A. Thus it is vital that the complexity of these calculations is not over-looked. According to Harrington (1987: 167)

there are four questions practitioners must address in the process of calculating the return on the market portfolio:

1. How should the return be calculated?
2. If an Index is used, should it be value- or equal-weighted?
3. Over what period should the return be calculated?
4. What proxy should be used for the market?

## 2.5.2 Calculating Market Return: Geometric versus Arithmetic Returns

In estimating the return on the market using a proxy one of the first issues a practitioner must face is the choice between using geometric rates of return or arithmetic returns (Cooper, 1996: 157; Jacquier, Kane and Marcus, 2003: 46; Correia and Uliana, 2004: 72). Arithmetic returns can be defined as “the sum of returns in each period divided by the number of periods” (Bodie *et al*, 2007: 129) and are known as the simple averages of past returns (Ibbotson and Sinquefeld, 1979: 44; Bruner *et al*, 1998: 20). Whilst geometric returns are defined as “the single per-period return that gives the same cumulative performance as the sequence of actual returns” (Bodie *et al*, 2007: 129), alternatively geometric returns can be described as “the internal rate of return between a single outlay and one or more future receipts” (Bruner *et al*, 1998: 20). In simple terms, geometric returns measure the compound rate of return investors earned over past periods (Ibbotson and Sinquefeld, 1979: 44; Bruner *et al*, 1998: 21). The two measures can be represented by the following formulae:

$$\text{Arithmetic mean} = (r_t + r_{t+1} + \dots + r_{t+x})/n \quad (2.4)$$

Where:

- R is the rate of return
- t is the time period
- n is the number of periods

$$\text{Geometric mean} = [(1 + r_t)(1 + r_{t+1}) \dots (1 + r_{t+x})]^{1/n} - 1 \quad (2.5)$$

(Carleton and Lakonishok, 1985: 39; Bodie *et al*, 2007: 129)

There has been much debate over which method is the most appropriate in a CAPM framework. According to a survey conducted amongst 27 “highly regarded corporations” by Bruner *et al* (1998: 20), when estimating the market return, respondents mainly differed in their use of either arithmetic or geometric returns, further illustrating that the choice between the two methods is not a clear cut one. The choice between the methods is especially important as the two methods can result in very different outcomes (Carleton and Lakonishok, 1985: 39; Harrington, 1987: 167; Bruner *et al*, 1998: 20). In order to illustrate this an analysis was conducted on the ALSI over a twelve year period, the results of which are displayed in table 2-1. The table displays annual historical returns of the ALSI using both arithmetic and geometric means, as well as the difference between the two methods. The analysis was carried out over varying time periods between 1998 - 2010.

**Table 2- 1      Annualised mean returns of the ALSI**

<b>Period</b>	<b>Arithmetic Return</b>	<b>Geometric Return</b>	<b>Difference</b>
1998-2010	20.51%	17.94%	2.57%
1999-2010	22.71%	20.18%	2.53%
2000-2010	18.34%	16.40%	1.94%
2001-2010	20.14%	18.14%	2.00%
2002-2010	18.75%	16.63%	2.12%
2003-2010	22.14%	20.20%	1.94%
2004-2010	23.00%	20.79%	2.20%
2005-2010	22.59%	20.04%	2.56%
2006-2010	17.66%	15.23%	2.43%
2007-2010	11.77%	9.52%	2.25%

(Source: own calculations, data obtained from McGregor’s BFA, 2011)

It can be seen that there can be quite large differences in the mean returns according to which method is used. For example for the period 1998 - 2010 the geometric mean for the ALSI is found to be 17.94% whilst the comparable arithmetic mean is found to be 20.51%, this is a large discrepancy of 2.57%. The differences between the two methods ranged from 2.57% to 1.94%, and averaged 2.25%. The value of 2.57% as discussed earlier can translate into a large sum of money, for example with company A who’s equity value is R5 billion, this difference translates into R128.5 million, whilst even at the lowest end of the scale a difference of 1.94% translates into R97 million. According to Cooper (1996: 158), similar analyses were conducted on the equity markets in the U.S. and the UK, for the period 1926 – 1992 and it was found that in the

U.S. the arithmetic mean return was 9.0% and the geometric 7.0%, whilst in the UK for the period 1919 – 1994, the arithmetic mean was found to be 10.3% and the geometric 7.7%. Thus it can be seen that this problem is not specific to South Africa and therefore the decision for practitioners should not be taken lightly.

The difference of the two means is sizeable and is directly attributable to the difference in methods used when calculating them. It is also worth noting that the difference between the two means would be even more profound when dealing with individual securities because of the higher variability they are associated with (Carleton and Lakonishok, 1985: 39; Bruner *et al*, 1998: 21; Jacquier *et al*, 2003: 47). Since the choice of which method to use can make such a large difference, it is important to answer the next question correctly – which of the two methods should be used?

The truth is, each of the methods is suitable under different conditions. The geometric method is suitable when calculating changes in wealth over multiple periods with a buy and hold (with dividends reinvested) strategy (Carleton and Lakonishok, 1985: 39; Ehrhardt, 1994: 9; Jacquier *et al*, 2003: 46). The geometric mean is said to be a better measure at linking returns across time (Ibbotson and Sinquefeld, 1979: 44), whereas the arithmetic method would be a more suitable method when calculating the performance of a portfolio over a single period (which in the above example is one year) (Carleton and Lakonishok, 1985: 39; PriceWaterhouseCoopers Corporate Finance, 2009: 32). Bruner (1998: 20) states that “assuming the distribution of returns is stable over time and that the periodic returns are independent of one another, the arithmetic return is the best estimator of expected returns”. According to Cooper (1996: 165), the use of arithmetic means ignores the estimation errors and serial correlations in returns, however what is worth noting is that when Cooper (1996:165) derived discount rates that corrected for estimation errors and serial correlations in returns, these discount rates were still found to be closer to the arithmetic means than the geometric.

Many academics such as Correia and Uliana (2004: 72) and Reilly and Wright (2004: 67-68) avoid making the choice between the two means and instead report both. However, it has been suggested that because the CAPM is a single-period model, the arithmetic approach is the appropriate choice, as it calculates returns based on a single holding period (Ibbotson and Sinquefeld, 1979: 44; Harrington, 1987: 162). This point was further supported by Bruner *et*

*al's* (1998: 22) survey where it was found that in the CAPM framework 71% of respondents used the arithmetic mean. However in contrast, Ibbotson and Sinquefeld (1979: 44), Harrington (1987: 163) and Reilly and Wright (2004: 66) argue that there is no reason to suggest that investors ignore the effects of compounding when the CAPM is expanded to a multi-period world. Thus it can be seen that for this area of debate there is no clear answer.

### **2.5.3 Calculating Market Return: Value- versus Equally Weighted Returns**

Indices or asset return series come in many different forms. For example the S&P 500 and Wilshire 5000 in the U.S. and the ALSI from South Africa are value weighted indices, whilst the S&P 500 Equal Weight Index, the NASDAQ-100 Equal Weighted Index and the Financial Times Ordinary Share Index from the U.S. are equal weighted indices (Reilly and Norton, 1999: 165). A debate amongst academics and practitioners alike still exists over which is the more appropriate to use when calculating the market return, a value-weighted index or equally weighted index. A value-weighted index is an index in which each stock's return is weighted by the market value of the stock itself (Harrington, 1987: 168; Reilly and Norton, 1999:163; Bodie *et al*, 2007: 46; Brown and Reilly, 2009: 131). Whilst an equally weighted index is an index in which each stock's returns are simply averaged by the number of stocks contained in the relevant index (Harrington, 1987: 168-170; Bodie *et al*, 2007: 48; Brown and Reilly, 2009: 131).

According to research conducted by Carleton and Lakonishok (1985: 39), the discrepancies between returns on value-weighted and equally weighted indices are even more profound than the discrepancies between arithmetic and geometric returns. In their study, Carleton and Lakonishok compared the equally weighted Fisher index to the value weighted Fisher index (which according to Carleton and Lakonishok are both widely used market portfolios in the U.S.), and found that for the period 1926-80 the equally weighted index had an average return of 17.1% whilst the value-weighted portfolio had an average return of 11.4%, when calculated using the arithmetic method. When the geometric method was used it was found that the two indices were closer (12.5% equally weighted vs. 9.1% value-weighted), this was because the equally weighted index had a higher standard deviation of 33.1% compared to the value-weighted index's standard deviation of 21.9%. According to Hawkins (2010) the S&P 500 Equal Weighted Index has outperformed the value weighted S&P 500 since its formation in 2003. Despite these statistics the choice is far from simple.

Some of the advantages of an equal weighted index are that the portfolios are highly diversified, the index does not overweight overpriced stocks and underweight underpriced stocks, the index is easy to construct and manage, and finally it appears, on the basis of returns, to outperform the equivalent value weighted index (Reilly and Brown, 1997: 156; Bodie *et al*, 2007: 48; Hawkins, 2010). Further to these is an advantage specific to South Africa's segmented market. Due to the fact that traditionally the largest firms in South Africa are from the resource sector there is a risk that a value weighted index could comprise of up to 80% resource firms. Raubenheimer (2010: 1) highlights this point by stating that the ALSI "has more than 20% of its weight in the largest two mining-resources companies. The largest five companies together make up more than 40% of the index". This suggests that an index such as the ALSI, which supposedly represents the market, would be made up of companies the majority of which would be from one or two sectors, which is hardly representative of all market risk (Bowie and Bradfield, 1993: 6; Van Rensburg and Slaney, 1997: 1-2; Van Rensburg, 2002: 84, Correia and Uliana, 2004: 65; Raubenheimer, 2010: 1).

Despite the advantages that equally weighted indices have, it must be considered in which context these two methods are being examined. As pointed out by authors such as Firer (1993: 31), Laubscher (2002: 134) and Goltz and Le Sourd (2010: 15) the definition of the market portfolio requires special attention to the fact that each of the risky assets held in it are held in proportion to their market value. Carleton and Lakonishok (1985: 40) go as far as to suggest that there is no more sense in creating an equally weighted index than there is forming an index weighted according to the length of a company's name. What Carleton and Lakonishok are trying to get across is that the difference between a large company on the JSE such as BHP Billiton and a small company cannot be ignored; as investors have committed more funds to BHP Billiton than a small company. What equally weighted indices do is they give more weighting to these smaller companies. Due to the fact that smaller companies are generally more risky than larger companies, part of the average returns calculated and discussed earlier can be attributed to these risk differences. Despite the fact that equally weighted indices are argued to be more useful when calculating rates of return for certain companies – especially smaller ones, the definition of the market portfolio dictates that the size or value of a company cannot be ignored. This issue is particularly important in the context of the South African market as the larger firms make up a large percentage of the market. The weighting of these firms and the five smallest firms on the JSE are shown in the following tables:



**Table 2- 2 Weightings of the five largest firms on the JSE as at 01 Jan 2010**

<b>RANK</b>	<b>FIRM</b>	<b>WEIGHTING</b>
1	BHP Billiton	13.69%
2	Anglo American PLC	11.50%
3	SABMiller PLC	7.16%
4	MTN Group LTD	5.90%
5	SASOL LTD	4.97%

(Source: own calculations, data obtained from Johannesburg Stock Exchange, 2010)

**Table 2- 3 Weightings of the five smallest firms on the JSE as at 01 Jan 2010**

<b>RANK</b>	<b>FIRM</b>	<b>WEIGHTING</b>
248	Kairos Industrial Holdings	0.0002%
249	Intertrading LTD	0.0002%
250	Village Main Reef G M CO	0.0001%
251	Awethu Breweries LTD ORD	0.0001%
252	Decillion LTD	0.0001%

(Source: own calculations, data obtained from Johannesburg Stock Exchange, 2010)

**Table 2- 4 Grouped weightings of the largest and smallest firms on the JSE as at 01 Jan 2010**

<b>FIRMS</b>	<b>WEIGHTING</b>
2 Largest Firms	25.1915%
3 Largest Firms	32.3557%
5 Largest Firms	43.2279%
5 Smallest Firms	0.0007%

(Source: own calculations, data obtained from Johannesburg Stock Exchange, 2010)

Following the above analysis on the JSE it illustrates further the importance of using a value-weighted index compared to the equally weighted index. It can be seen from the above tables that the two largest firms on the JSE make up a quarter of the equities market, whilst the five largest firms contribute almost half of the market. When you consider that as of the 1<sup>st</sup> of January 2010 there were 252 firms registered on the JSE and of those 252 firms, 5 made up 43.23% of the total markets returns, it means that the remaining 247 made up 57.77% of the

markets returns. The five smallest firms made up less than a hundredth of a percent of the market's returns. This illustrates that to give each firm equal weighting would be unsuitable. For example to give a firm such as BHP Billiton the same weighting as Decillion would be inappropriate. Further to this, in addressing the issue of whether the ALSI would represent all market risk with the segmented nature of the South African, it has to be said that if for example resource shares made up 80% of the market, and thus are represented as such in the market portfolio, then this would be an accurate portrayal of the risk in the market. It would be erroneous to, for example, assign retailing firms 10% of the market portfolio when the firms make up a much smaller percentage of the market as that would not accurately portray the risk of the market. Therefore, it is concluded that the value-weighted index is the more appropriate index to use when calculating the return on the market.

#### **2.5.4 Calculating Market Return: Time Period**

When it is decided that history should be used as a proxy for the future, the next question that should be asked is, what time period in history? This is because what period in history is used, will determine what returns will be obtained (Harrington, 1987: 170; Firer 1993: 31).

Many academics believe that when applying the CAPM, the market is viewed by investors as a long-term concept. This simply implies that the opinions investors have about various assets may change, but the expected return on the market should show long-term stability. It is generally accepted that investors look back over long periods of history in order to form estimates for the future (Firer, 1993: 31; Perold, 2004: 3; PriceWaterhouseCoopers Corporate Finance, 2009: 32). Investors often use 50 years or more of market returns as proxies for expected market returns. Where the problem lies however is that particular periods of history have a larger impact on individuals than other periods do. For example historical events such as the Great Depression, World War II, the Asian Crisis, the attacks on the World Trade Centre (9/11) and the sub-prime crisis, can all influence the results obtained from the proxy (Harrington, 1987: 170-171; Firer, 1993: 31; PriceWaterhouseCoopers Corporate Finance, 2009: 32).

Factors such as inflation can also have an impact on the result of a proxy. Inflation has been such an integral part of all South Africans lives for the recent past that many do not realise that

deflation is also a possibility (Firer, 1993: 31). Other factors have also changed, such as in the past the market was dominated by individual investors whereas now the market is dominated by large institutions. So depending on what time period an investor chooses to use when applying a proxy formed by historical data, all of these factors can influence the proxy's results (Harrington, 1987: 170-171; Firer, 1993: 31).

Table 2-5 illustrates actual market premiums over varying periods in the U.S.. Each period contains a different set of historical events. As an example, the period 1960-1970 represents a long bull-market, whilst the period 1973-78 represent a period that began with a bear market.

**Table 2- 5 Historical geometric market returns of various holding periods**

<b>Holding Period</b>	<b>Compound Rate of Return</b>
<b>Variable length Period:</b>	
1926-60	10.0
1926-74	8.5
1926-76	9.2
1926-78	8.9
1931-69	9.9
1931-74	8.4
1950-70	13.0
1950-78	10.6
1960-70	7.5
1960-78	6.5
1970-78	4.5
1973-78	0.9
<b>25-year periods:</b>	
1950-74	10.1
1951-75	10.3
1952-76	10.3
1953-77	9.2
1954-78	9.5
1955-79	8.4
1956-80	8.4
1957-81	7.9
1958-82	9.3
1959-83	8.6
1960-84	8.4

(Source: Harrington, 1987: 171)

As table 2-5 is dated and from the U.S. a similar analysis was conducted on the ALSI over the period 1996 to 2010, to get a more specific understanding of the importance of the choice of time period. The results are displayed in table 2-6.

**Table 2- 6 Historical arithmetic returns of the ALSI over various holding periods**

<b>Period</b>	<b>Arithmetic Return</b>
<b>Variable length periods:</b>	
1996-2010	17.95%
1997-2010	18.55%
1998-2010	20.51%
1999-2010	22.71%
2000-2010	18.34%
2001-2010	20.14%
2002-2010	18.75%
2003-2010	22.14%
2004-2010	23.00%
2005-2010	22.59%
2006-2010	17.66%
<b>10-year periods</b>	
1996-2005	18.10%
1997-2006	21.27%
1998-2007	23.88%
1999-2008	22.14%
2000-2009	18.28%
2001-2010	20.14%

(Source: own calculations, data obtained from McGregors BFA, 2011; Adapted from: Harrington, 1987: 171)

Both exhibits help to highlight another important factor to consider when using historical data – the results are influenced by the choice of starting and ending dates. For example in the U.S. study, if it was decided to use a starting point in a bull-market (i.e. 1926) and end in a bear market (i.e. 1974), the final results of the proxy will be very different compared to a proxy that used the starting point in a bear market (1931) and end point in a bull-market (1969). In the South African analysis in a period of only fifteen years the choice of starting point and ending point can make as much as a 5.78% difference, which is a very significant amount. Thus choosing beginning and ending points is very important. In short this process is an attempt to

derive a long-term trend from short-term cycles. What can minimise the problem is choosing beginning and ending points with comparable market yields (Harrington, 1987: 172; PriceWaterhouseCoopers Corporate Finance, 2009: 32).

Thus the choice of which time period to use is still not simple. Harrington (1987: 172) addresses this question as follows: “the period chosen reflects our best judgement of the period of history that will most nearly resemble the market that we expect over the investor’s horizon”, whilst Firer (1993: 31) reiterates this point stating that “when extrapolating from history, the results obtained would depend on the choice of starting and ending points because of the cycles of the market. The choice should reflect the best judgment as to which period of history is expected to most nearly resemble the anticipated market over the investors’ horizon”. So in conclusion to the debate surrounding the choice of time period, when using historical data, the decision of starting and ending points will have a direct impact on the results obtained because of the cycles of the market coupled with varying inflation rates. Thus when deciding on the period of history to be used, the choice should reflect the best judgement as to what the forecasting period will resemble.

Following these issues, the fourth and final question to be answered by practitioners when formulating a market proxy is the choice of the proxy itself. This area of the CAPM has been widely debated amongst practitioners and academics alike for some time now. As mentioned, the market portfolio, according to theory, is mean-variance efficient and said to contain all risky assets held in proportion to their market value (Brown and Reilly, 2009: 236), as a portfolio of this nature is unobtainable it is crucial for practitioners to obtain an adequate proxy for it (Laubscher, 2002: 134). The following chapter will explore, in depth, the choice of proxy for the market portfolio, highlighting the importance that the market portfolio is mean-variance efficient and that theoretically it contains all the risky assets in the world.

## CHAPTER 3

# THE MEAN-VARIANCE EFFICIENCY OF MARKET PROXIES AND ESTIMATING THE MARKET RETURN IN THE SOUTH AFRICAN CONTEXT

### 3.1 Overview

In this chapter, the importance of the appropriate choice of market proxy is discussed. Within this discussion it is highlighted that the market proxy is mean-variance efficient and hence any proxy employed in its place should be too. Building on from this discussion a number of leading studies in the testing of a proxies mean-variance efficiency are reviewed including Roll's critique (1977). Following that, the choice of market proxy in the U.S. is explored. The addition of a bond index to the market proxy is discussed as a possible method to attain mean-variance efficiency, after which three U.S. studies are reviewed. The three studies were selected because, in an attempt to obtain a mean-variance efficient portfolio, they modified their market proxies by adding assets (including bonds) to them. Next, the choice of market proxy in South Africa is examined, with particular attention being paid to the issue of market segmentation on the JSE. Studies on the choice of market proxy in South Africa are also reviewed.

### 3.2 The Choice of Market Proxy

The accuracy of results from any model are reliant on the quality of inputs, and it is no different when it comes to the CAPM. Incorrect inputs, in this case parameter values, will result in flawed cost of equity estimates. These flawed estimates can then lead to a company making incorrect decisions regarding the distribution of resources. It is thus very important that academics and more importantly practitioners learn to distinguish between good inputs and bad inputs when estimating the parameters of the CAPM (Harrington, 1987: 3; Laubscher, 2002: 134). The common trend amongst academics, when concerned with the market portfolio is to use a broad based common stock index such as the S&P 500 or the ALSI as a proxy for the market portfolio (Harrington, 1987; Firer, 1993; Reilly and Wright, 2004). The largest problem

with this method is when it is considered that the market portfolio comprises of all risky assets in the world, and indices are only limited portions of the real market for risky assets it is near impossible to know whether these individual indices will serve as a suitable proxy or not (Brown and Reilly, 2009: 229). For example, Brown and Reilly (2009: 228) dispute the use of proxies such as the S&P 500 because of the fact that it only includes U.S. stocks when theoretically they should include U.S. stocks as well as foreign stocks and bonds along with many other risky assets such as art, real estate and human capital (Jagannathan and Wang, 1996: 5). This goes back to the original argument of finding the best input, as the result of the model and thus its success can hinge on the components of the market proxy.

In chapter 2 it was discussed that possibly the most important feature of the market portfolio is that it is mean-variance efficient as the market portfolio is the optimal portfolio available to investors. Due to the fact that proxies are used in the place of the market portfolio it is very important that these proxies, in order to be good inputs or effective proxies, are mean-variance efficient, as this trait is vital to the success of the CAPM as a whole.

### **3.3 The Mean-Variance Efficiency of the Market Proxy**

Throughout the growth of modern portfolio theory and the subsequent development of the CAPM, investors have strived for mean-variance efficient portfolios, which simply dictates that a rational investor will choose a portfolio that offers the highest return for a given level of risk or the lowest risk for a given return (Fama, 1976: 279; Cuthbertson, 1996: 26). It was based on this theory that the market portfolio was established (Fuller and Farrell, 1987: 494; Goltz and Le Sourd, 2010: 15). As mentioned, it is very important that the proxies used in the CAPM to represent the market portfolio are also mean-variance efficient. However, whether the proxies are mean-variance efficient or not has stirred much debate amongst academics (Roll, 1977; Kandel and Stambaugh, 1987; Basak, Jagannathan and Sun, 2002; Levy and Roll, 2009) . As the condition of mean-variance efficiency is of central importance to the success of the proxy and the CAPM as a whole, a number of these studies will be reviewed in the following sections, beginning with the pioneer of this debate, Roll (1977).

### 3.3.1 Roll (1977)

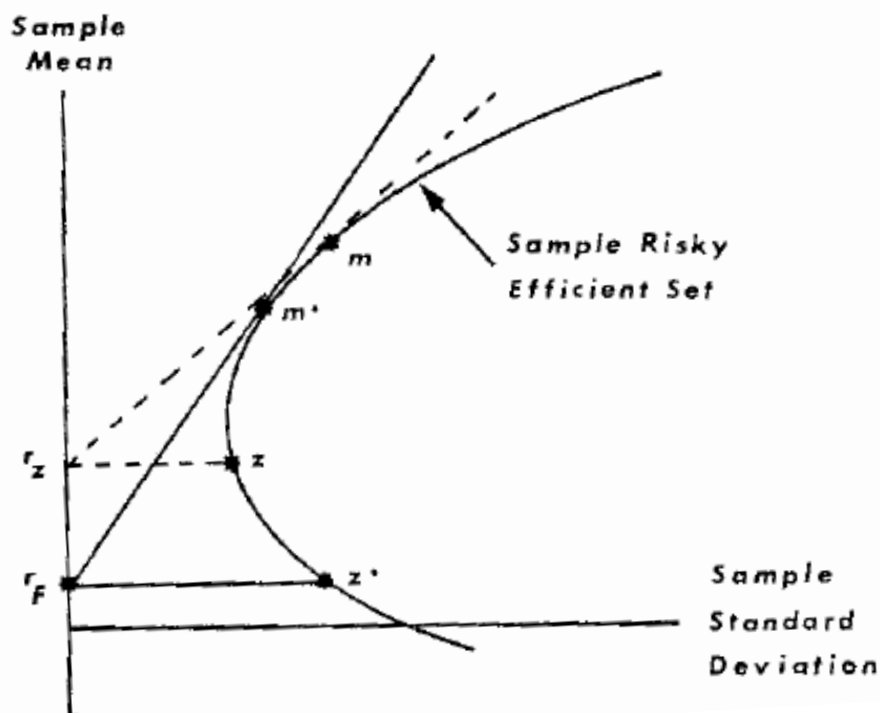
Richard Roll (1977) was the first academic to question the ability to empirically test the legitimacy of the CAPM. His paper is of particular relevance to this study as he questioned the testability of the CAPM due to its dependence on the existence of a true market portfolio. Most researchers recognize that it is impossible to identify the true market portfolio, but assume that certain indices can be used as a proxy. Although this is not ideal, as these series are likely to be highly correlated with the true market portfolio the deficiency is not considered severe. However, Roll (1977: 130) did not agree with this and concluded that the use of indices as a proxy for the market portfolio did in fact have severe implications on the tests of the CAPM and in particular the legitimacy of the model to evaluate portfolio performance. Roll (1977: 149) described this problem as a “benchmark error” as the performance of portfolio managers is usually compared to the performance of an unmanaged portfolio of equal risk, i.e. the market portfolio adjusted for risk would be the benchmark. Roll’s point to this argument was that if the market portfolio and hence the benchmark is wrongly specified, it means the performance of a portfolio manager cannot be assessed properly.

After outlining the mathematical relationships required for mean-variance efficiency, Roll (1977: 136) reviewed a number of asset pricing theory tests, namely, Black, Jensen and Scholes (1972), Blume and Friend (1973) and Fama and MacBeth (1973). Roll (1977: 136-140), provided a detailed discussion of these papers, especially with respect to their rejection of the CAPM. Roll (1973: 136-140) illustrated how the results of these studies are “fully compatible” with the CAPM and a specification error in the estimated market portfolio. Roll (1973: 131) went on to mention that misspecification of the market portfolio in these studies would have “created bias *and* non-stationarity in the fitted cross-sectional risk/return lines even if there were a constant riskless return”. As an example, Roll (1977: 131) used the Black, Jensen and Scholes (1972) study; as their data established what was believed to be a “mean-variance efficient market proxy” that supported the CAPM “perfectly”. This proxy had a correlation of 0.895 with the market proxy that was actually used. However, as Roll (1977: 131) points out, it cannot be known that the proxy that was actually used as the market portfolio was an adequate proxy and satisfied all the requirements of a good market proxy as the real market portfolio has never been established and hence researchers have nothing to compare it to.



As was discussed in chapter 2, the development of the CAPM involved the addition of a risk-free asset, which allowed the CML to be formed, which in turn helped with the establishment of the market portfolio. Roll (1977: 140-141) in continuation of his review on past studies again discusses the Black, Jensen and Scholes' (1972) paper, and in particular their use of a zero-beta portfolio in place of the riskless asset. Roll (1977: 142) shows how by using different assets as the risk-free rate of return, different market portfolios can be obtained. This is shown in figure 3-1, where it can be seen that when using the riskless asset,  $r_F$ , the point of tangency with the sample risky efficient set, point  $m^*$ , is different when compared to using portfolio  $z$ ,  $r_z$ , whose tangency is found to be  $m$ . This illustrates that there is no clear-cut choice for the market portfolio, and as Roll (1977: 142) points out "along the positively-sloped boundary, there is an infinite amount of these linear relationships", meaning an infinite choice of market proxies.

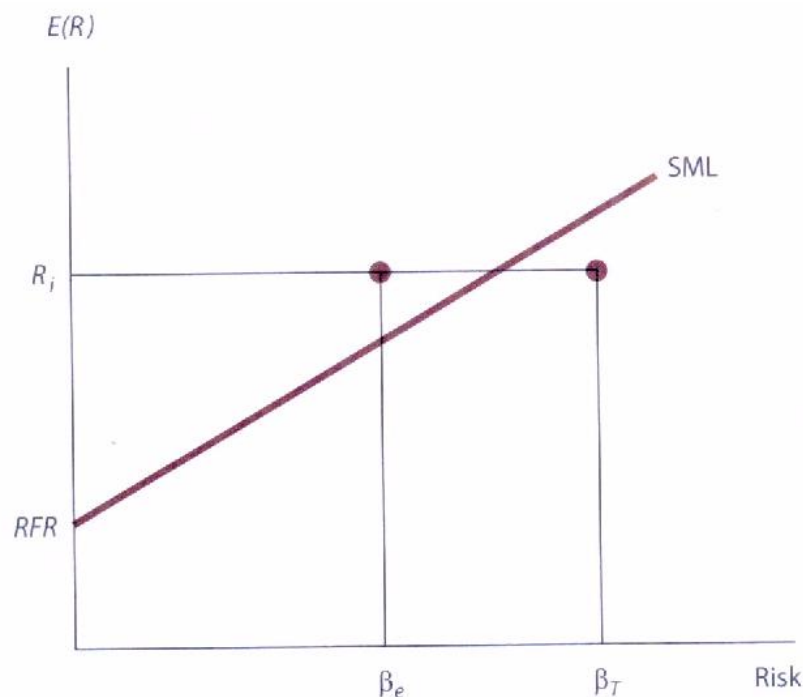
**Figure 3-1** The impact of varying riskless assets on estimating the market portfolio



(Source: Roll, 1977: 141)

Building from his discussions of the past studies, Roll (1973: 149) discussed that the misspecification of the market portfolio could have two effects. Firstly, it would mean that the betas that are calculated for alternative portfolios would be incorrect as the market portfolio that was used to estimate the portfolio's systematic risk is inadequate. Secondly, the risk-return trade off, i.e. the security market line (SML) would be incorrect because it would plot from the risk-free rate to the wrongly specified market portfolio. Figure 3-2 illustrates the effect that this would have; if it is assumed that the true market risk ( $\beta_T$ ) is underestimated ( $\beta_e$ ), which would be the result of an erroneous market portfolio being used to calculate the beta, it can result in the portfolio that is being assessed appearing above the SML. This would suggest better management. However, the reverse is actually true, if  $\beta_T$  is used the management would be inferior as the portfolio would be located below the SML.

**Figure 3-2 Differential performance based on an error in estimating systematic risk**

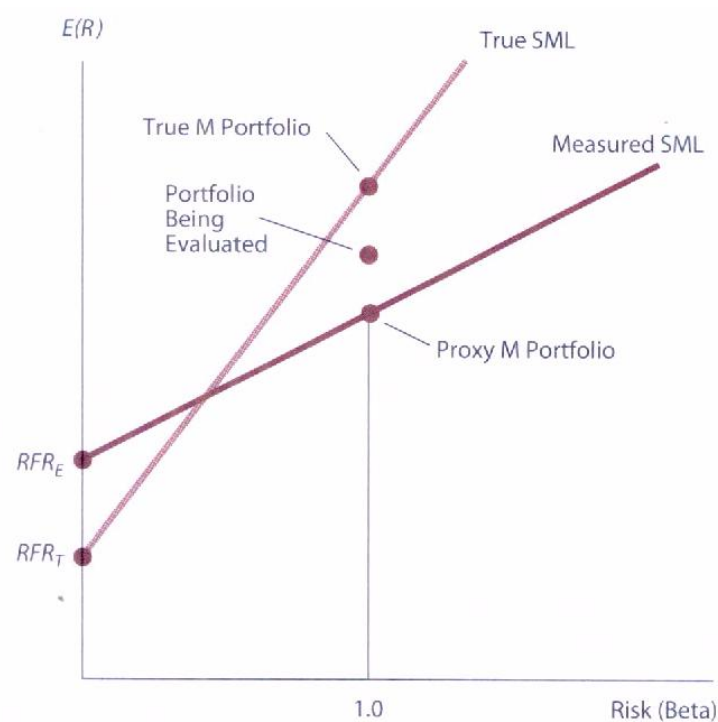


(Source: Brown and Reilly, 2009: 229)

Combining the two issues discussed above, i.e. the lack of certainty with the choice of risk-free asset and the fact that the market portfolio is very difficult to accurately estimate, the result could be what is displayed in figure 3-3. It is possible that a portfolio could be judged to be

superior to the measured SML, whilst in fact it is inferior when compared to the true SML, as is illustrated below.

**Figure 3-3 Differential SML based on measured risk-free asset and proxy market portfolio**

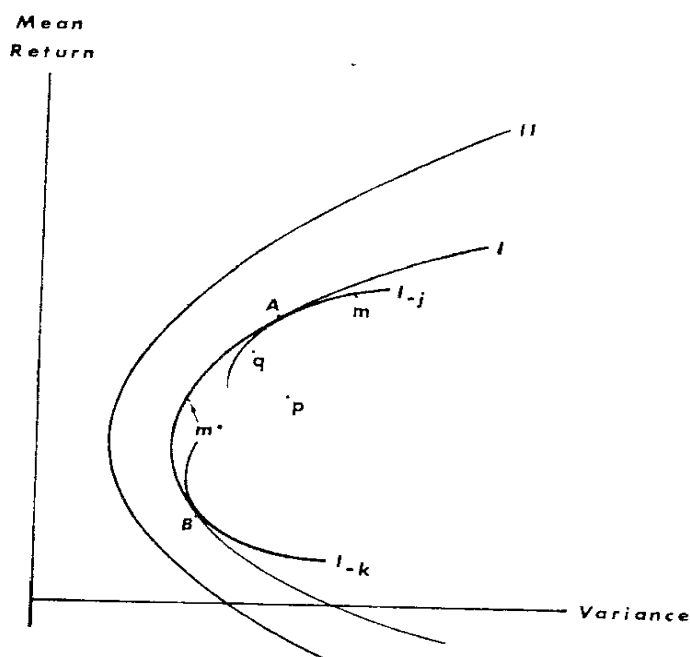


(Source: Brown and Reilly, 2009: 230)

Following these arguments, the next part of Roll's study looked closer at the actual efficiency of the market portfolio (Roll, 1977: 154-158). Roll (1977: 154) stated that when testing the CAPM, and in particular given the fact that the true market portfolio contains all risky assets, "the identifiability of the market portfolio is a serious problem". Roll (1977:155) pointed out that the assumption that the market portfolio is efficient merely requires that the market portfolio is located somewhere along the positively sloped portion of the efficient frontier. Roll (1977: 155) then mentioned that for "small (time-series) sample sizes" the assumption is very prone to a type I error, i.e. being accepted when it is false, however, he went on to say that as the sample size increases the hypothesis will almost definitely be rejected even if it is true. Roll (1977: 155) explains this by saying "first consider the fact that the true market portfolio has a positive proportion invested in every individual asset. This implies that every reasonable candidate for the market proxy must have totally positive investment proportions. In many

cases, in fact, the investment proportions are either the positive constant  $I/N$  for the included assets (and zero for the excluded assets), or the proportions display little cross-sectional variation. We know, therefore, that all such candidates for the proxy market portfolio must lie in a relatively small region of the mean-variance space". Roll (1977: 155) explains this further in an example:

**Figure 3-4** Totally positive portfolios and the efficient boundary



(Source: Roll, 1977: 156)

Suppose, that the true efficient frontier is represented by the curve labelled I in figure 3-4. In the example Roll used, efficient portfolios between point A and B are assumed to have investments with positive weightings. Above point A and below point B, at minimum one asset will have negative weighting. Suppose that the asset that is excluded from the efficient set at point A is j. Then the curve  $I_j$  would become the efficient frontier if j did not exist. I and  $I_j$  are tangent at one point at the very most – it is possible that there may have been no finite tangency due to the fact that j could have had a positive or a negative weight in all the portfolios along I. However, due to the fact that the weight is assumed to be positive below A and negative above A, it has to be zero at A. As it is zero all along  $I_j$ , A has to be a tangency (I and  $I_j$  cannot cross because they are minima). If the market is mean-variance efficient, the true market portfolio must be situated on the boundary I between A and B, assume  $m^*$  is the mean-variance portfolio. If m is

selected as the market proxy, all empirical tests will support the hypothesis that the proxy is mean-variance efficient, because the portfolio  $m$  lies on the reduced efficient frontier  $I_j$  which does not include asset  $j$ . Despite the fact that proxy portfolio  $m$  is inefficient (as it lies below  $I$ ), “this fact will not be detectable by any test using the reduced subset without  $j$ ” (Roll, 1977: 155-156). Resulting in the hypothesis that the proxy is mean-variance efficient being supported correctly but for the wrong reason. On the other hand, consider that the true market portfolio is actually inefficient and is situated at point  $p$ , within  $I$ . Then the same test with the proxy  $m$ , will support the mean-variance hypothesis incorrectly (Roll, 1977: 156). According to Roll (1977: 156) “it seems this is the greatest danger”. Roll (1977: 156) goes on to state that for a subset of assets there will be an ‘efficient frontier’ whose component portfolios will comply with all empirical tests of the mean-variance efficiency. As long as the investment weights in the subset of assets are completely positive at some point along the reduced frontier, an adequate or ‘reasonable’ proxy will be available that will support the mean-variance hypothesis due to the fact it will be subset efficient.

Roll (1977: 129-176) draws several conclusions from his research on the CAPM and in particular the market portfolio. The paper’s conclusions are as follows:

1. There are limits on the tests of the CAPM – the only testable implication from the CAPM is whether the market portfolio is mean-variance efficient, that is whether it lies on the efficient frontier.
2. Linear risk-return relationship – all the other implications of the CAPM including the linear relationship between risk and return (beta and expected return), follow the market portfolios efficiency and are not independently testable.
3. Incorrect specification of the market portfolio – there are numerous mean-variance efficient portfolios. For each of these, the betas estimated against such a portfolio will satisfy the linear relationship regardless of if the market portfolio is efficient or not.
4. Composition of the market portfolio – the CAPM as a theory is not testable unless the composition of the market portfolio is exactly known and used in tests. Suggesting that *all* assets need to be included in any test.
5. Conflicts between proxies – for example, a mean-variance efficient proxy might be used when the true market portfolio is not efficient, and vice versa. The most acceptable proxies may prove to be very highly correlated with each other and the true market portfolio if they are mean-variance efficient or not.
6. Range of SMLs – Essentially every efficient portfolio has an SML, thus every security has a different beta estimate, based on the efficient portfolio with which it is correlated.

Finally Roll (1977: 158) concludes that the only viable theory of the CAPM is that the market portfolio is mean-variance efficient. He stated that theory is relatively simple in nature yet it still had not been satisfactorily met. The main problem Roll (1977:158) pointed out is that in a particular sample there will always be a portfolio that does not reject the efficiency theorem, and that very little information on the exact composition of the true market portfolio is available. Lastly, Roll (1977:158) stated that even the slightest miss-specification could result in an erroneous conclusion, what could appear to be a minor mistake in a normal statistical test can be of “crucial importance” for testing the efficiency of the market.

Following Roll’s critique his finding that the only testable hypothesis of the CAPM is the market portfolio’s mean-variance efficiency has led to much research on the topic. Numerous researchers have attempted to find out whether or not the market portfolio is mean-variance efficient and it’s implications on the proxy for the market portfolio. A number of these studies are now reviewed in the following sections.

### **3.3.2 Kandel (1984)**

Kandel (1984) in his paper called “On the Exclusion of Assets from Tests of the Mean Variance Efficiency of the Market Portfolio” presented a study into the testability of the mean-variance efficiency of the “market index when the returns on some of the components of the index itself are not perfectly observable” (Kandel, 1984: 63).

Kandel (1984: 63-64) agreed with Roll, in the sense that the market portfolio identification problem severely hampers the testing of the theory but states that “the question of the mean-variance efficiency of a particular market index with respect to a subset of assets is a typical problem of statistical inference. The mean-variance efficiency can be tested directly or by testing the linear security market line relation”. Kandel (1984: 64) in explaining the study and discussing the fact that not all assets are observable, mentioned that the relative weights of the assets that are included in the market index could be known, and the total weight of the excluded assets may, or may not, be low. Furthermore only very little information, if any may be available on these missing assets. The question Kandel (1984: 64) attempted to answer is “what can be said , if anything, about the mean-variance efficiency of the market index in these cases of partial observability”.

Using vector analysis, Kandel (1984: 65) looked at a number of different scenarios in which variable amounts of information are known regarding the assets included in tests of the market index and assets that are missing from the tests, known as the “missing asset”. Kandel (1984: 65) attempted to “distinguish between the efficient frontier in the sense of minimum variance and the stricter sense of efficiency that comes from maximizing return at each level of variance”. To begin with, Kandel (1984: 65-67) set out the situation as if perfect information was available, essentially his control of the study – upon which the other scenarios would be compared. Kandel (1984: 67-74) reviewed four scenarios, namely:

1. No information is available about the missing asset
2. Information on the expected return of the missing asset is only available
3. Information on the variance of the missing asset is available
4. Information on both the expected return and variance of the missing asset is available

In conclusion, Kandel (1984: 74) stated that the basic finding of the study was that if no information about the missing asset is available then the mean-variance efficiency hypothesis cannot be rejected. The same was found to be the case when perfect or partial information was known about the expected return of the missing asset. What was interesting was that it was found that there was an empirically testable implication if perfect or partial information was available on the variance of the missing asset. This was because if the variance is available or an “upper bound” for it is known, this means that, in principle, the mean variance hypothesis can be rejected. Rejection happens when the portfolio of the included asset is adequately far from the efficient frontier in the mean-variance space created by these assets alone. Kandel (1984: 74) following this finding stated that “It is interesting that our results highlight the importance of the variance of the missing asset. However, the requirements that the variance be bounded and that the market share of the missing asset be small, constitute a severe limitation on using a subset of assets to test the theory”. Finally it was found that if information on both the variance and expected return of missing asset is available, then the null hypothesis can be correctly rejected if the distance is either too small or too large from the efficient frontier. Finally Kandel (1984: 65) stated that “this can be the basis for a future mean-variance efficiency test in which a higher level of uncertainty about the market index is allowed”.

### 3.3.3 Kandel and Stambaugh (1987)

In their 1987 paper entitled “On Correlations about Mean-Variance Efficiency”, Kandel and Stambaugh presented a framework for testing the mean-variance efficiency of an unobservable portfolio based on its correlation with a proxy portfolio (Kandel and Stambaugh, 1987: 61). Kandel and Stambaugh (1987: 61) began their study by mentioning that a number of asset pricing models such as the CAPM imply the mean-variance efficiency of one or more benchmark portfolios. Kandel and Stambaugh (1987: 61) acknowledged the dual problem of testing the mean-variance efficiency of a portfolio in a finite sample and how to make inferences about the mean-variance efficiency of a benchmark when this portfolio is unattainable; or as Kandel and Stambaugh (1987:61) stated “when its exact rate of return is unobservable”. On this, Kandel and Stambaugh (1987: 62) admit that the “precise measurement of the relevant benchmark return can be difficult”, and go on to mention that one way of tackling this problem would be to question whether any portfolio in a set of portfolios would lead to different inferences, where the set of portfolios all comply with a given relation (e.g. correlation) with the original proxy.

Kandel and Stambaugh (1987: 62) stated that they had characterized “an alternative proxy portfolio in terms of the correlation between its return and the return on the original proxy”. This characterization allowed Kandel and Stambaugh (1987: 62) to “define a class of alternative proxies as all portfolios having a sample correlation of at least, say, 0.9 with the original proxy”. They then went on to question if any of these portfolios provide an inference about mean-variance efficiency that is different from the inference about the original proxy. The question is addressed in a finite-sample context. Kandel and Stambaugh (1987: 62) also tested whether or not the ex ante correlation between the portfolio at the point of tangency with the CML and efficient frontier (i.e. the market portfolio) of the global asset universe exceeds a certain value. Kandel and Stambaugh (1987: 62) thus attempted to integrate the issues of the finite-sample tests and the benchmark portfolio measurement.

Kandel and Stambaugh (1987: 63) divided their study into three sections. The first looked at the above issues when all parameter values were available. This framework allowed Kandel and Stambaugh (1987: 62) to “introduce the relevant mean-variance mathematics before turning to the complications of finite-sample variability”. At the starting point of the section Kandel and Stambaugh (1987: 65) showed that the correlation between the market portfolio and the proxy is



sensitive to how the efficient set is constructed. This section also addressed a number of questions such as “where, in mean-variance space, are the portfolios having correlations with a given proxy of at least, say, 0.9? Do such portfolios include points on the minimum-variance boundary? Do they include the Sharpe-Lintner tangency? Do they exist at all levels of return? The next section, expanded the investigation to include a finite-sample inference. Kandel and Stambaugh (1987: 63) analyzed “the sensitivity of inferences based on the likelihood ratio test of tangency in the presence of a riskless asset”. The final section of the paper presents a “new test of the hypothesis that a given proxy is correlated ex ante at least  $\rho_0$  with the ex ante tangent portfolio” (Kandel and Stambaugh, 1987: 63). The null hypothesis for this section of the paper is a joint hypothesis that a portfolio whose exact return is unobservable, for example, the true market portfolio, is firstly (i) the ex ante tangent portfolio of the global universe and (ii) correlated ex ante at least  $\rho_0$  with the given observable proxy (Kandel and Stambaugh, 1987: 63).

Kandel and Stambaugh (1987: 87) found that the correlation between the tangent portfolio and the market proxy is dependent on how the efficient set is constructed, both ex ante and in the sample. Starting with the minimum-variance boundary constructed by Roll (1977), Kandel and Stambaugh (1987: 87) showed that the sample tangent portfolio and the proxy constructed by Black, Jensen and Scholes in their (1972) paper, decreases as additional assets are added to the observed universe. This decrease in the correlation as stated by Kandel and Stambaugh (1987: 88) “is easily understood when one realizes that the correlation between the proxy and the tangent portfolio is the ratio of the Sharpe measures of the two portfolios”. The relationship between the Sharpe measures and the correlations also suggests that the mean-variance efficiency of a „true’ benchmark portfolio, which possibly contains all assets, is rejected if one rejects the efficiency of a certain alternative benchmark portfolio in an observed universe made up of a subset of assets. This alternative benchmark is the portfolio (from the observed universe) with the highest correlation to the true benchmark (Kandel and Stambaugh, 1987: 88).

In the next section, where Kandel and Stambaugh (1987: 73-80) investigated a finite-sample inference. Kandel and Stambaugh (1987: 88) attempted to find “the highest sample correlation between the proxy and a portfolio that reverses the inferences about the proxy’s tangency. It was found that when monthly data of lengthy periods (26-52 years) was used to examine the tangency of the equally weighted or value-weighted NYSE, there are some instances where no rejection area exists at standard test sizes, and other instances where the correlation that reverses the inference about the tangency of the NYSE portfolio is fairly high. When weekly

data of shorter periods (6 years) was used, the tangency of both the value- and equally weighted NYSE-AMEX portfolios was rejected (Kandel and Stambaugh, 1987: 88). Kandel and Stambaugh (1987: 88) found that the maximum correlation between the NYSE-AMEX proxy and a sample portfolio, inferred to be tangential at the 5 percent level of significance, ranged from 0.76 – 0.48 for the value-weighted portfolio and 0.9 – 0.46 for the equally weighted portfolio.

In the final section, Kandel and Stambaugh (1987: 81-87) extended the preceding sensitivity analysis. The test was applied to weekly returns data for common stocks, along with the value- and equal weighted NYSE-AMEX indices as the observable proxies. The null hypothesis which was joint hypothesis that the unobservable benchmark proxy was (i) the ex ante tangent portfolio and (ii) highly correlated ( at least  $\rho_0 = 0.9$ ) with the NYSE-AMEX index. The hypothesis was most of the time rejected for  $\rho_0$  equal to 0.9 and is even rejected most of the time for  $\rho_0 = 0.8$  and  $\rho_0 = 0.7$  (Kandel and Stambaugh, 1987: 88). Which indicates that the NYSE-AMEX would be an inefficient proxy for the market portfolio.

### **3.3.4 Basak, Jagannathan and Sun (2002)**

Basak, Jagannathan and Sun (2002) in their study, “A Direct Test For The Mean Variance Efficiency Of A Portfolio” developed a direct test for testing the degree of mean-variance efficiency of a particular benchmark return with reference to the efficient frontier which was formed by a set of primitive assets. Basak *et al* (2002: 2) highlight that “a natural direct measure of efficiency is the difference between the variance of the return on an efficient portfolio of primitive assets that has the same mean as the bench-mark and the variance of the bench-mark return. The hypothesis that the bench-mark asset is mean-variance efficient can be tested by examining whether the estimated measure of efficiency is greater than zero after allowing for sampling errors”. Unlike traditional studies, this study allows for the “possibility” that short positions in some or all of the primitive assets may not be possible (Basak *et al*, 2002: 2).

Basak *et al* (2002: 2) mentioned that in the past, empirical studies have focussed on examining the mean-variance efficiency of the return of a value-weighted index of exchange traded stocks. The hypothesis in these studies is that, firstly, there are no restrictions on short sales, and secondly, the return on the index benchmark is efficient. Based on these assumptions Basak *et*

*al* (2002: 2) stated that the expected return on “any primitive asset is the exact linear function of the covariance between the return on the asset and the return on the bench-mark”. What Basak *et al* (2002: 2) pointed out is that traditional tests for mean-variance efficiency test whether such a (linear) relationship exists. If the first assumption is violated, “the linear relation between the expected return on a primitive asset and the covariance between the return on that asset and the return on the bench-mark will not in general hold” (Basak *et al*, 2002: 2). Thus there was no simple way in which Basak *et al*, could develop these tests to include restrictions to short sales (Basak *et al*, 2002: 2).

Basak *et al* (2002: 3) use 25 stock portfolios which were constructed by Fama and French in their 1993 study, as the set of primitive assets. Basak *et al*'s (2002: 3) measure of efficiency is the difference between the return variances of, (i) the portfolio from the 25 primitive assets that provided the smallest sample variance amongst all the portfolios that had the same mean returns as the stock index bench-mark (value-weighted return on exchange listed securities) and (ii) the stock index bench-mark. Basak *et al* (2002: 3) then attempted to illustrate that the “estimated measure of efficiency converges in probability to its population counterpart as the sample size becomes large”. They also attempt to illustrate how to interpret the sampling error related to the estimated measure of mean-variance efficiency.

The results of the examination of the mean-variance efficiency tests associated with the value weighted portfolio exchange traded stocks with reference to the efficient frontier derived by the 25 stock portfolios courtesy of Fama and French (1993) were used. These portfolios were sorted according to size and book-to-market figures. The results are displayed over page in table 3-1. It was found that only two of the primitive assets had variances below that of the bench-mark portfolio, of which one also had a higher return (Basak *et al*, 2002: 18). Furthermore it was found that none of the primitive assets were superior to the bench-mark in the mean-variance space.

**Table 3- 1 Results of the Basak *et al* (2002) study**

<b>Mean of the monthly rates of return (%)</b>				
1.47	1.51	1.5	1.56	1.48
1.77	1.79	1.73	1.43	1.44
1.87	1.93	1.76	1.64	1.4
1.96	1.92	1.89	1.85	1.64
2.08	2.1	2.05	2.13	1.67
<b>Variance of the monthly percentage rates of return</b>				
59.42	52.29	44.57	35.23	24.08
46.32	40.82	32.23	29.31	21.92
39.03	33.77	27.38	24.97	18.97
35.37	28.16	23.79	24.12	18
38.71	36.37	32.15	32.73	23.29
<b>Correlation Coefficient with the bench-mark asset return</b>				
0.81	0.88	0.92	0.94	0.94
0.83	0.89	0.91	0.95	0.96
0.82	0.87	0.89	0.93	0.92
0.8	0.87	0.89	0.89	0.89
0.78	0.84	0.86	0.87	0.83
<b>Portfolio weights (%) with the no short-sale constraint</b>				
0	0	0	0	11
0	0	0	0	0
0	0	0	0	46
0	0	0	0	43
0	0	0	0	0
<b>Portfolio weights (%) without short-sale restrictions</b>				
-10	-26	-29	0	57
-18	-28	-1	-26	7
20	10	55	5	35
84	10	34	-23	24
1	-54	-3	-49	26
Summary Statistics				
<b>Monthly rate of return (%) on the bench-mark portfolio</b>				
mean 1.51				
variance 20.26				
<b>Minimum-variance portfolio having same mean as bench-mark</b>				
(t-statistic in parenthesis and standard error in square brackets)				
No short-sale restrictions 10.42 (t=3.36) [p=0.0%]				
Short-selling prohibited 3.08 (t=0.90) [p=18.4%]				

(Source: Basak *et al*, 2002: 24-25)

Basak *et al* (2002: 18) found that when there were no short-sale restrictions in place, the minimum-variance portfolio that had the exact same sample mean as the bench-mark had a variance of 9.84. This meant that there was a reduction in variance of 10.42, which is a decrease in the sample variance of 52% when compared to the bench-mark. The standard error of the estimated variance reduction was found to be 3.10. Thus Basak *et al* (2002: 18) rejected the hypothesis “that the bench-mark is mean-variance efficient against the alternative that it is inefficient at 0.04 percent”. Basak *et al* (2002: 18) state that the mean-variance efficient portfolio that has the exact mean of the bench-mark contains short positions in 11 of the 25 assets, and that in addition to this, the weights include large positive and negative values (highest being 84 percent and lowest being -54 percent). Basak *et al* (2002: 18) acknowledge that this is in line with past studies and quote Green and Hollifield (1992) who made the following remarks, “The extreme weights in efficient portfolios are due to the dominance of a single factor in the covariance structure of returns, and the consequent high correlation between naively diversified portfolios. With small amounts of cross-sectional diversity in asset betas, well-diversified portfolios can be constructed on subsets of the assets with very little residual risk and different betas. A portfolio of these diversified portfolios can then be constructed that has zero beta, thus eliminating the factor risk as well as the residual risk”. It was found by Basak *et al* (2002: 19) that this explanation by Green and Hollifield (1992) was also valid in their sample.

Basak *et al* (2002: 20) found that the mean-variance efficiency of the bench-mark improved dramatically when short selling restrictions were imposed, which was in line with previous studies. Finally, Basak *et al* (2002: 20) found that when the short-selling restrictions were imposed, the minimum variance portfolio which had the same mean as the bench-mark consisted of only three primitive assets. Thus Basak *et al* (2002: 20) concluded that they could not reject the hypothesis that the value-weighted return on exchange listed securities is mean-variance efficient with reference to the efficient frontier which was generated by the 25 portfolios constructed by Fama and French (1993), when short selling was not permitted.

### **3.3.5 Roopanand (2001)**

Roopanand (2001) in his paper entitled “The Mean Variance Efficiency of the JSE All Share Index (ALSI) and it’s Implications for Portfolio Management” attempted, through the use of portfolio theory and pricing models, to test the efficiency of the South African market and its

implications for investment decision-making. This paper is obviously of particular relevance to this study, because not only does it examine the mean-variance efficiency of a market proxy, it does so in a South African context. Hence the paper will be examined in more detail.

Roopanand (2001: 3) posed the question what if the return on the market, using a proxy like the ALSI, was inefficient? What would this mean for the CAPM and would it still be a useful measure upon which investment decisions can be made? Roopanand (2001: 5) stated that the goal of his paper was to determine the efficiency of returns of the ALSI using the CAPM model of linearity and to compare the returns to returns given by the Markowitz portfolio selection model of efficiency frontiers using indices such as the local Industrial and Gold Index and the Dow Jones Index internationally. Roopanand (2001:5) proposed to test the mean-variance efficiency of the ALSI returns from the point of view of a local investor and to gauge its relevance, if any, to the CAPM.

In describing his methodology, Roopanand (2001: 18) admitted that the major weakness or limitation of his study was that it is an ex post facto explanatory study, meaning that the study makes use of historical data to predict the future. Nevertheless, the two models upon which the methodology was based were the CAPM and the Markowitz theory of portfolio selection. The analysis began with tests on the suitability of the market proxy in the CAPM model by making use of an index model equation:

$$E(r_i) - r_f = \alpha_i + \beta_i[E(r_m) - r_f] \quad (3.1)$$

The equation is a simple regression equation, which provided Roopanand (2001: 18) with a testable hypothesis based on the index model. The assets premium over the risk-free rate was treated as the dependant variable, whilst the excess market return was the independent variable. The coefficient of the excess market return is the beta or slope of the CAPM, meaning that the expected return on the asset can... “be explained by its sensitivity coefficient ( $\beta$ ) to the market index. If there were a weak relationship between the ALSI and the true market portfolio then the alpha term would turn out to be significantly different to zero” (Roopanand, 2001: 19). The hypotheses that were tested were:

$H_0: \alpha = 0$  The ALSI is mean-variance efficient

$H_1: \alpha \neq 0$  The ALSI is not mean-variance efficient

And

$H_0: \beta = 0$  The asset returns are unrelated

$H_1: \beta \neq 0$  The asset returns are related

(Roopanand, 2001: 19)

Using this methodology allowed Roopanand to solve for the ex post beta and thus determine if the empirical beta was related to the market proxy. To begin with, Roopanand (2001: 19) used the ALSI as a proxy and calculated the beta for the gold index (GOLDI) and the industrial index (INDI), after which, Roopanand (2001: 19) used the Dow Jones as a market proxy and tested the indices further. The results of the betas were substituted into equation 3.2, and from the results obtained, Roopanand recommended the use of the proxy according to its ability to predict returns within the 95% confidence level of the mean return.

$$\lambda_i = \beta_i \lambda_m \quad (3.2)$$

(Roopanand, 2001: 20)

Roopanand (2001: 30-34) found that based on the above criteria that the ALSI was an adequate proxy for the INDI but not the GOLDI. Following the tests on the ALSI, Roopanand (2001: 20) discussed “the implications for an asset universe of four assets in terms of portfolio optimisation tools and compared the results of the methodologies”. Initially it was assumed that the SA investor was only allowed to invest in SA and hence was limited to a three asset universe, consisting of the market proxy and the two major sectors (gold and industrial sectors). Next, a fourth asset, representing international stocks (Dow Jones) was included. A 15% weighting constraint was initially placed on the international asset and was later lifted (Roopanand, 2001: 20). Put simply, Roopanand’s (2001: 21) analysis was concluded with the construction of an efficient frontier for the differing scenarios, and it was determined both graphically and mathematically whether or not the ALSI is situated on the efficient frontier. Mathematically, the market portfolio was determined inefficient if its Sharpe ratio was lower than any asset in this universe.

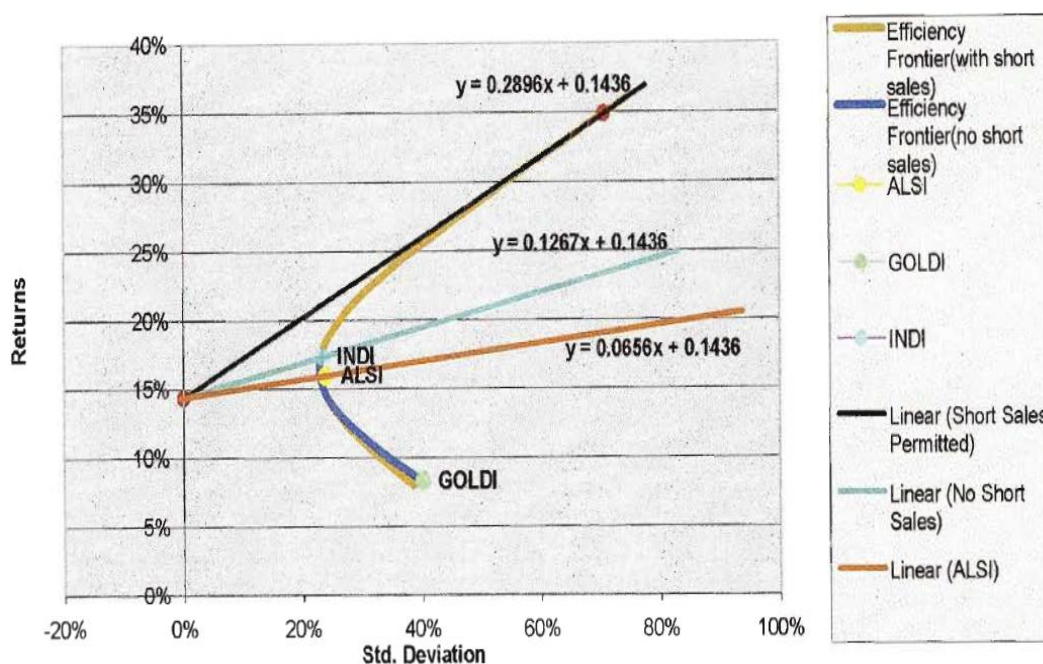
When testing the ALSI using the GOLDI, the null hypothesis that alpha was equal to zero was rejected and thus it was concluded that the ALSI was mean-variance inefficient (Roopanand, 2001: 31), suggesting that the ALSI is not an adequate proxy to use when determining the fair price of gold in South Africa. For the second hypothesis test it was found that there was a strong relationship between the ALSI and the GOLDI, contradicting the earlier result (Roopanand, 2001: 32). When testing the ALSI using the INDI, Roopanand (2001: 34) failed to reject the null hypothesis, concluding that the ALSI is mean-variance efficient in the case of the industrial index, and is suitable for use in the CAPM. It was also found that the ALSI and INDI were related, supporting the earlier finding. The implication for portfolio management based on this finding is that it would be efficient to hold the ALSI as a proxy for the market portfolio when assessing industrial shares (Roopanand, 2001: 34).

Next Roopanand (2001: 41) used the Dow Jones in place of the ALSI as the market proxy. When testing the Dow Jones using the GOLDI it was found that, as with the ALSI, the null hypothesis was rejected and the Dow Jones was deemed mean-variance inefficient. Furthermore, it was found that the Dow Jones was not as correlated to the GOLDI as the ALSI was. When testing the Dow Jones using the INDI, Roopanand (2001: 43) found that the null hypothesis could not be rejected and that the Dow Jones in relation to the INDI displayed efficiency.

Following this, Roopanand (2001: 52) looked at the placing of the ALSI with regards to efficient frontiers of differing scenarios, both mathematically and graphically. From the first scenario, without any foreign assets, it was found that the ALSI was not placed on the efficient frontier as shown in figure 3-5. The INDI was actually placed closer to the efficient frontier. Roopanand (2001: 53) stated that due to the fact that so many institutions are prevented from taking short positions, the restricted flatter sloped portfolio is the “decisive frontier to the portfolio creation decision”.



Figure 3- 5 SA efficient frontiers and their CMLs

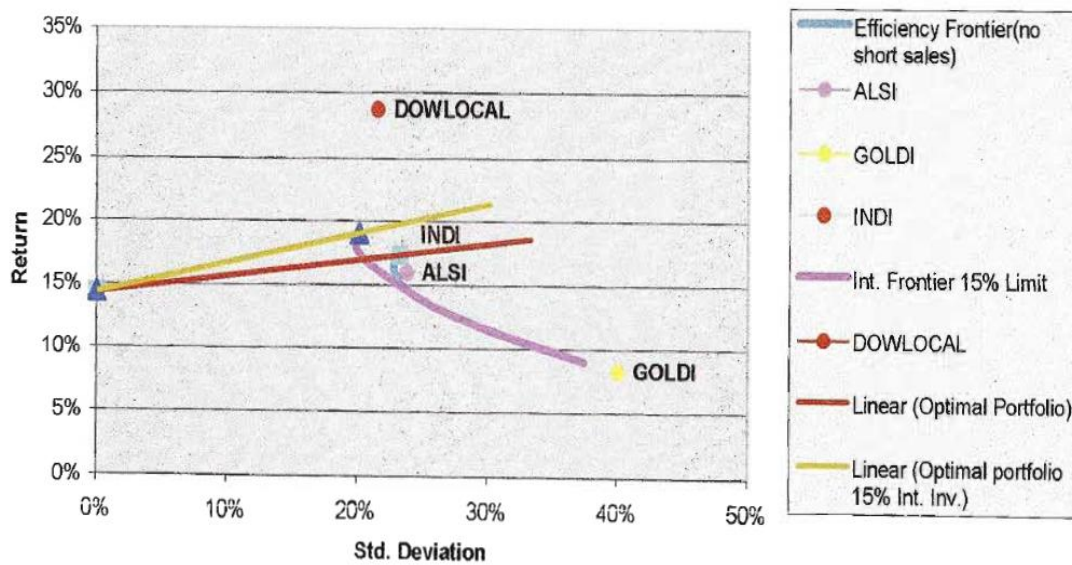


(Source: Roopanand, 2001: 53)

Thus according to this graph, an investor should have invested 100% of his/her wealth in the INDI and none in the ALSI or GOLDI. The Sharpe ratios of the ALSI slope, the INDI slope and the short sales slope were found to be 0.0655, 0.1267 and 0.2896 respectively. Whilst the Sharpe ratio of the GOLDI was found to be -0.1528 (Roopanand, 2001: 55). Not only does this illustrate that the ALSI is mean-variance inefficient on the JSE, it also shows the impact of short sales.

When lifting the constraints on international investing to 15%, the following graph was obtained. The graph is superimposed onto the graph before any foreign investment was allowed, to show the benefits of international diversification (Roopanand, 2001: 56). The ALSI is now even further from the efficient frontier and it was found that its Sharpe ratio is even less than the optimal portfolio, which comprised of 15% Dow Jones and 85% INDI.

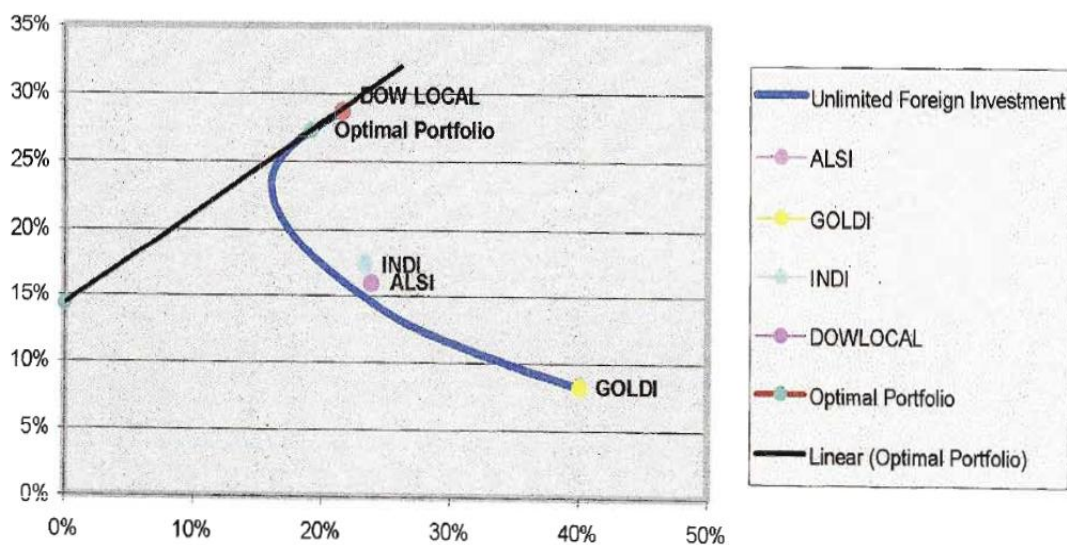
**Figure 3- 6 SA portfolio with 15% foreign investment allowance**



(Source: Roopanand, 2001: 56)

Finally the scenario with unlimited foreign investment was examined and the results obtained are displayed in figure 3-7. The ALSI is found to be further yet from the optimal portfolio, which comprised of 12.4972% INDI and 87.5028% Dow Jones. This proves to be the portfolio with the highest Sharpe ratio.

**Figure 3- 7 SA frontier with unlimited international portfolio**



(Source: Roopanand, 2001: 58)

Thus in conclusion, Roopanand (2001: 75-78) found that in the South African context, the ALSI was efficient when based on industrial shares and inefficient when based on gold shares. On the whole when introducing foreign investments the ALSI was not found to be efficient, and the more investors were allowed to invest internationally the more obvious this became.

### 3.3.6 Levy and Roll (2008)

In their study “The Market Portfolio may be Mean-Variance Efficient After All”, Levy and Roll (2008: 1) stated that “many studies”<sup>1</sup> that have tested the mean-variance efficiency of various market proxies have discovered that these proxies are inefficient. Furthermore, according to Levy and Roll (2008: 1) it is widely acknowledged that a portfolio located on the efficient frontier typically involves a number of short positions, which suggests that due to the fact that, by definition, the market portfolio contains all assets held in proportion to their market value it cannot be efficient. This obviously creates much doubt regarding one of modern finance’s most fundamental models. Following this evidence, Levy and Roll (2008: 1) pose the question “should the CAPM be taken seriously by financial economists, or is it just a pedagogical tool for MBA classes, grossly inconsistent with the empirical evidence”? In testing the efficiency of a market proxy themselves, Levy and Roll (2008: 1) given a market proxy, attempted to find the minimal variation of the sample parameters needed to guarantee that the proxy was efficient.

Whilst most studies before Levy and Roll (2008: 1-2) had suggested numerous variations of the return parameters relative to the sample parameters and then assessed whether or not these changes led to an efficient market proxy, Levy and Roll (2008: 2) looked at the reverse approach: “we look for the return parameters that ensure that the market proxy is efficient, and that are as ‚close’ as possible to their sample counterparts”. Levy and Roll (2008: 2) then made small variations to the sample parameters, within the estimation error bounds, in an attempt to make the proxy efficient.

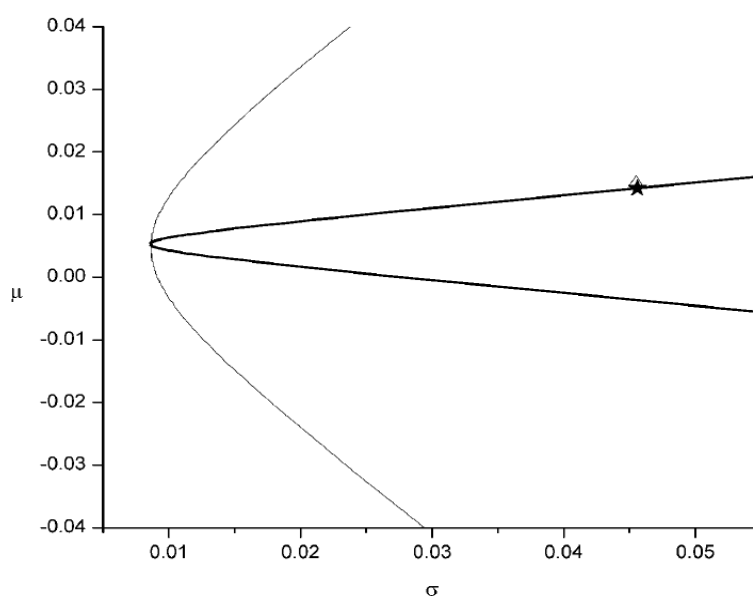
When Levy and Roll (2008: 6) first assessed the positioning of the proxy portfolio with respect to the sample efficient frontier, it was found that the two were far apart, as illustrated in figure 3-8, where the thin line is the sample efficient frontier and the triangle denotes the proxy. In

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<sup>1</sup> Ross (1980); Gibbons (1982); Jobson and Korkie (1982); Shanken (1985); Kandel and Stambaugh (1987); Gibbons, Ross and Shanken (1989); Zhou (1991); and MacKinlay and Richardson (1991).

order to make the proxy mean-variance efficient, Levy and Roll (2008: 7) examined the efficient frontier and the position of the proxy in the mean-standard deviation plane with the set of parameters  $(\mu^*, \sigma^*)$ , that make the proxy mean-variance efficient. These are shown by the bold line and star in figure 3-8. As can be seen from the figure,  $(\mu^*, \sigma^*)$  is located on the efficient frontier, what Levy and Roll (2008: 7) point out is that although the parameters  $(\mu^*, \sigma^*)$  do not have a big impact on the expected return or the standard deviation of the proxy (as can be seen the star is located very close to the triangle), they do have a big effect on the efficient frontier.

**Figure 3- 8 The efficient frontier and market proxy with the sample and the adjusted return parameters**



(Source: Levy and Roll, 2008: 18)

Levy and Roll (2008: 10) in discussing the implications of their research on asset pricing, mentioned that whilst their research did not “prove that the SML relationship holds empirically with the ex ante parameters, our analysis does provide another reason for employing betas for estimating the cost of capital”.

Levy and Roll (2008: 10-11) go on to prove that the SML may also be sufficient. They stated that if it is assumed that the CAPM holds with the true ex ante parameters  $(\mu^*, \sigma^*)$ , and that the

empirically measured parameters are  $(\mu^{sam}, \sigma^{sam})$ , it is shown that the true and sample betas of asset  $i$  are given by the equations 3.3 and 3.4 below

$$\beta_i^* = \frac{\sum_{j=1}^N x_{mj} \sigma_i^* \sigma_j^* \rho_{ij}}{x_m C x_m} \quad (3.3)$$

$$\beta_i^{sam} = \frac{\sum_{j=1}^N x_{mj} \sigma_i^{sam} \sigma_j^{sam} \rho_{ij}}{x_m C^{sam} x_m} \quad (3.4)$$

Where  $x_m$  are the market portfolio weights. Levy and Roll (2008: 11) go on to mention that the true cost of equity of firm  $i$  is  $\mu_i^*$ , and ask the question if  $\beta_i^{sam}$  was used in the CAPM instead of  $\beta_i^*$  how would this impact on the cost of equity? Basically Levy and Roll (2008: 11) ask how close are  $\beta_i^{sam}$  and  $\beta_i^*$ ? The answer is illustrated in figure 3-9. The figure shows that the difference between the two betas is very small. This is because both the denominators of equation 3.3 and 3.4 are very alike. The variance of the proxy is very similar whether the sample or true parameters are used as shown by the star and triangle in figure 3-4 (Levy and Roll, 2008: 11). The covariances in the numerators according to Levy and Roll (2008: 11) are  $\sigma_j^* \approx \sigma_j^{sam}$ , and furthermore, the deviations often cancel each other out when they are added, as in certain cases  $\sigma_j^* > \sigma_j^{sam}$ , whilst in others  $\sigma_j^* < \sigma_j^{sam}$ . Now Levy and Roll (2008: 11) state that because of the fact that the proxy is efficient with the parameters  $(\mu^*, \sigma^*)$ , the following equation (3.5) holds exactly:

$$\mu_i^* = r_f + \beta_i^*(\mu_m - r_f) \quad (3.5)$$

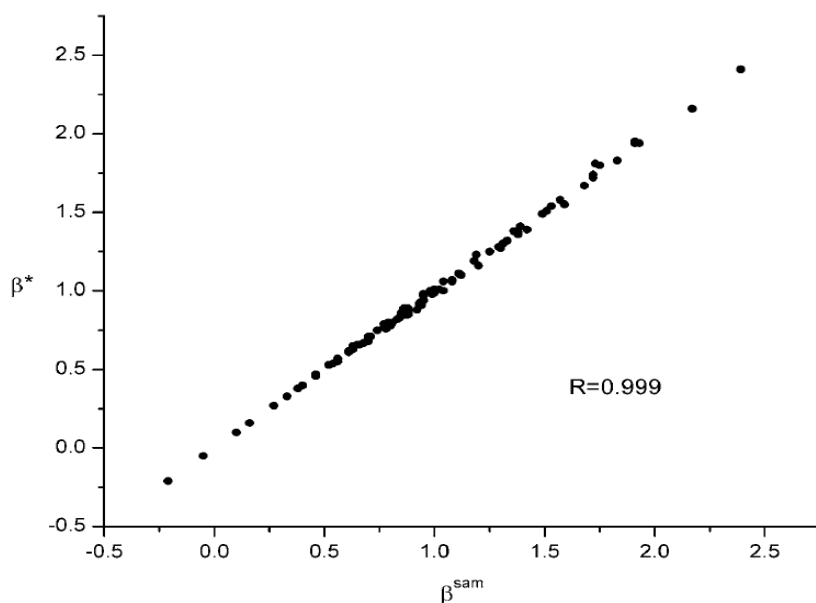
Thus as  $\beta_i^* \approx \beta_i^{sam}$ , using the sample beta in applications of the CAPM, as is done so often in practice, provides a very good estimate for the true expected rate of return (Levy and Roll, 2008: 11):

$$\mu_i^* - [r_f + \beta_i^{sam}(\mu_m^{sam} - r_f)] = \beta_i^*(\mu_m^* - r_f) - \beta_i^{sam}(\mu_m^{sam} - r_f) \approx 0 \quad (3.6)$$

Thus as Levy and Roll (2008: 11-12) point out, “it is not only the case that the estimates of betas are statistically more stable than those of the expected return. In addition, if the CAPM

holds in a way that is consistent with the sample parameters, the difference between the sample betas and true beta is much smaller than the difference between the sample average returns and the true expected returns”.

**Figure 3-9 The relationship between sample betas and the true betas**



(Source: Levy and Roll, 2008: 23)

In conclusion, Levy and Roll (2008: 12-13) state that market proxies have invariably been large distances from the sample efficient frontiers and numerous studies have attempted to make adjustments to the sample parameters to try and make the market proxy efficient, without success. And as a result it is a common view that “the empirical return parameters and the market portfolio weights are incompatible with the CAPM theory” (Levy and Roll, 2008: 12). However, Levy and Roll (2008: 12) show that minor variations of the sample parameters, within the estimation error, can in fact make the proxy efficient. Levy and Roll (2008: 12) admit that these adjustments are similar to “shrinkage”, but are different in the sense that the result is obtained through “reverse optimization”. In this reverse optimization Levy and Roll (2008: 12) search for return parameters which can make the proxy efficient, and importantly, are as close as possible to their sample equivalents. Thus Levy and Roll (2008: 13) conclude that these findings suggest that the CAPM is one hundred percent consistent with the empirically observed return parameters and proxy portfolio weights, and finally that in this framework using a sample beta gives a good estimate of true expected returns. Thus in conclusion to this

section of past studies, it can be seen that there are mixed results, the results are summarised in the following table (table 3-2).

**Table 3- 2 Empirical tests of the mean-variance efficiency of the market proxies**

<b>Authors</b>	<b>Proxy</b>	<b>Conclusion</b>
Roll (1977)	-	Untestable
Kandel (1984)	-	Cannot reject the hypothesis that the proxy is mean-variance efficient
Kandel and Stambaugh (1987)	Equally and value-weighted NYSE; equally and value-weighted NYSE-AMEX	Inefficient
Basak, Jagannathan and Sun (2002)	Value-weighted return on exchange traded stocks	Cannot reject the hypothesis that the proxy is mean-variance efficient
Roopchand (2001)	ALSI; Dow Jones	Not conclusive
Levy and Roll (2008)	-	Efficient

Following the numerous studies on mean-variance efficiency and in particular the study of Roll (1977) there has been increased attention paid to the appropriate choice of market proxy in the CAPM. In an attempt to obtain mean-variance efficient portfolios many modifications of the proxy have been used and tested, a few of these studies are reviewed in the following sections. However first, the choice of market proxy is examined briefly in the context of the U.S..

### **3.4 The Choice of Market Proxy in the U.S.**

As mentioned, the common trend amongst academics in the U.S. when conducting research (for example Fama and MacBeth, 1973: 614; Jagannathan and Wang, 1996: 12; Bruner *et al*, 1998) and advocated in numerous texts (Harrington, 1987; Firer, 1993; Reilly and Wright, 2004; Reilly and Brown, 2006) is to employ a comprehensive stock market index as a proxy for the market portfolio. According to Reilly and Wright (2004: 66) the traditional approach in the U.S. is to use the S&P 500 index as a proxy because it is a value weighted index (as specified in the theory behind the model); and because it was regarded to be a well diversified portfolio of U.S. stocks when the CAPM was first developed in the mid-1960s.

However, in the U.S. there are a number of alternative market proxies available, such as, the S&P 400, the Dow Jones Industrial Average and the Wilshire 5000. Each of these indices, however, do face problems when used as a proxy for the market portfolio, as stated earlier they

exclude numerous assets and to further compound the problem, because every possible index comprises of different kinds of assets, the results can be and should be quite different (Stambaugh, 1982: 237; Harrington, 1987: 174; Reilly and Wright, 2004: 65). The difference of these indices can be seen in the following table. The table illustrates the returns for 5 commonly used indices in the U.S. for the period 2007 - 2011.

**Table 3- 3 Index returns for the period 2007-2011**

INDEX	RATE OF RETURN
Standard & Poor 500	2.81%
Standard & Poor 400	6.92%
Dow Jones Industrial	4.69%
Russell 2000	4.46%
NASDAQ Composite	4.84%

(Source: Morningstar, 2011)

Building on from the argument in the previous paragraph that assets are excluded from these indices, and as was discussed in chapter two; aside from the common definition that the market portfolio was mean-variance efficient, numerous authors such as Fama (1993: 31), Campbell, Lo and MacKinlay (1997: 213), Bodie *et al* (2007: 205) and Brown and Reilly (2009: 228) describe the market portfolio as containing *all* risky assets in held in proportion to their market value. Thus the question needs to be asked: is using indices such as the S&P 500 as a proxy for the market portfolio sufficient? This method ignores a large number of risky assets from the proxy for the market portfolio, such as bonds, art, real estate and even human capital (Brown and Reilly, 2009: 228; Jagannathan and Wang, 1996: 5). As a result, numerous academics have begun to look at incorporating additional assets into their proxies for the market portfolio.

### **3.5 The Incorporation of Additional Assets to the Market Proxy**

According to Goltz and Le Sourd (2010: 27), following Roll's critique (1977) many researchers have begun to use far more complex proxies of the market portfolio in their empirical studies. The proxies include assets such as bonds and property. In addition to financial assets, researchers have gone so far as to include non-tradable assets, all in an attempt to obtain a



mean-variance asset (Goltz and Le Sourd, 2010: 27). In chapter two it was discussed that two important features of the market portfolio are that it is mean-variance efficient and contains all risky assets – however these two features could work hand in hand. It is possible that adding assets, such as bonds, to the proxy for the market portfolio will help the proxy get closer to that mean-variance efficiency which is so important. Numerous authors such as Van Rensburg and Slaney (1997: 1), Van Rensburg (2002: 83) and Elton *et al* (2003: 161) advocate the use of multi-index models. Furthermore the 2009 survey conducted by PriceWaterhouseCoopers (2009: 26) found that more and more practitioners were “exploring alternative approaches” such as multi-index models. A number of studies that looked at the addition of assets to their proxies, are summarised by Goltz and Le Sourd (2010: 27) in table 3-4.

**Table 3- 4 Market portfolio proxies tested in empirical studies**

Author(s)	Journal(s)	Description of the proxy	Assets included in the proxy			Conclusion
			Stocks	Bonds	Other assets	
Black, Jensen, and Scholes (1972); Fama and MacBeth (1973); Gibbons (1982)	<i>JPE; JFE</i>	Equal-weighted portfolio of all NYSE-listed stocks	*			Efficient
Frankfurter (1976)	<i>JF</i>	Dow Jones Ind. Average, S&P 500, Geometric mean market value index (522 stocks)	*			Not conclusive
Zhou (1981)	<i>JFE</i>	CRSP value-weighted index of NYSE stocks	*			Not efficient
Gibbons (1982)	<i>JFE</i>	Equally weighted index of NYSE stocks	*			Efficient
Stambaugh (1982)	<i>JFE</i>	NYSE common stocks, US corporate and government bonds and bills, residential real estate, house furnishings, and automobiles.	*	*	*	Efficient
Shanken (1985, 1987)	<i>JFE</i>	Equal-weighted CRSP index and/or long-term US government bond portfolio	*	*		Not efficient
Brown and Brown (1987)	<i>JPM</i>	Different market proxies including common stocks, fixed-income corporate issues, real estate, government bonds, municipal bonds	*	*	*	Not conclusive
Gibbons, Ross, and Shanken (1989)	<i>Emtrca</i>	Value-weighted CRSP index of all NYSE stocks	*			Not efficient
Harvey and Zhou (1990)	<i>JFE</i>	Value-weighted portfolio of all NYSE stocks	*			Not efficient
Harvey (1991)	<i>JF</i>	MSCI indices for a collection of countries.	*			Not efficient
Haugen and Baker (1991)	<i>JPM</i>	Wilshire 5000	*			Not efficient
Grinold (1992)	<i>JPM</i>	Commercial indices like S&P 500, FTA, All Ordinaries, TOPIX, DAX	*			Not efficient
Jagannathan and Wang (1993, 1996)	<i>FRBM, JF</i>	Market portfolio proxy including human capital (labour income)	*		*	Not conclusive
Fama and French (1998)	<i>JF</i>	MSCI global index	*			Not efficient
Dalang, Marty, and Osinski (2001/2002)	<i>JPM</i>	FT Global Equities Index	*			Not efficient
Kandel, McCulloch, and Stambaugh (1995)	<i>RFS</i>	Stocks listed on the NYSE and AMEX	*			Not efficient
Fama and French (2004)	<i>WP</i>	Value weighted portfolio of all NYSE, AMEX and NASDAQ stocks	*			Not conclusive

*Journal abbreviations: JPE, Journal of Political Economy; JFE, Journal of Financial Economics; JF, Journal of Finance; JPM, Journal of Portfolio Management, Emtrca, Econometrica; RFS, Review of Financial Studies; FRBM, Federal Reserve Bank of Minneapolis; WP: working paper*

(Source: Goltz and Le Sourd, 2010: 27)

As can be seen in table 3-4, three studies investigated the addition of bonds to the proxy for the market portfolio, namely, Stambaugh (1982) Shanken (1987) and Brown and Brown (1987). This method could prove to be a simple remedy to the problems discussed earlier, in that theoretically a large asset class is not being ignored by a portfolio that supposedly contains *all* risky assets, and that through the addition of such a large asset class a step towards mean-variance efficiency could be achieved.

### 3.6 The Market Proxy and Bonds

Following Roll's Critique (1977), Stambaugh (1982: 237), Brown and Brown (1987: 26) Benefield, Anderson and Zumpano (2007: 191) and Goltz and Le Sourd (2010: 26) acknowledge that stock market indices are theoretically far from adequate proxies for the market portfolio. Stambaugh (1982: 237) stated that "many discussions on the Capital Asset Pricing Model (CAPM) in recent years have centred on problems of excluding assets". Amongst other assets one of the asset classes these authors identify to be missing is bonds (Roll 1978; 1980; 1981; Stambaugh, 1982: 237; Brown and Brown, 1987: 26; Shanken, 1987: 92). Although the common trend has been to use equity indices, as table 3-5 shows these indices make up only a small portion of the total market and ignore the large asset class of bonds. The table shows that in 2009 listed bonds counted for over 20% of the exchange listed securities on the JSE. These statistics illustrate that the practitioners are far from using an accurate proxy for the market portfolio.

**Table 3- 5 Actual market weightings of bonds and equities as at Nov 2009**

Value of Bonds	951 385 459 985.80
Value of Equities	3 109 358 535 494.85
Value of Total Market	4 060 743 995 480.65
Bonds as Percentage of Total Market	23.43%
Equities as Percentage of Total Market	76.57%

(Bond Exchange of South Africa; Johannesburg Stock Exchange 2009)

The inclusion of bonds into the proxy for the market portfolio could serve as a simple yet effective improvement to the market proxy. Furthermore the inclusion of bonds would allow the proxy to incorporate factors that it otherwise would not, such as interest rate risk, a very real

issue in South Africa. The first person to suggest the inclusion of bonds into the market proxy was Stone (1974), he stated that “a two-index model involving return on equity and debt markets is a useful framework for quantifying the concept of systematic interest rate risk, for refining our concept of equity risk, for including more information in the return generating process, and for expanding the asset class treatable by an index model beyond equities to include bonds and hybrid securities” (Stone 1974: 718).

Stone (1974: 710) stated that the “introduction of the multiperiod aspect of investment forces one to recognize the existence of debt instruments with a series of maturities and the concomitant possibility of gains and losses from changes in interest rates analogous to the gains and losses from changes in the level of the equity market”. Stone believed that to ignore debt instruments when specifying the market portfolio would result in the incomplete treatment of systematic interest rate risk. Stone’s paper expanded the market portfolio to deal with interest rate effects and studied the implications for portfolio theory, performance measurement, and asset pricing theory. Stone (1974: 718) argued that ignoring systematic interest-rate risk, which is inherent in a single-index model, could result in biased performance measures. According to Stone the model would also help include more information in the return generating process, and aid in expanding the asset class treatable by an index model beyond equities to include bonds and hybrid securities.

Shanken (1987: 92) alluded to Roll’s critique (1977), and in particular where he mentioned that the best proxies would be those that are highly correlated with each other and the true market portfolio. Shanken (1987: 103) believed that the addition of a bond index would serve to increase the multiple correlation between the market proxy and the true market portfolio, and hence according to Roll (1977) improve the proxy.

The points put forward by Stone and Shanken are very relevant. The option of including bonds into that proxy may ultimately improve the results of the CAPM. Moreover, the process of including a bond index, (such as the All Bond Index (ALBI) which was formed in 2000, and is an index that consists of the top 20 listed bonds, ranked by market capitalisation and liquidity (BESA/ASSA 2000: 5)), in the proxy is not cumbersome, and thus could prove a simple way for practitioners to enhance their valuation techniques. As this method may appear theoretically sound, there is a need to explore empirical evidence on the matter. As was pointed out in table

3-4, Stambaugh (1982), Shanken (1987) and Brown and Brown (1987), all acknowledged that the addition of assets to the proxy of the market portfolio may enhance the use of the CAPM, and in particular all three discussed the addition of bonds to the proxy. These papers and their findings are now discussed to find out whether the empirical findings support the theoretical ideas.

### 3.6.1 Stambaugh (1982)

In response to Roll's critique, Stambaugh (1982: 237) conducted a study to investigate the sensitivity of tests of the CAPM to different sets of asset returns. Stambaugh's (1982: 246) primary focus was to investigate the choice and makeup of the proxy for the market portfolio, and how it influenced statistical inferences of the CAPM. Stambaugh tested for linearity between risk and return, the sign and size of the market risk premium, and finally compared the intercept of the SML and the risk-free proxy returns.

Stambaugh (1982: 238) tested the influence of the choice and makeup of the market proxy on the CAPM's inferences by constructing various market indices. Apart from NYSE common stock, the indices included six other classes of assets, namely, corporate bonds, U.S. government bonds, Treasury bills, residential real estate (structures), house furnishings and automobiles. The portfolios were formed by varying the weights of each of these classes. The crux of the study was based on the linear risk-return relationship as Stambaugh (1982: 238) stated, "The basis for the tests conducted here is the familiar linear relation between expected return and systematic risk implied by mean-variance efficiency of the market portfolio". The equation Stambaugh tested was that of the market model. That is, for any asset  $i$ :

$$E(r_i) = \gamma_1 + \gamma_2 \beta_i \quad (3.7)$$

Where:

$E(r_i)$  is the excess return of the asset  $i$

$\gamma_1$  is the estimated intercept of the model

$\gamma_2$  is the estimated coefficient of beta

$$\beta = \frac{\text{cov}(r_i, r_M)}{\sigma^2(r_M)}$$

$r_i$  is the return on asset  $i$

$r_M$  is return on the market portfolio

(Stambaugh, 1982: 238)

As stated, Stambaugh had three basic tests for this model. These are illustrated in his three testable hypotheses:

Hypothesis 1: Linearity – Expected return is linearly related to beta.

Hypothesis 2:  $\gamma_1 = r_f$ . The intercept is equal to the risk-free rate.

Hypothesis 3:  $\gamma_2 > 0$ . The risk premium,  $\gamma_2$ , is positive.

The first and third hypotheses, are equivalent to the condition that the market portfolio is situated on the positively-sloped portion of the efficient frontier. While hypothesis two is implied by the Sharpe-Lintner version of the model (Stambaugh, 1982: 246). When it came to the formation of Stambaugh's (1982: 251) portfolios, he expanded previous methodologies which based their formations on estimates of beta, and instead compiled industry based portfolios, which included not only ordinary shares, but preference shares and bonds too.

To test the risk-return relationship, Stambaugh (1982: 250) used a Lagrangian Multiplier (LM) test. What Stambaugh found was that the p-values obtained from the LM test were on average above 70 percent across the four market portfolios that were formed. This result indicated that the fundamental relationships of the CAPM did hold over the period that Stambaugh examined (Stambaugh, 1982: 254). Leading on from these positive results, Stambaugh (1982: 255) examined the equality of the intercept of the model and the risk-free rate, which in this case was the return on one-month T-Bill. Stambaugh conducted these tests using a Maximum Likelihood (ML) test. He found that the two values over the time period 1953 to 1976 were not equal across any of the four market proxies, as all the p-values were lower than 1 percent. However,

Stambaugh did highlight that the estimates obtained from the LM tests of the intercept had lower standard errors (greater efficiency) than previous studies, due to the fact that bonds and preferred shares had been included which led to a larger dispersion in the values of beta. Following these findings, Stambaugh (1982: 257) concluded that inferences about the CAPM are not sensitive to varying market indices, as all the tests conducted had produced identical inferences across the different market indices. More specifically, he concluded that the tests conducted had accepted linearity (hypothesis 1), and found a positive risk premium (hypothesis 3) but reject the equality of the zero-beta return to the t-bill rate (hypothesis 2).

The first set of tests described above, used different market indices, but with the same group of 28 assets, i.e. the weighting of the separate assets varied whilst the assets remained the same throughout. The next step in Stambaugh's (1982: 260) study was to investigate the impact of varying the actual assets themselves. In this set of tests Stambaugh (1982: 260-261) made use of five alternative sets of assets, namely:

- Set 1: 19 common stock portfolios alone
- Set 2: Industry portfolios combined with 4 preferred stocks
- Set 3: Industry portfolios combined with 5 bond portfolios
- Set 4: 20 beta-sorted portfolios (common stock) – these are sorted according to the Black, Jensen and Scholes (1972) methodology
- Set 5: 40 beta-sorted portfolios – sorted using the Gibbons (1982) methodology

(Stambaugh, 1982: 260-261)

The linearity tests, which again are performed using LM tests, revealed that of the five market proxies, their p-values were all at least 40 percent or above, thus meaning that the linearity hypothesis was not rejected. Results from the tests also illustrated that for the hypothesis  $\gamma_1 = r_f$ , inferences were sensitive to the choice of assets used. In the cases of asset sets 1, 2 and 3, the equality was rejected, whilst for sets 4 and 5, equality was not rejected. It was a similar story when concerned with the third hypothesis of  $\gamma_2 > 0$ , as inferences varied across the different asset sets. The results for the tests when asset sets 1 and 2 were used, do not reject  $\gamma_2 = 0$  in favour of  $\gamma_2 > 0$ . Whilst the other three sets supported the positive risk premium (Stambaugh, 1982: 261).

In conclusion Stambaugh (1982: 266) stated that the various market proxies that were constructed produced identical inferences about the CAPM. However, despite these findings, Stambaugh (1982: 266) goes on to mention that “It remains possible that alternative market portfolios can reverse inferences about the model”. Suggesting that it is possible that there is room for improvement in South Africa, especially when it is considered that the two markets are very different.

### 3.6.2 Shanken (1987)

In Shanken’s (1987: 91) study, a framework was developed in which inferences could be made regarding the legitimacy of an equilibrium asset pricing relationship, despite the fact that the central aggregate of this relationship was unobservable. Shanken (1987: 91) employed a multivariate proxy for the true market portfolio, which was made up of an equal-weighted stock index and a long term bond index, in an examination of the Sharpe-Lintner CAPM.

Shanken (1987: 92) discussed how, because proxies for the market portfolio are not perfect, there will always be room for discussion and debate with regards to the output of the CAPM. Shanken (1987: 92) went on to mention that high correlations between decent proxies and the true market portfolio can mask the fact that the proxies are not mean-variance efficient. The masking can create an illusion that the exact composition of the proxy is irrelevant, which is not the case, as differing compositions of the market proxy can result in different inferences of the CAPM.

On the empirical side of Shanken’s (1987) study, the normal practice of using a proxy was expanded to use a vector of variables which, combined, account for much of the variation in the market portfolio return. The focus of the research was on the multiple correlation between the proxy and the market portfolio. If the statistical evidence of the proxy’s inefficiencies was sufficiently strong, then the efficiency of the true market portfolio may indeed be correctly inferred and the CAPM rejected. Shanken (1987: 98) set out to test the following hypothesis:

$$H_0: \quad \lambda \leq T\theta_p^2(\rho^{-2} - 1)/(1 + \widehat{\theta}_p^2) \quad (3.8)$$

Shanken (1987: 98), as an initial exploration of his framework, ran a test of the Sharpe-Lintner CAPM using the returns of the CRSP index, which is an equal-weighted common stock index in the U.S., as a proxy for the market portfolio. Shanken (1987: 98) carried out these tests over five sub periods of equal length for the period February 1953 through November 1983, he also eliminated January returns as a result of the January effect, meaning that each period had 68 months of data. The dependent variables in Shanken's regression were the excess returns of different portfolios made up of 20 stocks that were equal-weighted and sorted according to their market value of equity at the beginning of each sub period.

Shanken (1987: 98-99) proceeded to propose that if the CRSP index is a perfect proxy for the market portfolio ( $\rho = 1$ ), then the non-centrality parameter,  $\lambda$ , should equal zero according to equation 3.8, and the test statistic should have a central F distribution; put simply the null hypothesis requires that the proxy (CRSP index) be the tangency portfolio. The results of the five sub periods with the index as the proxy for the market portfolio are reported in table 3-6 below:

**Table 3- 6 Results of using the CRSP index as a proxy for the market portfolio**

<b>SUB PERIOD</b>	<b>F-STATISTIC</b>	<b>P-VALUE</b>
2/53 - 3/59	2.09	0.02
4-59 - 5/65	1.78	0.05
6/65 - 7/71	1.57	0.10
8/71 - 9/77	0.84	0.65
10/77 - 11/83	1.01	0.45

(Shanken, 1987: 99)

Shanken (1987: 98) then went on to calculate a p-value for the overall period, which was found to be 0.02. Therefore, Shanken (1987: 99) concluded that if the CAPM is true, it can be deduced that the CRSP index is not a perfect proxy. Next Shanken (1987: 99-102) performed a sensitivity analysis in which he observed the p-values for  $\rho = 0.7$ ,  $\rho = 0.8$ ,  $\rho = 0.9$ . Following the analysis Shanken (1987: 102) concludes that the p-values barely changed for  $\rho = 0.8$  and  $\rho = 0.9$ , and that he continued to reject  $\rho = 0.7$  at a 10 percent significance level. Therefore, Shanken rejected the joint hypothesis that, the CAPM is valid and  $\rho$  is greater than 0.7.



Following the analysis of the CRSP index as a proxy, Shanken (1987: 103) investigated adding a bond index to a stock index as a proxy for the market portfolio. In doing so, Shanken (1987: 103) extended the original proxy used to include both the Ibbotson-Sinquefeld long-term government bond index and the CRSP stock index. Following this Shanken (1987:103) stated, “of course, including the bond index can only increase the multiple correlation between the proxy and the market. Hence, for any given value of  $\rho$ , our confidence in the validity of the joint hypothesis should increase as well”. Tests of the hypothesis that the two factor proxy encapsulates all the variation in the true market return are shown in table 3-7 below:

**Table 3- 7 Results of combining the CRSP index and the Ibbotson-Sinquefeld long-term government bond index as a proxy for the market portfolio**

SUB PERIOD	F-STATISTIC	P-VALUE
2/53 – 3/59	2.50	0.01
4-59 – 5/65	1.72	0.06
6/65 – 7/71	1.52	0.12
8/71 – 9/77	0.85	0.65
10/77 – 11/83	0.91	0.57

(Shanken, 1987: 104)

The restriction as Shanken points out here, is that some combination of the stock and bond indices is equal to the tangency portfolio. As can be seen the sub-period results are quite similar to those for the stock index alone, and the aggregate p-value for the entire period, 0.02, which was the same as for the proxy comprising of only the CRSP stock index. Thus on this evidence Shanken concluded that  $\rho$  is less than one, provided the CAPM is true. Shanken (1987: 105) then proceeded to test the performance ratio:  $\theta_p/\theta_t$ , which must exceed  $\rho$ , in which  $\theta_t$  is the Sharpe measure of the tangency portfolio, t. Shanken found from this test that the hypothesis that  $\theta_p/\theta_t$  is larger than 0.7 is rejected at the 10 percent significance level. This means that either the CAPM is incorrect or the proxy only captures a small portion of the movement in aggregate wealth.

In Shanken’s (1987: 107) concluding comments he reiterates that the empirical evidence suggests that either the CAPM is invalid or the proxies developed account for at most two-thirds (rejected at the 0.05 significance level), or even worse only a half (rejected at the 0.1

significance level) of the total variation in the true market return. Further, Shanken (1987: 107-108) stated that these results did not change whether a proxy comprising solely of a stock index was used or if a proxy comprising of both a stock index and a bond index was used.

### **3.6.3 Brown and Brown (1987)**

Brown and Brown's (1987: 26) study attempted to examine the historical performance of a number of publicly traded investment portfolios with respect to six different market proxies. More specifically, Brown and Brown (1987: 27) used an evaluation method established by Jensen (1986), to analyse the annual returns of 32 mutual funds over the period 1947-1978. To begin their empirical research, Brown and Brown (1987: 27) constructed a set of market proxies. To create each proxy Brown and Brown obtained historical returns and relative market values of five different classes of capital market assets, namely:

1. Common Stocks
2. Fixed-Income Corporate Issues.
3. Real Estate
4. United States Government Issues
5. Municipal Bonds

(Brown and Brown, 1987: 27)

Brown and Brown (1987: 27) make a valid point, that although it may seem as though a proxy comprising of all five of the above classes would be the optimal proxy, this is not the case. This is due to the fact that some assets such as, consumer durables and human capital are left out whilst others in the existing portfolio may be over emphasised. Despite these issues, Brown and Brown (1987: 27) believed that the asset classes covered in the study represented the most identifiable and liquid of the capital market securities. Furthermore, they believed that the identified asset classes represented the opportunity set for a large percentage of investors, and thus believed it was a reasonable representation of the investment market.

To begin the formation of the various market proxies, Brown and Brown (1987: 27) mimicked Stambaugh's (1982) methodology, and began by using only a portfolio of common stock and

then added the remaining securities incrementally to create an increasingly broader portfolio. To further extend the sensitivity analysis, the final proxy formed comprised of all the securities except common stock. For each of the proxies the weightings of the separate components were determined by their annual market value. The six market proxies that were created are outlined below:

Proxy 1: Common stock

Proxy 2: Proxy 1 plus fixed-income corporate issues

Proxy 3: Proxy 2 plus real estate

Proxy 4: Proxy 3 plus U.S. government issues

Proxy 5: Proxy 4 plus municipal bonds

Proxy 6: Proxy 5 less common stock

(Brown and Brown, 1987: 27)

Once the proxies had been formed, and the remaining necessary inputs had been obtained (i.e. 32 mutual funds and the risk-free rate) the necessary tests could be run. In explaining the equation that was to be used in the following tests, Brown and Brown (1987: 28-29) utilised the original CAPM as a starting point. As has been alluded to on numerous occasions the formula for the CAPM is as follows:

$$E(R_i) = R_f + \beta_i [E(R_m) - R_f]$$

From this equation Brown and Brown (1987: 29) explain that Jensen's performance measure,  $\alpha_j$ , is formed by adapting the equation into a regression of ex post excess returns:

$$(R_{it} - R_{ft}) = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \mu_{it} \quad (3.9)$$

Equation 3.9 is the equation Brown and Brown set out to utilise in their research. Brown and Brown (1987: 27) when discussing equation 3.5 and in particular  $\alpha_j$ , stated that, "the estimate for  $\alpha_j$  represents the constant periodic return that the portfolio generated above or below its expected risk premium. One advantage of this regression-based indicator is that it can be

interpreted in a statistically meaningful way". To begin the testing procedure Brown and Brown (1987: 29) regressed the historical returns of the 32 mutual funds against the returns of each of the market proxies. The average results for each of the proxies are shown in table 3-8. The table shows the cross-sectional averages for  $\alpha_j$ ,  $\beta_j$ , and  $R^2$ , as well as significance levels for the estimated parameters.

**Table 3- 8 Cross-sectional average regression results for each market proxy**

	<b>ALPHA</b>	<b>T-STAT</b>	<b>BETA</b>	<b>T-STAT</b>	<b>R-SQUARED</b>
<b>Proxy 1</b>	-0.72	-0.84	0.79	16.85	0.86
<b>Proxy 2</b>	0.20	0.05	1.02	15.66	0.86
<b>Proxy 3</b>	-4.40	-2.67	2.18	10.21	0.76
<b>Proxy 4</b>	-3.96	-2.53	2.63	10.60	0.77
<b>Proxy 5</b>	-3.33	-2.16	2.65	10.30	0.76
<b>Proxy 6</b>	2.24	0.42	1.41	1.22	0.06

(Source: Brown and Brown, 1987: 29)

These results showed that, as measured by the coefficient of determination, only the first five proxies significantly provide explanations for the movement in the mutual funds yields. This was interesting because  $R^2$  can be interpreted as the level of diversification of the underlying investment portfolio (Brooks, 2006: 106-107). As a result Brown and Brown (1987: 29) determined that proxy 6 was "worthless", and was to be ignored for the rest of the study. The second finding of note was that the proxies containing real estate, proxies 3, 4 and 5 produced different results compared to those without real estate .

Brown and Brown (1987: 29) went on to say that the encouraging thing to come out of the test is that the specification of the market portfolio does make a difference. Following these findings, Brown and Brown (1987: 29) investigated whether they would come to the same conclusion if they examined investment performance on an individual basis. In doing so, Brown and Brown (1987: 29) sorted the 32 mutual funds by ranking them according to each mutual fund's alpha estimate. In order to establish the degree of association between the rankings, Brown and Brown (1987: 30) employed the Spearman rank correlation coefficients for each pairwise comparison. The results are shown in table 3-9:

**Table 3- 9 Spearman rank correlations between market indices and mean returns**

	Index 1	Index 2	Index 3	Index 4	Index 5	Mean Return
Index 1	1.0					
Index 2	0.9512 [9.93]	1.0				
Index 3	0.7749 [5.56]	0.6298 [3.99]	1.0			
Index 4	0.8669 [7.11]	0.8288 [6.38]	0.871 [7.20]	1.0		
Index 5	0.8981 [7.87]	0.8992 [7.91]	0.7676 [5.46]	0.9216 [8.61]	1.0	
Mean Return	0.6367 [4.05]	0.7823 [5.66]	0.1580 [0.86]	0.4663 [2.72]	0.6221 [3.96]	1.0

(Source: Brown and Brown, 1987: 30)

With the 32 mutual funds being ranked, the 5 percent critical value for each coefficient is 2.04, meaning that, all of the estimated correlations for the risk-adjusted rankings are significantly positive with 95 percent surety, suggesting that the five proxies produced rankings that are very similar to each other.

In conclusion Brown and Brown (1987: 31) stated that by creating broader proxies, they could generate a large variety of inferences for the same set of individual funds, suggesting that the composition of the market proxy does matter. When addressing the question of why the composition of the market portfolio matters, Brown and Brown (1987: 31) suggested that it may be because “the composition of the sample of securities to be tested is the element that actually matters and that the ‘market index’ should be selected to reflect this universe”. Thus it is suggested that the attempts to establish the all-inclusive market portfolio is “futile” and instead investors should rather focus on defining the market in terms of its relevant components (Brown and Brown, 1987: 31).

Drawing from the three U.S. studies it can be seen that the composition of the market portfolio is an important element in the use of the CAPM. The studies, although varied in nature, help reveal that the make-up of the proxy for the market portfolio is important as all conclude that it

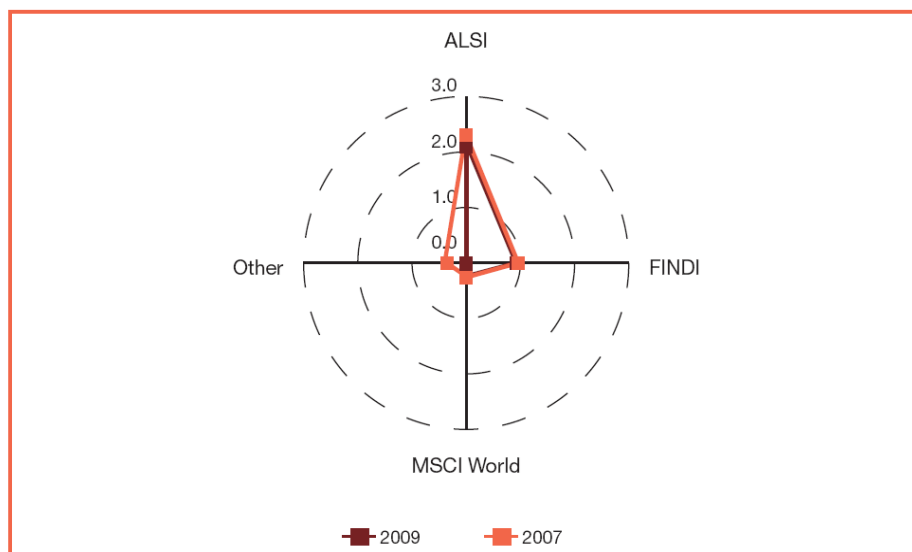
is possible for inferences to be altered according to the composition of the proxy. However, there is still no agreement as to what is the best method in forming a proxy.

Following the analysis of the U.S. market it is very important to examine the choice of proxy in the South African context, as the different markets have very different characteristics.

### 3.7 The Choice of Market Proxy in South Africa

The choice of market proxy in South Africa is by no means an easier one than in the U.S.. The process of estimating the return on the market in South Africa is fraught with problems, and there is little guidance if any on how to get around the problem (Firer, 1993: 31; Corriea and Uliana, 2004: 66). In a recent survey carried out by PriceWaterhouseCoopers (PWC) (2009: 31), PWC surveyed the views of 27 financial analysts and corporate financiers. One question that PWC asked was: “What would you consider to be an appropriate market index to use as a market proxy for a beta calculation in the South African market?” The respondents were given the options ALSI, FINDI, MSCI World, or Other. The results to this question are illustrated in figure 3-10 below.

**Figure 3- 10 Use of market proxy in South Africa**



(Source: PriceWaterhouseCoopers Corporate Finance, 2009: 31)

The survey illustrates that the ALSI is the most popular proxy for the market portfolio, as was the case in 2007 (PriceWaterhouseCoopers Corporate Finance, 2009: 31). Most respondents use the ALSI either frequently or always. What is worth noting however, is that since 2007 the MSCI and other indices have become less popular, whilst the FINDI has proportionally gained in popularity, with more than half of the respondents using the FINDI for a portion of their valuation projects (PriceWaterhouseCoopers Corporate Finance, 2009: 31).

The findings from the PriceWaterhouseCoopers (2009) survey support the historical trend amongst academics and practitioners of using a broad based common stock index. This method is alluded to in articles by Firer (1993), Ward (1994), Laubscher (2002) and Corriea and Uliana (2004). This trend is similar to the trends in the U.S., however, whilst in the U.S. there is a selection of broad based indices to choose from, in South Africa there is really only one – the ALSI (Ward, 1994: 99). As in the U.S., many academics such as Bowie and Bradfield (1993), Van Rensburg and Slaney (1997), Van Rensburg (2002) and Corriea and Uliana (2004) question the method of using a broad based stock index, such as the ALSI, as it is only a small portion of the real market for risky assets.

There is much debate on this issue, for instance, Van Rensburg (2001) believed that the market proxy should be derived from the FINDI and the RESI, whilst Ward (1994) believed that the ALSI would suffice. Firer (1993: 35) reports that due to the volatility of the South African equities market, the source of the estimate for the return on the market should be consistent with the one that is used by the provider of the beta service. Another issue that is unique to South Africa, and cannot be ignored in this study, is the issue of market segmentation of the JSE.

### **3.7.1 Market Segmentation of the JSE**

The total capitalization on the JSE is dominated by two sectors – the Resource and the Financial and Industrial sectors. The dichotomy in returns underlying the resource and financial and industrial stocks is one of the primary and unique characteristics of the JSE (Van Rensburg and Slaney, 1997: 2; Van Rensburg, 2002: 83). This characteristic market segmentation of the JSE, is acknowledged by numerous authors such as Bowie and Bradfield (1993), Firer (1993), Ward (1994), Van Rensburg and Slaney (1997), Van Rensburg (2002) and Corriea and Uliana (2004) and practitioners as illustrated in the PWC 2009 survey where it was found that the FINDI had

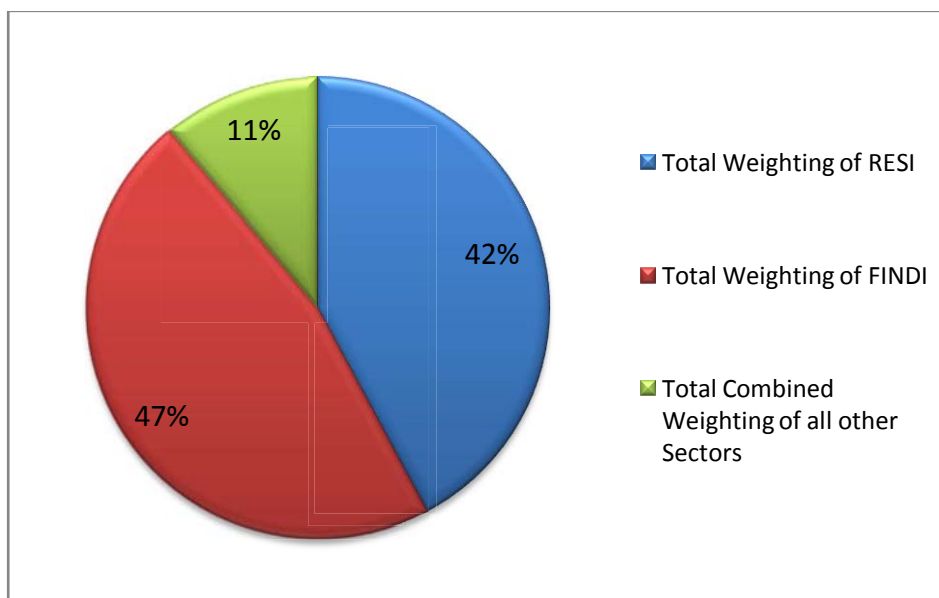
grown in popularity as a market proxy due to the “bias” towards certain sectors on the JSE (PriceWaterhouseCoopers, 2009: 30-31). Market segmentation can be described as a financial market that is dominated by specific sectors within that market (Van Rensburg, 2002: 84). The segmentation on the JSE is a result of the traditional strength of mining companies in South Africa (Bowie and Bradfield, 1993: 7; Van Rensburg and Slaney, 1997: 1, Van Rensburg, 2002: 84; Corriea and Uliana, 2004: 66). The segmentation on the JSE is illustrated in table 3-10 and figure 3-11 below.

**Table 3- 10 Segmentation on the JSE as at 01 Jan 2010**

Total Weighting of RESI	42.19%
Total Weighting of FINDI	46.08%
Total Combined Weighting of RESI & FINDI	88.98%
Total Combined Weighting of all other Sectors	11.08%

(Johannesburg Stock Exchange 2010)

**Figure 3- 11 Segmentation on the JSE as at 01 Jan 2010**



(Johannesburg Stock Exchange 2010)

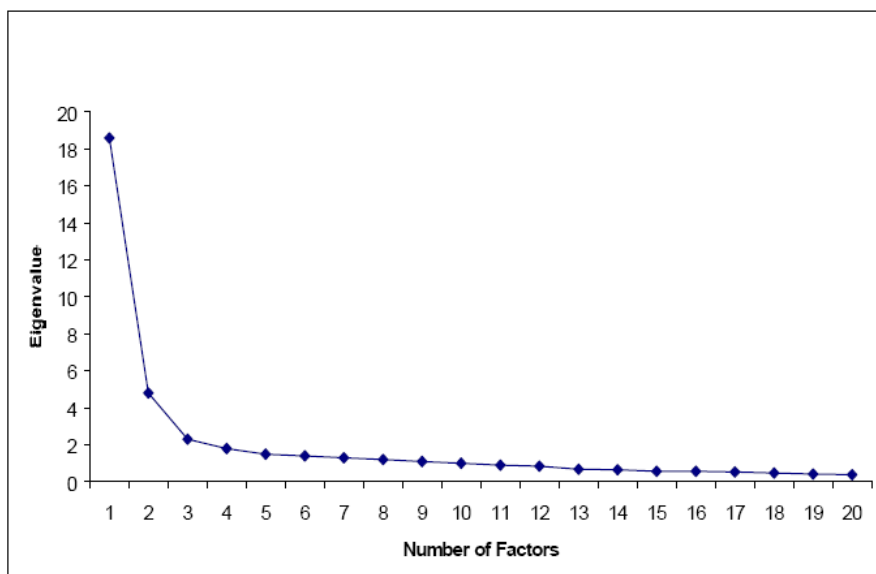


As can be seen from the table and diagram above, the resource and financial and industrial sectors as at the beginning of 2010, make up nearly 90% of the market capitalisation on the JSE. Due to the segmentation of the JSE, authors such as Van Rensburg and Slaney (1997: 1), Van Rensburg (2002: 83) and Correia and Uliana (2004: 65) question the use of the ALSI as a proxy for the market portfolio suggesting that it is not sufficiently representative of the risks associated with the JSE, whilst Van Rensburg (2002: 83) goes as far as to suggest that the ALSI is not mean-variance efficient. Bowie and Bradfield (1993: 6) argue that the Financial and Industrial (FINDI) or Mining Index (RESI) should be employed as proxy for the market portfolio. Correia and Cramer (2008: 45) also believed that “the over-weighting of resources on the JSE Securities Exchange may imply that companies may wish to use the Financial and Industrial Index (FINDI) rather than the All Share Index (ALSI). As this is a very real issue in South Africa, a paper by Van Rensburg (2002) on the matter is now reviewed.

### **3.7.1.1 Van Rensburg (2002)**

Van Rensburg (2002: 83) in his paper entitled “Market Segmentation on the Johannesburg Stock Exchange II” updated the factor analytic procedure conducted by Van Rensburg and Slaney (1997) following the reclassification of the JSE sector indices in March 2000. Van Rensburg (2002: 84) attempted to prove that a two factor Ross (1976) arbitrage pricing theory (APT) model, using the JSE Financial-Industrial index (FINDI) and the Resources index (RESI) as the priced sources of risk, would provide a better way of pricing assets in South Africa when compared to the CAPM.

Through the use of a scree plot of eigenvalues (shown in figure 3-12), it was found by Van Rensburg (2002: 85) that “there is no compelling evidence that the third factor explains considerably more than the fourth factor and so on” thus for the APT model it is suggested that only two factors should be extracted.

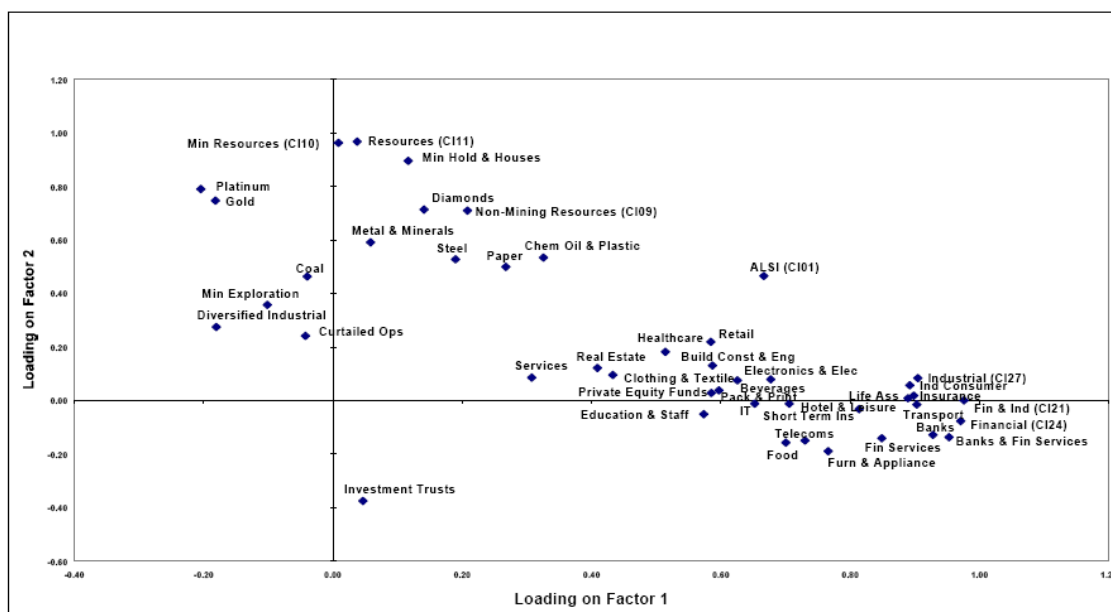
**Figure 3- 12 Scree plot of eigenvalues**

(Van Rensburg, 2002: 86)

Figure 3-13 “plots the factor loadings of the returns on the reclassified sector indices after (oblique) promax rotation. The most appropriate observable proxy for a factor is a share index with a loading as close to unity as possible on the factor concerned and as close to zero as possible on the other factor” (Van Rensburg, 2002: 85).

As can be seen from figure 3-13, there were two main clusters of factor exposures (around the two factors obtained earlier from the results of figure 3-12), firstly, the financial-industrial cluster along the horizontal axis and, secondly, the resource cluster along the vertical axis. Whilst it was found that the ALSI was in ‘no man’s land’ as it is made up of the two. The FINDI which was found to have a factor loading of zero to factor two and very close to one on the first factor, was used assumed the best representative of factor 1 (Van Rensburg 2002: 86). Whilst it was found that factor two is most closely associated with the Mining Resource index but the ‘total’ Resource index was a close second. Van Rensburg (2002: 86) stated that because of the “more inclusive nature of the latter index and the fact that it is defined at the same tier of aggregation as the Financial-Industrial Index it is suggested that, for practical purposes, it may be taken as a proxy for factor two”. Thus it was concluded by Van Rensburg (2002: 86) that a two factor APT model comprising of the FINDI and the RESI would be a more appropriate model to use in the South African context than the CAPM.

**Figure 3- 13 Plot of promax rotated factor loadings**



(Van Rensburg, 2002: 87)

However, not all academics agree with Van Rensburg's findings. Ward (1994: 99) had a different opinion, stating the use of the ALSI as a market proxy is acceptable practice in South Africa. Firer (1993: 31) also believed that the ALSI was a sufficient proxy for the South African market. Practitioners also seem to believe that the ALSI is a sufficient proxy as was shown by a survey carried out by Corriea and Cramer (2008: 45) in which it was found that close to 77 percent of companies use the ALSI index and only 23 percent use the FINDI, this finding was then supported by the PWC 2009 survey (figure 3-10) in which a majority of practitioners still believed the ALSI to be the most adequate proxy for the JSE (PriceWaterhouseCoopers, 2009: 31). Thus it can be seen that there is a lot of debate surrounding the market proxy in South Africa. Although not all academics and practitioners have come to a consensus on the most suitable proxy for the JSE, the important point to be taken out of these arguments is that market segmentation of the JSE is a real problem and thus cannot be ignored.

Building on from that, Laubscher (2002: 136) agrees that the market proxy is a very difficult parameter to estimate and to choose, but emphasises that the most challenging part is identifying or developing better proxies for the market portfolio. Academics in the past have attempted to identify or develop better proxies for, in particular, the South African market. A

few of these leading studies are discussed in the following sections; as will be noticed in these studies the issue of market segmentation is prevalent.

### **3.7.1.2 Bowie and Bradfield (1993)**

Bowie and Bradfield's (1993: 6) paper reviews developments in beta estimations on the South African market. Whilst the crux of the paper is the estimation of beta, Bowie and Bradfield do spend a considerable time discussing the choice of market proxy in South Africa. They also allude to some specific problems faced by the South African market – the dual phenomenon of “extreme thin trading” and the evidence of segmentation between the industrial and mining sectors (Bowie and Bradfield, 1993: 6).

Bowie and Bradfield (1993: 6) highlighted that since the founding of asset pricing models such as the CAPM, a lot of effort in financial literature has been devoted to the accurate estimation of the parameters in the models. Bowie and Bradfield (1993: 7) stated that at the time of the study the majority of research that had been conducted on the JSE focused on the beta and market proxy estimation, this was due to the two phenomena mentioned earlier – thin trading and the “dichotomy” between the mining and industrial sectors.

Bowie and Bradfield (1993: 9) emphasised the problem of using a broad based market index as a proxy in South Africa by citing a study by Affleck-Graves (1977). The study found that in only a third of the securities that were tested could the market index explain more than 10 percent of the movement in returns. This was compared to a study conducted by King (1966) where it was found that a market index in the U.S. explained on average 31 percent of the movements in security returns. Affleck-Graves (1977) also found that the correlation between the returns of securities and the market index (when averaged across all securities) on the JSE was only 0.26. This value is much lower than corresponding studies in the French market where the correlation was found to be 0.41 (Altman *et al*, 1974 cited in Bowie and Bradfield, 1993: 9) and the U.S. market where the correlation was found to be 0.53 (Blume, 1977 cited in Bowie and Bradfield, 1993: 9). These results illustrated the uniqueness of the JSE, and raises the question, whether estimation techniques used in other markets such as the U.S. are appropriate in the South African market?

According to Bowie and Bradfield (1993: 13) the choice of market proxy on the JSE is based on whether there is self imposed segmentation occurring between the mining and industrial sectors. They emphasised the point that the market represents the universe of shares available to the investor. Bowie and Bradfield (1993: 13-14) then stated that “if segmentation between the Mining and Industrial sectors on the JSE is evident, then it can be argued that shares would be priced to compensate investors for bearing the risk of the Mining and Industrial market proxies (indices) separately. Therefore if sufficient investors separate their funds by investing in industrial rather than mining shares (or vice versa) then segregation of the two sectors is expected to impact on the estimation of the beta coefficients associated with the two markets”. Bowie and Bradfield (1993: 14) then went onto argue that “the estimation of systematic risk must take account of the segmentation by using appropriate (different) market proxies for the securities in mining and industrial sectors”.

It is obvious that the use of an inappropriate market proxy can cause a “spurious” decrease in the correlation between the security returns and the returns measured (Bowie and Bradfield, 1993: 14). Venter, Bowie and Bradfield (1992) (cited in Bowie and Bradfield, 1993: 14-15) conducted a study in which they compared the use of various market proxies by assessing their separate predictive powers in a single index model. They compare the results of using the JSE-Actuaries<sup>2</sup> Overall Index in forming betas with the betas formed using the Financial and Industrial index for non-mining shares and a mining index for mining shares. The results and comparisons are based on the capacity of the beta estimates to forecast the one step ahead returns on the security using a single index model. What was found was that the error in forecasts is “dramatically reduced when the sector specific indices are used. Further to this, they present evidence that the single index model has less forecasting ability when the JSE-Actuaries Overall Index is used as opposed to when the Mining or Financial and Industrial indices are used. These results are reported in table 3-11. It can be seen from the table that the Mean Squared Error (MSE) produced are considerably lower in the major indices when compared to the overall index (Bowie and Bradfield, 1993: 14).

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<sup>2</sup> The JSE-Actuaries indices used in the Bowie and Bradfield (1993) study were replaced by the FTSE/JSE Index Series on the 24<sup>th</sup> of June 2002 (Raubenheimer, 2010: 1).

**Table 3- 11 Mean Squared Errors (MSEs) in forecasting the return on a portfolio based on beta estimates using various market indices**

<b>Index:</b>	<b>Overall(a)</b>	<b>Gold(b)</b>	<b>Financial and Industrial (c)</b>
<b>Industrial Shares</b>	0.031	-	0.026
<b>Mining Shares</b>	0.103	0.049	-

(a) The JSE-Actuaries Overall Index

(b) The JSE-Actuaries All Gold Index

(c) The JSE-Actuaries Financial and Industrial Index

(Adapted from Venter, Bowie and Bradfield, 1992 cited in Bowie and Bradfield, 1993: 15)

In concluding their study, Bowie and Bradfield (1993: 21) state that as a consequence of the apparent segmentation on the JSE between the mining and industrial sectors, that the relevant Mining or Financial and Industrial index should be used as the market proxy. They argue that if the wrong choice is made regarding the market proxy, it will result in the underestimation of the systematic risk, which will in turn reduce the forecasting ability of the CAPM. This is especially the case when evaluating either mining or industrial shares.

### **3.7.1.3 Ward (1994)**

Ward (1994: 99) explained that as a result of the strong influence of mining shares on the JSE the use of the CAPM in South Africa had become more complicated. Ward (1994: 99) alluded to the fact that some academics such as Bowie and Bradfield (1993) have suggested that sectoral indices be used as market proxies in place of the ALSI. Ward (1994: 99) set out to use a multivariate graphical technique, correspondence analysis, in an attempt to study the underlying structure of risk in the sectors of the JSE. Ward (1994: 101) discussed that studies such as the one by Bowie and Bradfield (1993) had found there to be segmentation on the JSE. He suggested that the evidence of segmentation throws into question Sharpe's (1981) definition of the market portfolio. He also mentioned that by restricting the market to a portion of "similar" securities it is no longer possible to remain on the efficient frontier. Using a specific sectoral index will also result in different risk premiums every time a different proxy is used, which is not consistent with the theory underlining the CAPM (Ward, 1994: 102).

Through studying the underlying risk structures on the JSE, the validity of the CAPM can be seen and the dimensions of risk identified (Ward, 1994: 102). Correspondence analysis is described by Ward (1994: 102) as a “graphical method of data analysis and is typically used to represent simultaneously both the rows and columns of a contingency matrix in a joint plot”. However, Ward (1994: 102) did mention that in his paper the use of the technique is slightly different, as it is used as a more robust choice to factor analysis. The goal of the correspondence analysis in Ward’s paper was to graphically illustrate the structure of the sectors on the JSE, as well as the varying characteristics of these sectors (Ward, 1994: 110).

A total of 38 sectors were analysed over a ten year period (January 1983-December 1992). The 91 day Bankers Acceptance discount rate was used as a proxy for the risk-free rate. Once the two dimensional correspondence plot was developed, it was analysed visually. For the first correspondence plot the reference matrix was calculated using the ALSI as the market proxy and was included in the analysis as supplementary columns. This process was repeated using the Financial and Industrial sectors only. In an effort to find the main dimensions of risk in the Industrial and Financial sectors the plot co-ordinates of the sectors were correlated with the sectoral financial statistics from INET. Lastly a chi-squared trees method was utilised to examine the level of segmentation of the sectors on the JSE (Ward, 1994: 104).

Through the correspondence analysis Ward (1994: 110) found that the JSE had three clear segments, which he classified as precious metals and minerals, other metals and minerals and financials and industrials. However the cluster analysis, illustrated that at no stage were the clusters found to be significantly different, meaning that there was no clear distinction between the sectors examined. This finding supports the use of the ALSI in the CAPM. During the correspondence analysis the CAPM was discovered to “correspond to the major dimensions of risk” in the data set (Ward 1994: 110), thus advocating the use of the ALSI as a market proxy in the CAPM when evaluating both industrial and mining shares. Finally, it was found that when the Financial and Industrial index was used as a market proxy, it did not represent the major dimension of risk in these sectors. Thus Ward (1994: 112) concluded that the proxy for the return on the market parameter in the CAPM should be the ALSI and not the relevant major sectoral index.

#### **3.7.1.4 Corriea and Uliana (2004)**

Corriea and Uliana (2004: 65) also posed the question of whether the ALSI should be used as a proxy for the market portfolio on the JSE, or if it is more appropriate to use a major sectorial index such as the FINDI. Their study seeks to address whether the ALSI and FINDI, when used as market proxies, produce different results. The study also attempts to examine the results for magnitude and pattern, as well as if these results are related to each other. The ultimate goal of the study was to establish findings that would enhance the capacity of investors to apply judgement in computing the cost of equity (Correia and Uliana, 2004: 65).

According to Correia and Uliana, recent evidence had shown that market capitalization of mining firms on the JSE adds up to 35 percent of the market, whilst the Resource sector, which includes mining companies, contributes 40 percent of the total market capitalization on the JSE. As a result of such characteristics, according to Corriea and Uliana (2004: 67), when the parameters of the CAPM are derived from an entire market (i.e. the ALSI) results in models such as the CAPM producing biased measures and ultimately incorrect results. More specifically, the major worry is that the ALSI will lower the cost of equity for industrial companies. This is due to the fact that the betas will be lower because of the low correlation of the mining sector with the other sectors, as well as because of a greater volatility of returns in the mining sector (Correia and Uliana, 2004:67).

Correia and Uliana (2004: 68) cited Van Rensburg and Slaney (1997) mentioning that many practitioners that use the Financial Risk Service required the FINDI as a market proxy rather than the ALSI. Corriea and Uliana (2004: 68) went on to cite Bradfield (1993) stating that most investors believe that mining shares and especially gold shares represent a different type of risk and thus form a different market. If there is segmentation on the JSE between Mining and Industrial sectors, then it can be argued that investors would be compensated for bearing the risk of Industrial and Mining proxies, and thus shares would be priced accordingly.

In response to these discussions, (Correia and Uliana, 2004: 69) examined the cost of equity of selected industrial firms on the JSE using both the ALSI and FINDI as the proxies for the market portfolio. The research questions and hypothesis for the study are outlined below:



1. *Is there a difference between the costs of capital using the ALSI and F&I data?*

$$H_0: K_{e\text{ALSI}} = K_{e\text{FINDI}}$$

2. *Do the different data bases (ALSI and FINDI) randomly result in higher answers, and are the differences large?*

In this case, the results will be examined for systematic bias, as well as for frequency of size difference

3. *Is there an association between the two sets of results?*

In this case, correlation analysis will be carried out to test for an association.

(Correia and Uliana, 2004: 70)

A sample of 155 firms was chosen from the Financial and Industrial sectors. The risk-free rate for the study was taken as the Negotiable Certificate of Deposit (NCD) rate. The market risk premium was calculated for both the ALSI and FINDI by subtracting the geometric mean of the two indices from the risk-free rate for the time period 1960 to 1997. Thus, the market risk premium for the ALSI was found to be 7.4 percent, and for the FINDI it was found to be 8.3 percent. Finally the betas for the ALSI and FINDI were supplied by UCT Financial Risk Service (Correia and Uliana, 2004: 70-73).

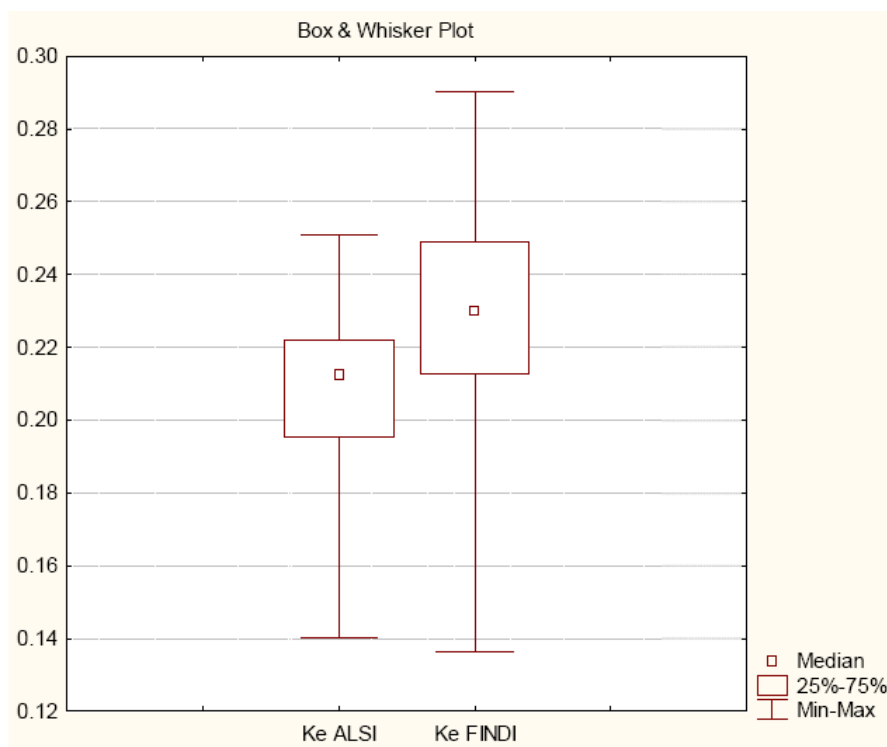
To begin the discussion of the results, Correia and Uliana (2004: 75) rejected the hypothesis that the cost of equity calculated using the ALSI and the FINDI are equal. These results are displayed in table 3-12 and figure 3-14:

**Table 3- 12 Summary statistics for the cost of equity**

<b>Index</b>	<b>ALSI</b>	<b>FINDI</b>
Observations	155	155
Mean	.2085	.2287
Median	.2124	.2300
Std. Dev.	.02135	.02893

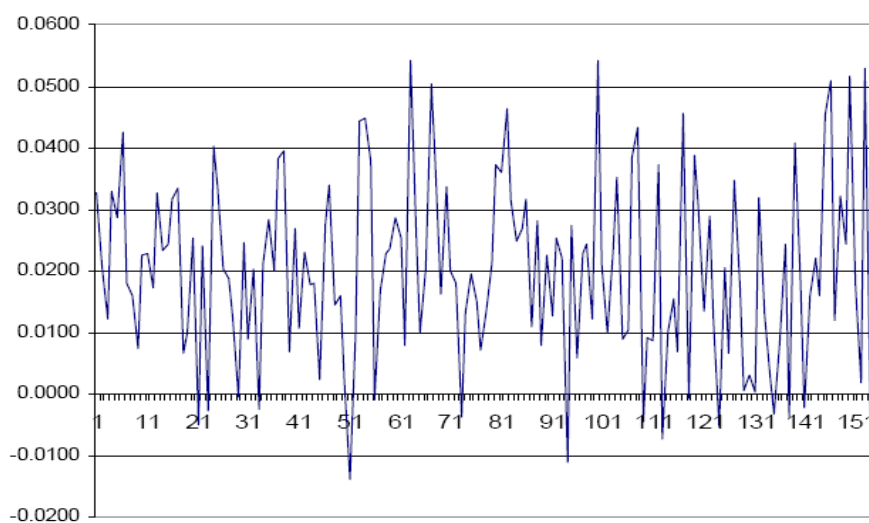
(Source: Correia and Uliana, 2004: 75)

**Figure 3- 14 Box and whisker plot Ke using the ALSI and Ke using the FINDI**



(Source: Correia and Uliana, 2004: 74)

The next question answered by Correia and Uliana (2004: 75) was question 2, do the different data bases (ALSI and FINDI) result in higher answers, and are the differences large? What was found was that the cost of equity when using the FINDI as a market proxy was found to be higher than with the ALSI as a market proxy, 90 percent of the time. It was also found that 85 percent of the time the differences between the two results was found to be between 0.5 percent and 5.5 percent, and 74 percent of the time, the differences were above 1 percent. What this means is that the majority of differences are probably “material” in any valuations (Correia and Uliana, 2004: 76). The results for the second question are displayed below in figure 3-15 and table 3-13.

**Figure 3- 15 Difference between the ALSI and FINDI cost of equity for each firm**

(Source: Correia and Uliana, 2004: 76)

**Table 3- 13 Frequency of differences in cost of equity**

From	To	No. of Companies	%
-0.015	-0.010	2	1.3%
-0.010	-0.005	3	1.9%
-0.005	0.000	11	7.1%
0.000	0.005	7	4.5%
0.005	0.010	17	11.0%
0.010	0.015	17	11.0%
0.015	0.020	18	11.6%
0.020	0.025	27	17.4%
0.025	0.030	13	8.4%
0.030	0.035	14	9.0%
0.035	0.040	11	7.1%
0.040	0.045	6	3.9%
0.045	0.050	3	1.9%
0.050	0.055	6	3.9%
		155	100.0%
Ke ALSI => Ke FINDI		16	10%
Ke ALSI < Ke FINDI		139	90%
		155	100%

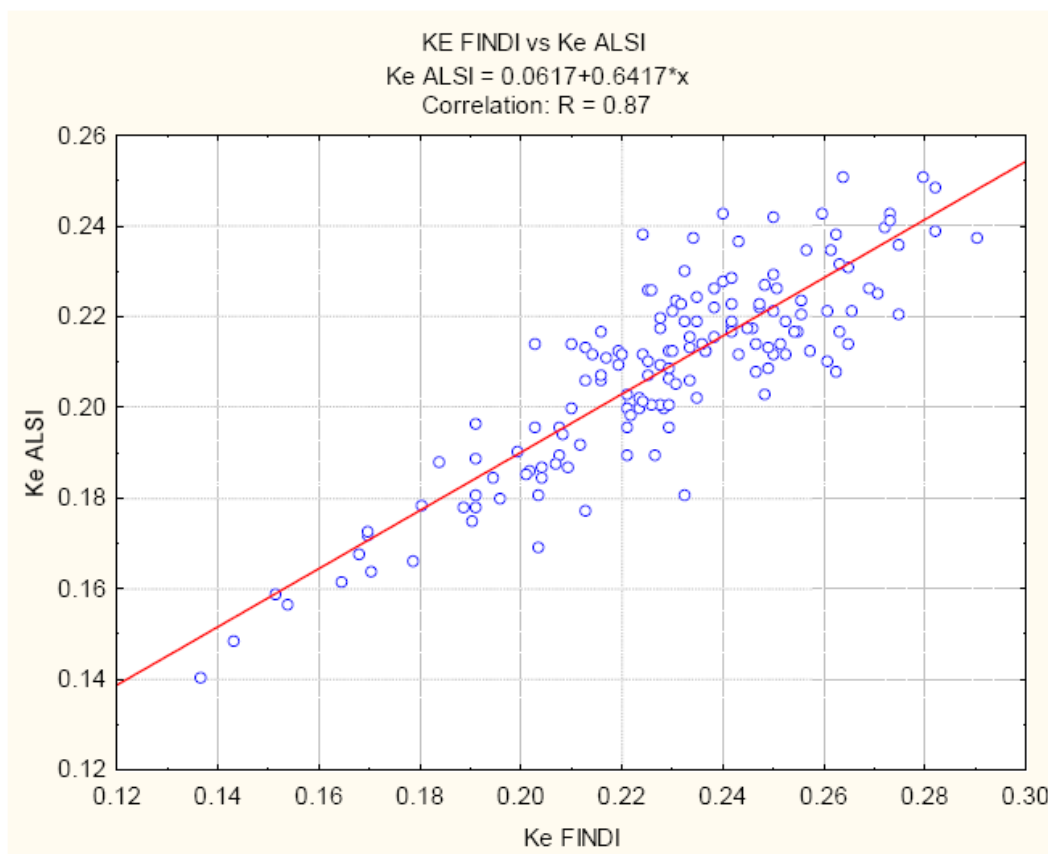
(Source: Correia and Uliana, 2004: 77)

The final question answered by Correia and Uliana (2004: 76) was whether there was an association between the results of the tests on the different data bases? The answer was yes, as it was found that there was a high correlation between the two sets of results. The correlation coefficient was found to be 0.87, with an  $R^2$  value of 0.76, a t-statistic value of 21.78 and a very

highly significant p value of 0.00. The results of the final question are illustrated in the scatter plot, figure 3-16.

In conclusion, Corriea and Uliana (2004, 78) stated that it was found that the results when using the ALSI and FINDI as separate market proxies were different. Thus the choice between the two will have an effect on the results of the CAPM, with the FINDI producing on average a higher cost of equity.

**Figure 3- 16 Cost of equity using the FINDI versus the cost of equity using the ALSI**



(Source: Corriea and Uliana, 2004: 78)

Thus from these studies, it is very apparent that there is much debate in South Africa as to the appropriate proxy to use for the market portfolio parameter in the CAPM and yet, as shown in the last study by Corriea and Uliana (2004) the choice can have a material impact on the cost of equity value obtained. One fact is definitely clear however and was a common point of

discussion in each of the studies was the issue of market segmentation on the JSE. This highlights the unique nature of the South African market.

### 3.8 Summary

Thus in conclusion of the literature review, the CAPM is a very popular and hence vital model in the calculation of any firm's equity. The parameters of the model, and in particular the return on the market parameter is surrounded by controversy. The proxy according to theory, needs to be mean-variance efficient and contain *all* risky assets held in proportion to their market value. As the market portfolio is impossible to obtain, a proxy is usually employed in its place. Despite the intricacies associated with calculating the returns of this proxy the major problem lies in finding an appropriate proxy, a proxy that is mean-variance efficient. This task has proven very troublesome for numerous academics, as the common trend of using a broad based common stock index has very often been found inappropriate. A possible reason for the failure of this method is that it ignores large asset classes such as bonds. It was discussed that theoretically it makes sense to add a bond index to the proxy for the market portfolio as was highlighted by Stone (1974), Stambaugh (1982) and Shanken (1987). Studies on the U.S. market by Stambaugh (1982), Shanken (1987) and Brown and Brown (1987) investigated the addition of bonds to the proxy for the market portfolio had mixed results. However, it was found that both theoretically and empirically in the U.S. that bonds can add value to the market proxy. Upon review of studies based on the South African market, two points were clear; firstly that an investigation into the addition of bonds to the market proxy has not been undertaken, and secondly that the issue of market segmentation on the JSE cannot be ignored. Due to the fact that the addition of bonds to the market proxy appears theoretically sound and has not been tested in South Africa, it is proposed that through the addition of bonds that the market proxy will be enhanced. Thus the feasibility of adding bonds to the proxy for the market portfolio will be empirically tested in the subsequent chapters. The following chapters will also examine the segmentation of the JSE, as it too is a critical characteristic of the JSE. The methodology that was followed in order to perform such tests in South Africa will be described in Chapter 4.

## CHAPTER 4

### METHODOLOGY

#### 4.1 Overview

The research questions in Chapter 1 of this study asked if the incorporation a bond index into the proxy for the market portfolio would enhance the efficacy of the CAPM in South Africa, and whether the apparent segmentation on the JSE would allow a further enhancement of the proxy. Following the theoretical and empirical analyses conducted in Chapters 2 and 3, it was established that in order to fully answer this question it is necessary to empirically examine whether the consideration of these factors will improve the usefulness of the CAPM in South Africa. The methodology that was followed to perform the empirical research is set out in this chapter. To begin with, the dataset is discussed, as well as the time period of the analysis and which assets are included in the analysis, including the identification and justification of the all important proxies. Next, the way in which the returns of all the selected assets are calculated is explained. Following this, the tests to examine the suitability of the proposed proxies are outlined, including the preliminary step of forming ordinary and preference share portfolios. Next, the Black *et al* (1972), the Fama and MacBeth (1973) two-pass regression methodologies as well as the pooled regression methodology are outlined and explained. Subsequently, the estimation considerations that need to be taken into account when running these two-pass regressions are discussed. Finally, the tests on the forecasting ability and explanatory powers of the various models are described.

#### 4.2 The Dataset

##### 4.2.1 The Time Period and Frequency of Data

The time period decided on for this study was determined by the availability of data. The time period was, in particular, constrained by the availability of data on the ALBI. The ALBI was formed in 2000 (Bond Exchange of South Africa, 2000: 4) and therefore the time period could

not be pushed further back than 2000. Therefore, share prices and dividend yields (the reasoning behind the inclusion of dividend yields is discussed in Section 4.2.3) were collected for each share on the JSE for the period January 1997 to December 2010. However, as will be explained in Section 4.3.1.1, the first three years (January 1997 to December 1999) were used for the initial estimation period, known as beta sorting. Thus the period over which the parameters were calculated and the tests performed was January 2000 to December 2010 (eleven years). The prices and dividend yields for the parameters were obtained from the JSE statistics and records department, McGregor's BFA and the South African Reserve Bank (SARB)

The frequency of the data in the study was based on similar empirical studies. These studies mostly made use of monthly data for the share prices (Black *et al*, 1972; Fama and MacBeth, 1973; Stambaugh, 1982; Fama and French, 2004). As a result monthly closing share prices and monthly dividend yields were obtained from the JSE.

## **4.2.2 Selection of Assets**

### **4.2.2.1 Dependant Variable**

South African studies on the usefulness of the CAPM have made use of varying assets as dependant variables in their research. For example, a study by Van Rhijn (1994) used shares listed only on the Industrial sector of the JSE, whilst a more recent study by Correia and Uliana (2004) made use of shares on the Financial and Industrial sectors. However internationally, several U.S. based studies on the appropriateness of the market proxy utilised all the shares on the NYSE for the duration of the study (Black *et al*, 1972; Fama and MacBeth, 1973; and Stambaugh, 1982). More recently, Jagannathan and Wang (1996) expanded this method to include not only all the shares on the NYSE, but also all the shares listed on the AMEX, whilst Fama and French (1992) and Fama and French (2004) expanded their methodology even further to include all the shares listed on the NYSE, AMEX and NASDAQ. Furthermore, in an Australian study conducted by Durack, Durand and Maller (2004) on the CAPM in Australia, made use of end of month price data for all shares listed on the Australian market. This last point is particularly relevant for a South African study as the Australian market is similar to the South African market as it is also segmented towards the resource sector (Jones, 2010). More

recently however, this trend has been adopted by a few studies in South Africa, as Basiewicz and Auret (2009: 24), and Basiewicz and Auret (2010: 14) adopted the method of using all shares listed on the JSE. Thus due to the fact that a large number of studies in the U.S., studies in Australia and more recently studies in South Africa use a much broader data set than previously was the case with South African studies, it was decided that this study would utilise all possible shares listed on the main board of the JSE, at the beginning of each month, for the period January 1997 to December 2010.

The criteria for a share to be considered for the analysis was that firstly the share was listed in the month of the analysis, as well as the 36 months leading to the month of analysis in order to allow for the initial estimation period. Thus for a share to be considered for analysis it had to have 37 months of relevant data, meaning that the number of shares used was adjusted from month to month. By adjusting the number of shares utilised each month, it ensured that the sample was not biased towards low-beta shares; this is because high-beta (high-risk) shares usually disappear from the market quicker. This simply meant that some of the high-risk shares would be excluded if the methodology stated that only shares that were listed for the full duration of the period were to be considered, avoiding what is known as survivorship bias (Morgan, 1975: 365; Van Rensburg and Robertson, 2003: 8; Mutooni and Muller, 2007: 17; Basiewicz and Auret 2009: 24; Basiewicz and Auret, 2010: 14). So for example, if an analysis was run on the returns for January 2003, the share would only be included if it was listed from January 2000 to January 2003 (37 months), also meaning that any shares that were listed after December 2008 had to be ignored as 37 months of data was not available. In order for this process to be facilitated, information on the dates of new listings and de-listings was gathered from the JSE statistics and records department.

Although authors such as Jagannathan and Wang (1996) and Fama and French (2004) included shares that were not on the main board of the NYSE, for this study, shares listed on the development and venture capital boards were not included. According to Mutooni and Muller (2007: 17) these shares have a tendency of being very small and highly illiquid, furthermore, research on these companies has been very sparse and they may contain a significant amount of unsystematic risk (Mutooni and Muller, 2007: 17). As a result, the stocks listed on the Alt-X, which was established in 2003 to replace the development and venture capital boards, were also not considered to remain consistent.



Stambaugh's (1982) study differed from the previous studies of Black *et al* (1972) and Fama and MacBeth (1973), in that Stambaugh's tests of the CAPM included preference shares as part of the dataset (Stambaugh, 1982: 251-253). The greater efficiency of Stambaugh's parameter estimates as compared with the previous studies, was attributed to the expansion of his dataset beyond ordinary shares (Stambaugh, 1982: 256). Accordingly, it was decided to expand the dataset of this study to include all preference shares listed on the JSE. The price and dividend information on the preference shares was collected from the same source as the ordinary share price data - the JSE statistics and records department.

#### **4.2.2.2 Proxy for the Risk-free Asset**

In the U.S., over the past forty years, the most common approach to estimating the risk-free rate for the CAPM, according to authors such as Black *et al* (1972), Malkiel (1995), and Fama and French (2004) and as supported in various texts such as Harrington (1987), Rees (1995), and Brigham and Ehrhardt (2005), is to use the yield on a government security. This fact was supported by a survey conducted by Bruner *et al* (1998) in which the authors surveyed a sample of highly regarded U.S. companies. The survey found that the method of using a yield on a government security was as prevalent in practice as it was in academia. Bruner *et al* (1998: 16) found that 85 percent of the corporations surveyed used the yields on government securities when estimating the risk-free rate whilst 90 percent of financial advisors also employed this method. Bruner *et al* (1998: 16) found that the most common choice in the U.S. is between the three month T-Bill and a long term Treasury bond (T-Bond).

However, according to authors such as Carleton and Lakonishok (1985:41), Harrington (1987:149), and Brigham and Ehrhardt (2005: 311) T-Bills have traditionally been the most commonly used surrogate for the risk-free rate. For example, Shanken (1987: 98) and Reilly and Wright (2004: 65) used T-Bills in their analysis of the CAPM. Whilst Harrington (1987: 149) goes as far as stating that "...whether in academic research or in practical applications of the CAPM, the 90-day Treasury bill rate has been virtually the only proxy used for the risk-free asset".

In South Africa, a study by Firer (1993: 29) reviewed all research papers published in South Africa in which a surrogate for the risk-free asset was required. Two papers by Affleck-Graves,

Burt and Cleasby (1988), and Page and Palmer (1991) both used the 90 day T-Bill yield as the surrogate whilst De Villiers, Lowlings, Pettit and Affleck-Graves (1986) used the 360 day T-Bill yield. In order to get a more recent understanding of the common practices in South Africa, a similar but brief study of published research over the period 2001 to 2010 was carried out. In the study it was found that there is still a strong U.S. influence on South African practices when finding an appropriate surrogate for the risk-free asset. An example of the U.S. influence was that authors De Wet (2005), Moolman and Du Toit (2005), De Wet (2006), De Wet and Hall (2006), and De Wet and Du Toit (2007) all used yields on government securities. Significantly, Van Rensburg (2001), Friis and Smit (2004) and Samoulihan (2007) and Basiewicz and Auret (2010), as is advocated in the text Firer *et al* (2008:469), chose simply to use the three month T-Bill yield as the risk-free rate in their respective studies.

Aside from all of the research conducted on the proxy for the risk-free rate suggesting the use of the T-bill, the fact that the ALBI (which is incorporated into the proxy for the market portfolio) contains long term government bonds which means that the T-bill should be used instead of the T-bond as it is not a long term government bond and thus will not be correlated with the ALBI. Therefore, in keeping with the findings in both the U.S. and South Africa and in avoiding possible correlation with the ALBI, the three month T-Bill was used as the proxy for the risk-free asset in this study. The yield on this instrument was only required for the period January 2000 to December 2010, as it was not required for the initial estimation period (January 1997 to December 1999). The data on the three month T-Bill was gathered from the South African Reserve Bank (SARB).

#### **4.2.2.3 Proxies for the Market Portfolio**

The final asset that was included in the study is the crux of this study. The final asset is the independent variable – the market portfolio. “A major component of the CAPM is a completely diversified market portfolio of all risky assets in the economy and the portfolio in which all investors commit funds to be on the efficient frontier” (Reilly and Wright, 2004: 66).

It is widely acknowledged, as discussed in the preceding chapters, that estimating the expected return on the market portfolio is fraught with problems (Stambaugh, 1982: 237; Kandel, 1984: 63; Brown and Brown, 1987: 26; Shanken, 1987: 91-92; Fama and French, 1992: 427; Reilly

and Wright, 2004: 66; Durack *et al*, 2004: 140). Compiling a portfolio of this nature is an impossible task and as a result proxies are used to represent it. The South African market is not immune to the problems faced by this parameter, in fact, due to the nature of the South African market, the choice of the appropriate proxy has been a particularly significant question posed by researchers (Bowie and Bradfield, 1993: 6; Firer, 1993: 33; Ward, 1994: 100; Van Rensburg and Robertson, 2003: 7-8; Correia and Uliana, 2004: 65; Basiewicz and Auret, 2010: 13). As discussed in section 3.2 a comprehensive market index, such as the S&P 500 in the U.S. or the ALSI in South Africa, is the most commonly used proxy for the market portfolio in both the U.S. (Harrington, 1987: 174; Reilly and Wright, 2004: 66; Bruner *et al*, 1998: 20; Reilly and Brown, 2006: 317) and South Africa (Ward, 1994: 99; Correia and Uliana, 2004: 67; Correia and Cramer, 2008: 45). Despite numerous researchers such as Stambaugh (1982) and Bowie and Bradfield (1993) questioning this method, studies by Ward (1994) and more recently Correia and Uliana (2004) found that using the ALSI as the market proxy in South Africa was acceptable. Further to this point, a 2009 survey conducted by PWC found that the most popular proxy for the market portfolio was still the ALSI (PricewaterhouseCoopers, 2009: 31). Thus, in line with these arguments it was decided that the first proxy to be used in this study was a proxy comprising solely of the ALSI. As the ALSI is viewed as the conventional proxy, it was used as a benchmark or control for the study, to which the remaining proxies and their performances were compared. Data on the ALSI was obtained from McGregor's BFA website.

Despite the fact that using a market index as a proxy for the market portfolio is widely accepted as conventional practice, many discussions over the years have focussed on problems faced by excluding assets from the market portfolio (Stambaugh, 1982: 237; Bowie and Bradfield, 1993: 6; Reilly and Wright, 2004: 66; Durack *et al*, 2004: 140-141; Basiewicz and Auret, 2010: 13). One large class of assets that is blatantly ignored when using a market index is bonds. This is especially true when it is considered that in 2009, bonds accounted for over 23 percent of the exchange listed shares on the JSE (Bond Exchange of South Africa; Johannesburg Stock Exchange, 2009). Stone (1974: 710) was one of the first academics that suggested the inclusion of debt instruments should not be ignored when employing the CAPM, whilst Firer (1993) also alluded to this problem in his study. Stambaugh (1982: 239) too investigated this point and incorporated bonds, in fixed proportions, into his proxy for the market portfolio. Thus, it was decided that the second model developed in this study would be a two factor CAPM. The proxy was specified using the ALSI and a bond index, the ALBI. The approach has the added benefit

that the weightings need not be pre-specified, as the weightings are incorporated into the estimated sensitivities. The data on the ALBI was collected from the SARB.

A further characteristic of the South African market that cannot be ignored is that of market segmentation. There are numerous academics such as, Bowie and Bradfield (1993), Firer (1993), Ward (1994) Van Rensburg and Slaney (1997), Van Rensburg (2002), Van Rensburg and Robertson (2003), Correia and Uliana (2004), and Basiewicz and Auret (2010) allude to the problem of segmentation on the JSE, and more specifically, the segmentation towards the Resource and Financial and Industrial sectors. When it is considered that in 2010, the combined weighting of the RESI and FINDI was just under 89 percent of the market, with the FINDI making up 47 percent of this 89 percent (Johannesburg Stock Exchange, 2010), it appears that the above authors have every right to question the use of the ALSI as a proxy for the market portfolio. Further to this last point, it was also found in the PricewaterhouseCoopers survey (2009/2010: 31) that the FINDI had gained in popularity as a proxy for the market portfolio. Half the respondents of the survey were found to use it for some of their valuation projects. Which is easy to understand as it is more typical of a conventional western economy, as it contains less resource assets. Therefore, in order to test this apparent segmentation it was decided that the third model developed was a two factor CAPM with the RESI and FINDI as the explanatory variables. Data on both the RESI and the FINDI was gathered from McGregor's BFA website.

Finally, a fourth model was formed that combined models two and three. This model brought together the two aspects of the study, the addition of debt instruments and the segmentation of the market. The fourth model was a three factor CAPM, with the RESI, FINDI and ALBI as the explanatory variables. The idea behind this model was to help test if there is in fact presence of segmentation on the market, whether or not the addition of bonds will enhance the proxy and therefore the use of the CAPM.

### **4.2.3 The Calculation of Returns**

Before each of the assets returns were calculated, several adjustments had to be made to the data. During the outlined period of the study (January 1997 to December 2010) various corporate activities took place which had an impact on the returns earned on the shares

(dependant variable). These activities included, mergers and acquisitions, swaps, share splits, and name changes. The data that was collected from the JSE had been back-dated to reflect swaps and share splits; however adjustments still had to be made for name changes and mergers and acquisitions. The double entry of companies as a result of name changes was eliminated based on the Who Owns Whom record of name changes over the period. Accounting for mergers and acquisitions however, was not as easy.

Given the way the shares were pooled into portfolios based on the beta-sorting procedure (Black *et al*, 1972: 9) (explained in section 4.3.1), it was far more advantageous to have shares listed for as long as possible (Basiewicz and Auret, 2010: 14); therefore to delist the acquiring and target firms as of the date of the acquisition and to treat the consolidated firm as newly listed on the same date was a great hindrance to this. However, combining the share prices of the acquiring and newly formed company in many cases (as done by Basiewicz and Auret, 2009: 24) resulted in share price changes of over 40 percent per month. As can be imagined this had a significant effect on the period beta estimates (as recognized by Mutooni and Muller, 2007: 18). This basically meant that when dealing with mergers and acquisitions that it was trade off between obtaining beta estimates which were not impacted by large fluctuations in share prices (outlier observations) and shares listed for lengthy periods of time. Consequently, it was decided that based on Who Owns Whom records share prices of the acquiring company and the merged entity were compared and where the share price were substantially similar (i.e. less than a 20 percent change) the share prices were combined. However, if the share prices were deemed to be significantly different (greater than 20 percent change), the target and acquiring firms were both recorded as delisted as of the date of the merger and the new entity was considered listed as of the same date.

The next issue to be addressed was whether to include dividends in the calculation of the total returns earned by holding shares. A review of studies both in the U.S. (Sharpe and Cooper, 1972; Fama and MacBeth, 1973; Soe and Dash, 2008) and in South Africa (Van Rensburg, 2001; Van Rensburg and Robertson, 2003; Mutooni and Muller, 2008; Samoulihan and Shannon, 2008; Basiewicz and Auret, 2009; Basiewicz and Auret, 2010) illustrated that some of the studies included dividends whilst other had not. In the U.S., Sharpe and Cooper (1972: 50) showed in their study that including dividends in the total return calculation did not significantly improve the results of their analysis and therefore concluded that due to the troubles faced when using dividends that they would be excluded from their study. Although U.S. studies by Black *et al* (1972), Fama and MacBeth (1973), Stambaugh (1982) and Fama

and French (2004), did not explicitly discuss the inclusion of dividends, the data in these studies was obtained from the Centre for Research in Security Prices and Black *et al* (1972: 10) as well as Fama and MacBeth (1973: 614) specify that this data is adjusted for dividends. In South Africa, recent literature revealed that authors such as Van Rensburg (2001: 5), Van Rensburg and Robertson (2003: 8), Mutooni and Muller (2007: 18), Basiewicz and Auret (2009: 24), and Basiewicz and Auret (2010: 14) had included dividends when calculating the total returns of the shares. To further enhance this point, when it is considered that the ALBI's returns include coupons, in order to maintain consistency, dividends should be included when calculating the returns of the shares. Thus, in light of all of the evidence, in the U.S. and South Africa as well as the need for consistency, dividend yields were incorporated in the computation of total returns for this study.

When calculating the total return of ordinary and preference shares, the common method is to calculate the natural log of the share price and dividend at the end of the period less the natural log of the share price at the beginning of the period (Brooks, 2006: 7-8). This equation is illustrated below:

$$\text{Returns} = [\ln(P_1 + D_1) - \ln(P_0)] \times 100 \quad (4.1)$$

Where:

$P_1$  is the price of the share at the end of the month

$P_0$  is the price of the share at the beginning of the month

$D_1$  is the rand value of the dividend

(Brooks, 2006: 7-8)

The data obtained from the JSE, contained dividend information that was expressed as an annual percentage that had had been smoothed across each month and as a result, the exact amounts and the dates of dividends paid were not available. Thus, continuously compounded returns could not be calculated and as a result holding periods were determined for both ordinary and preference shares. These were calculated using equation (4.2) below. For the

calculation of the returns for January 1997, the share prices from December 1996 were used, these were also obtained from the JSE.

$$\text{Holding Period Returns} = [(P_1 - P_0)/P_0 + D_1/P_0] \times 100 \quad (4.2)$$

(Brooks, 2006: 8)

The dividend yield was obtained by simply dividing the annual yield by twelve, this approach was used by Mutooni and Muller (2007: 18), due to the nature of the data obtained it was unnecessary to calculate the monthly dividend based on the assumption that the annual yields were compounded. The same method was used when computing the total returns for the preference shares.

The data on the risk-free asset, in this case the three month T-Bill, was gathered from the SARB and was available in annualised figures and thus there is a need to obtain monthly yields. T-Bills are not very complicated to calculate as they are priced using simple interest as opposed to compound interest (Botha, 2006: 240). The following method was used to obtain monthly returns from the annual rate, as suggested by Botha (2006: 240).

$$\text{Price of T - bill: } P_t = 100\,000 - (\text{Quoted Yield} \times 91/360 \times 100\,000) \quad (4.3)$$

$$\text{Compound Return} = 100\,000/P_t \quad (4.4)$$

$$\text{Monthly IRR} = \text{Compound Return}^{1/3} - 1 \quad (4.5)$$

(Botha 2006: 240)

Lastly, the data collected on the indices used in the formation of the proxies, namely the ALSI, ALBI, RESI and FINDI, was total return data. This means that for the three indices, the ALSI, RESI and FINDI, the values that were collected had been adjusted for dividends paid by the firms comprising the particular index, whilst the ALBI's returns included coupons. To ensure consistency with the share returns, holding period returns were also calculated for each of these

indices. The holding period returns were calculated as the difference in the index values over the period divided by the original index value, as is displayed in equation 4.6 below:

$$\text{Holding Period Returns} = [(P_1 - P_0)/P_0] \times 100 \quad (4.6)$$

### 4.3 Testing the Suitability of the Proxies for the Market Portfolio

In the preceding chapters it was discussed that many studies had empirically tested the legitimacy of various proxies for the market portfolio parameter of the CAPM. On review of a number of these studies it was clear that there is no consensus as to the best approach to estimate the market portfolio. Three studies in particular seem to be the most prevalent amongst the reviewed literature when estimating the parameters of the CAPM, the studies of Black *et al* (1972) (as used by Gibbons, 1982; Jagannathan and Wang, 1996; and Durack *et al*, 2004), Fama and MacBeth (1973) (as used by Fama and French, 1992; Jagannathan and Wang, 1996; Fama and French, 2004; and Basiewicz and Auret, 2009), and Stambaugh (1982) (as used by Faff, 2001; and Chou and Lin, 2002). Thus, it was decided that the methodology of this study would be primarily based on these studies. However, no single test was replicated in its entirety, rather each was reviewed and adjusted to build a methodology that best suited the unique characteristics of the South African market and its recent developments.

#### 4.3.1 Formation of Ordinary Share Portfolios

Black *et al* (1972), Fama and MacBeth (1973), and Stambaugh (1982) all used portfolios of ordinary shares to estimate the CAPM parameters, rather than basing their estimations on a single asset. Black *et al* (1972: 9) were the first researchers to use this procedure and its popularity has grown rapidly and according to Fama and French (2004: 31) is “standard in empirical tests” due to the fact that it results in more efficient and accurate values for the parameters of the CAPM. Betas that have been estimated using individual assets are often characterised by the error in variables problem which is minimised in a portfolio as the estimates normally counteract each other as long as the errors in the individual betas are not perfectly positively correlated (Fama and French, 2004: 31). A disadvantage to this method is that due to the grouping procedure, it could hide certain risk-return relationships and thus



reduces statistical power (Fama and French, 2004: 31). However, due to the popularity of this method (as used by Black *et al*, 1972; Blume and Friend, 1973; Fama and MacBeth, 1973; Stambaugh, 1982; Fama and French, 1992; Jagannathan and Wang, 1996; Van Rensburg and Robertson, 2003; Fama and French, 2004; Basiewicz and Auret, 2009) it is obvious that the advantages of forming portfolios are far greater than the disadvantages, and as a result the process of forming portfolios was implemented in this study.

There are a number of ways in which the ordinary share portfolios can be formed. Black *et al* (1972: 9) were the first to suggest the beta-sorting procedure, the process involves categorizing shares based on their betas, in which the first portfolio contains all the shares with the highest betas down to the last portfolio which contains all the shares with the lowest betas, thus allowing for maximum possible variability amongst the portfolios (Black *et al*, 1972: 9). However, this approach was questioned by Stambaugh (1982: 251), and in particular the use of historical betas to sort the portfolios (explained in section 4.3.1.1). Stambaugh (1982: 251) queries the reliability of the assumption that historical estimates of beta can provide a sufficient estimate of the future values. Thus to avoid using this method and more specifically this assumption, Stambaugh (1982: 251) implemented a simpler method of classifying shares into portfolios based on industry memberships. Stambaugh's (1982) approach allows for sufficient variability of beta values as risk varies from one industry to the next, but is fairly constant within an industry as is displayed by similar beta values for the shares. One of the drawbacks of forming portfolios based on industry affiliations is that there is no standardised classification system, for example, the Financial Mail classifies the JSE shares into 10 major industries and 19 sub-industries, whilst Sharenet also identifies 10 major industries, it stipulates 26 sub-industries, and I-Net Bridge 38, suggesting that industry classification relies on a fair amount of subjectivity. Despite this, it was found that Stambaugh's (1982) results were consistent with those of previous studies such as Black *et al* (1972), thus suggesting that there was no distinct advantage to using either approach. However it was decided, for the purpose of this study to implement the method used by Black *et al* (1972) due to the fact that Fama and French (1992: 432) justified the use of beta-sorting by demonstrating that historical estimates of beta based on a minimum of thirty-six months and a maximum of sixty months of previous data does in fact present a statistically sufficient estimate for the true beta values. Furthermore, Fama and French (2004: 31) state that the beta-sorting method of Black *et al* (1972) is the most widely accepted method for forming portfolios, and hence the methodology of beta-sorting was employed when forming the ordinary share portfolios.

#### 4.3.1.1 Formation of Portfolios Based on Beta-Sorting

As mentioned, beta-sorted portfolios are portfolios that are organised according to the individual shares betas, with the first portfolio containing the shares with the highest betas up to the last portfolio which contains shares with the lowest betas (Black *et al*, 1972: 9). However, these portfolios cannot be constructed using the current betas of the shares, or what is known as in-sample betas, as this will lead to a selection bias because the high beta shares will tend to be biased upwards above their true values while low beta shares will be biased downwards (Black *et al*, 1972: 9; Fama and MacBeth, 1973: 615). In an attempt to avoid this problem, Black *et al* (1972: 9) used historical betas to classify the securities as they suggested that these betas are likely to be highly correlated with the required period beta, with the added advantage of being observed independently. Black *et al* (1972: 11) used the five years of data that immediately preceded the required period to estimate betas for all the shares in their study (all securities listed on the NYSE). As an example Black *et al* (1972: 11) wished to start their analysis as of January 1931, thus they used the period January 1926 – December 1930 to estimate the betas for all shares listed on the NYSE in January 1931. From these beta estimates, the shares were divided into portfolios, in ten percentiles, that is, the top ten percent of shares were allocated equally into portfolio 1, down to portfolio 10, where the ten percent of lowest beta shares were allocated (Black *et al*, 1972: 11).

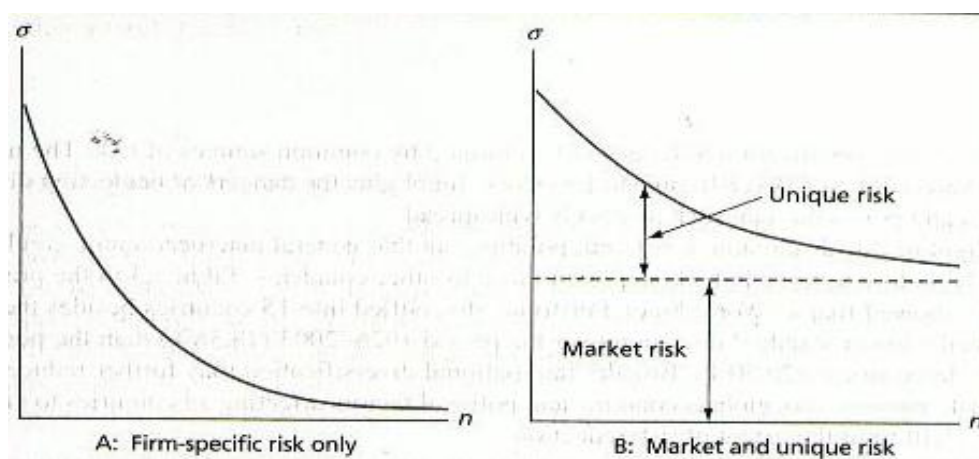
A further problem that Black *et al* (1972: 11) felt they might face, was that of stationarity, thus to avoid the beta estimates remaining stationary over the full period of the analysis, the portfolios were reformed each year, again using the immediately preceding five years of data to re-sort them. For shares to be considered for the study share price data had to be available for at least 24 months in order for the betas to be estimated; if this was not the case, Black *et al* (1972: 11) did not include the shares in the study until such information was available. Fama and MacBeth (1973) and various more recent studies (for example Kothari *et al*, 1995; and Fama and French, 2004) used an identical approach, varying only the duration of the portfolio formation and the testing period. An example of a slightly different methodology is the study carried out by Van Rensburg and Robertson (2003: 8), in which a beta-sorting procedure was employed for their tests of the CAPM in South Africa. Van Rensburg and Robertson (2003: 8) employed only five portfolios, with the composition of the portfolios altered every month as opposed to every year and between twelve and thirty months, on a rolling basis, was used to estimate their monthly betas.

Van Rensburg and Robertson (2003: 8) were not the only authors to vary the number of portfolios employed in the study, although they used only 5, Black *et al* (1972: 11) and Fama and French (2004: 32) used 10 portfolios, Stambaugh (1982: 251) employed 19, whilst Fama and MacBeth (1973: 615) employed as many as 20 ordinary share portfolios. Thus it was necessary to determine the optimal number of portfolios to form each period as well as the number of securities each portfolio should contain, a point which is clear from the above findings that the literature gives very little guidance in. What is important to note is that the JSE over the period of the study has far fewer shares listed on it than the NYSE, and the number of listed shares on the JSE over the time period fluctuated quite appreciably. Thus, regardless of the number of portfolios decided upon, it was very likely that the number of securities in each portfolio would be less than those formed in the U.S.. The number of portfolios chosen has a direct impact on the reliability of the cross-sectional regression coefficient estimates as they represent the sample to be used. Basically what had to be decided was at the point of the least number of shares listed on the JSE over the time period of the study, what would be the optimal number of portfolios for that number of shares. The decision on the optimal number of portfolios to be formed was a trade off between increased variability and diversification.

One of the major advantages of using the beta-sorting method is that it provides the empirical investigation with sufficient variability, whilst another advantage of using the method is that the portfolios formed help minimise the effect of non-systematic risk, as portfolios due to diversification, are far more efficient than single securities. Both these aspects lead to an overall more accurate investigation. Unfortunately the nature of the study dictates that in order to increase the effect of one of these advantages the other will have to decrease. For example, if at a particular time there were 200 shares listed on the JSE. In an attempt to obtain a high level of variability, it was decided to employ 20 portfolios, this would mean that although the variability was sufficient, the number of shares in each portfolio would be 10, which is not a sufficient number for diversification. Conversely, if it was decided that each portfolio should have 100 shares in it to ensure adequate diversification, that would leave two portfolios and very little variability. Thus it can be seen that there is a direct trade off between variability (number of portfolios) and diversification (number of shares in each portfolio). Another aspect that cannot be ignored is that the more portfolios that are used the larger the sample size of the tests, and as outlined by Brooks (2006: 45), the larger the sample size of a test the more consistent and efficient the tests become. Thus it is very important to determine a sufficient balance between the two.

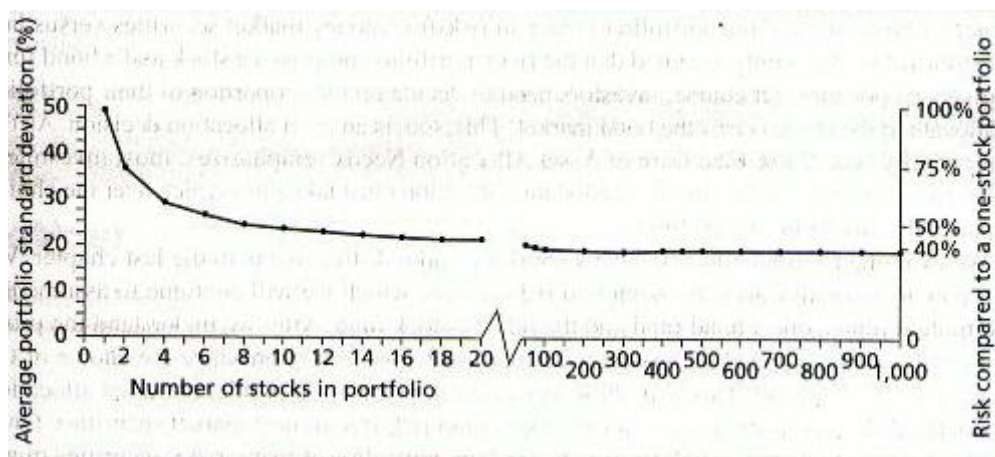
The goal of diversification is to minimize risk, but more specifically to minimize firm-specific risk (Reilly and Brown, 2006: 237; Fuller and Farrell, 1987: 456). Portfolios with relatively low numbers of assets may be exposed to more risk when compared to portfolios with larger amounts of assets. Put simply it is generally accepted that the more assets in a portfolio the lower the variance (shown in figure 4-1 below) and thus risk of the portfolio (Luenberger, 1998: 151). Neu-Ner and Firer (1997: 46) and Bodie *et al* (2007: 163-164) add to this point by mentioning that it is generally accepted that adding securities to a portfolio reduces unsystematic risk sufficiently up to a point of roughly 20 to 30 securities, where after the effects of adding securities (diversifying) is minimal, as shown by figure 4-2.

**Figure 4-1 Portfolio risk as a function of the number of stocks held**



(Bodie, Kane and Marcus, 2007: 163)

**Figure 4-2 Portfolio risk decreases as diversification increases**



(Bodie, Kane and Marcus 2007: 163)

Based on this information of diversification, it was decided that in order to appropriately determine the number of portfolios and the amount of shares in each portfolio, the number of shares listed on the JSE at its lowest number over the time period would be divided by 20-30 (depending on the most appropriate number) to determine the number of portfolios to be formed. This would ensure that the portfolios would contain a sufficient number of securities to be adequately diversified, and the number of shares per portfolio would never drop below that number. For example, if on the 31<sup>st</sup> of January 2009 the JSE had 200 shares listed at its lowest point then it would be appropriate to divide the 200 shares by 20 and form ten portfolios with 20 shares each, and for the entire period of the study form portfolios of ten percentiles. Thus if on the 31<sup>st</sup> of October 2000 the JSE is at its highest volume with 1000 shares listed then the portfolios would contain 100 shares each, thus allowing for both adequate diversification and sufficient variability. It was found that in November 2008 the JSE was at its lowest volume with 229 adequate shares listed, thus it was appropriate to divide this number by 10, to form 10 portfolios of a minimum of 22-23 shares each. As a point of interest it was found that at its peak, in April 2000 and December 2001, the JSE had 376 adequate shares listed, therefore meaning that the portfolios contained a minimum of 22 shares and a maximum of 38.

For the purpose of this study a slight variation was made to the methodology of Black *et al* (1972). Instead of adopting the method of altering the portfolios on an annual basis, it was decided to adopt the method used by Van Rensburg and Robertson (2003: 8), where the composition of the portfolios was changed every month. The composition was changed each month to not only reveal the changing number of shares on the JSE (any newly listed or delisted shares), but also to reflect the changes in the sensitivities of the shares to movements in the market portfolio. Therefore the shares were sorted using the immediately preceding 36 months worth of data to estimate the beta values (on a rolling basis).

When calculating the historical betas needed to organise shares into portfolios, Black *et al* (1972: 11) used the traditional CAPM, as displayed in equation 4.7 below:

$$E(\overline{R})_{jt} = \alpha_j + \bar{\beta}_j E(\overline{R})_m + n_{jt} \quad (4.7)$$

(Black *et al*, 1972: 7)

However, the problem with this approach is that it requires a parameter estimate for the risk-free rate, which if estimated incorrectly, could result in biased parameter estimates and standard errors. As a result, the formula was not used, and an approach suggested by authors such as Fama and MacBeth (1973: 610), Bowie and Bradfield (1993: 8-9), Laubscher (2002: 133), Reilly and Brown (2006: 240) and Firer *et al* (2008: 409), was adopted in which the beta of each security was found to be the security's (total return) covariance to the total returns of the ALSI divided by the variance in the ALSI. This process is displayed by equation 4.8 below:

$$\text{Beta } (\beta) = \text{cov}(R_i, R_{ALSI}) / \text{var}(R_{ALSI}) \quad (4.8)$$

(Reilly and Brown, 2006: 240)

The final issue to be faced when employing a beta sorting method is the issue of thin trading on the JSE. Bradfield and Barr (1989), Bowie and Bradfield (1997) and Bradfield (2002) all suggested that beta values in South Africa should be adjusted to take into account thin trading. However despite these findings, it is worth noting that these adjustments were made to studies covering data in the 1970s and 1980s (Bhana, 2008), and more recently there have been several authors that have not adjusted for the possibility of thin trading (Akinjolie and Smit, 2003; de Wet and Hall, 2006; Bhana, 2007; and Samoulihan, 2007). Van Rensburg and Robertson (2003: 8) did not adjust their beta estimates in accordance with some of the earlier papers such as Bradfield and Barr (1989) and Bowie and Bradfield (1997), they did however apply a thin-trading filter to eliminate shares that were not traded at least once a month. On review of the dataset employed in this study it was found that there were very few cases where any share was not traded at least once a month. Especially considering that the beta estimates were calculated over 36 months, it was deemed that there was an adequate number of different observations that existed over this period, thus no adjustments were made to account for thin trading.

#### **4.3.1.2 Expansion of the Analysis to Include Preference Shares**

The general method to estimating the CAPM parameters, and more specifically the market portfolio, is based on ordinary shares alone. However as discussed, Stambaugh (1982: 251) expanded this method to include preference shares. Stambaugh made this expansion in an attempt to "... extend the range of asset types and parameter values beyond those typically encountered in tests of the CAPM" (Stambaugh, 1982: 251). The parameter estimates attained

by Stambaugh (1982: 256) were found to be more efficient. This was reflected by the lower standard error estimates Stambaugh (1982: 256) obtained when compared to those of Black *et al* (1972) or Fama and MacBeth (1973). A result Stambaugh (1982: 256) attributes to the wider spread of assets included in the study. Thus in line with Stambaugh's (1982: 256) findings, it was decided that preference shares would be included in the analysis. The volume of preference shares as opposed to ordinary shares is considerably smaller (for example only 25 preference shares were listed in 2003 and 2004), as a result the preference shares were not placed in separate portfolios because there was the potential of them skewing the results of the study, which is not desirable especially from such a small asset class. Thus, the preference shares were incorporated into the ordinary share portfolios based on their beta estimates.

### **4.3.2 Methodology: Two-Pass Regression**

It is generally accepted that the two most commonly cited studies when concerned with empirical tests of the CAPM and its parameters are by Black *et al* (1972) (as cited by Morgan, 1975; Shanken, 1985; and Faff, 2001), and Fama and MacBeth (1973) (as cited by Fama and French, 1992; Jagannathan and Wang, 1996; Fama and French, 2004; and Basiewicz and Auret, 2009). Both studies follow similar methodologies in that they both incorporate a two-pass regression test. However, there are subtle differences between the two studies, thus both were used in the analysis. Further to this it has been suggested that a third type of two-pass regression, in which a pooled regression is used, might be an enhancement of the two earlier methods (Nair *et al*, 2009: 200). Thus all three methodologies were used in this study and will be outlined and discussed in the following sections.

#### **4.3.2.1 Methodology Based on Black *et al* (1972)**

Black *et al* (1972) were the first to use the two-pass regression. The method involves two stages, the first stage is a time series regression which entailed regressing the excess returns of the pre-constructed portfolio against that of the proxies of the market. This was carried out in order to obtain a beta estimate ( $\beta_p$ ) which was used in the second stage of the regression. The beta values for the portfolios were estimated using the traditional CAPM equation, which involved using a proxy for the risk-free rate (three month T-bill) to calculate excess returns for

both the pre-constructed portfolios and the various proxies. The first stage, for example using the ALSI as the market proxy, took the following form:

$$R_P - R_f = \alpha + \beta_P(R_m - R_f) + \bar{e}_j \quad (4.9)$$

Where:

$R_P$  is the return on the pre-constructed portfolio

$R_f$  is the return on the risk-free asset (3 month Treasury bill)

$R_m$  is the return on the market

(Black *et al*, 1972: 7)

The first pass regression was conducted over the entire period of the study (132 months), and the return on the market (shown in the above formula) was where the ALSI (for the first model) was substituted in. For the remaining proxies two-factor and three-factor models were employed. So for example, when the ALSI and ALBI, and the RESI and FINDI were employed as proxies, a two-factor model was used, whilst when the FINDI, RESI and ALBI were employed a three-factor model was utilised. The two factor model models took the following form:

$$R_P - R_f = \alpha + \beta_{P1}(R_{m1} - R_f) + \beta_{P2}(R_{m2} - R_f) + \bar{e}_j \quad (4.10)$$

In the above formula, the two returns on the market was where the proxies for the two factor models were substituted in, for example in the second model, the ALSI is substituted in  $R_{m1}$ , and the ALBI where  $R_{m2}$  is, and so on. This was also the case for the three-factor model as illustrated below:

$$R_P - R_f = \alpha + \beta_{P1}(R_{m1} - R_f) + \beta_{P2}(R_{m2} - R_f) + \beta_{P3}(R_{m3} - R_f) + \bar{e}_j \quad (4.11)$$



The results obtained from the regressions were the factor loadings  $\beta_{ps}$  for the well diversified portfolio. These beta estimates were then used in the second stage of the method. The second stage involved a cross sectional regression, which entailed regressing the average return of the pre-constructed portfolio (over the 132 month time period) to the betas obtained from the first stage. From this the following equations were formed:

Single Factor Model:

$$\overline{R_p} - \overline{R_f} = \gamma_0 + \gamma_1\beta_m + \bar{e}_j \quad (4.12)$$

(Black *et al*, 1972: 18)

Two-Factor Model:

$$\overline{R_p} - \overline{R_f} = \gamma_0 + \gamma_1\beta_{m1} + \gamma_2\beta_{m2} + \bar{e}_j \quad (4.13)$$

Three-Factor Model:

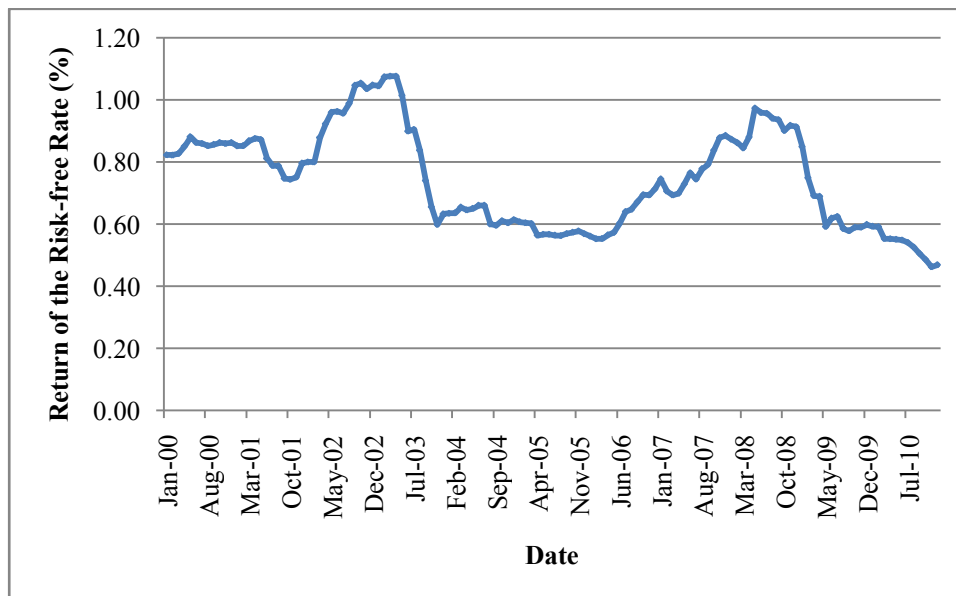
$$\overline{R_p} - \overline{R_f} = \gamma_0 + \gamma_1\beta_{m1} + \gamma_2\beta_{m2} + \gamma_3\beta_{m3} + \bar{e}_j \quad (4.14)$$

The  $\gamma_0$ ,  $\gamma_1$ ,  $\gamma_2$  and  $\gamma_3$  that were obtained from the above formulas were then studied to help determine which proxy is the superior. Theory states that  $\gamma_0$ , the y-intercept, should be zero because returns across portfolios should only be a function of the risk-free rate and the market risk premium (adjusted for the level of risk). Therefore because the model involves excess returns, the intercept should be zero, i.e. it reflects the return above the risk-free rate that investors required from an investment of zero risk.  $\gamma_1$ ,  $\gamma_2$  and  $\gamma_3$ , which are essentially the excess returns on the market, should have positive figures as this illustrates a positively sloped SML, which is one of the theories upon which the CAPM has been built. Black *et al* (1972: 23) found that over their entire period that the SML produced by their tests was positive, however, when the period was divided up into sub periods it was found that the steepness of the slope varied and even in one sub period the slope was found to be negative. Thus it can be seen that the results of prior tests have not always been in line with theory.

It is worth noting that the advantage of the Black *et al* (1972) method is that they used the risk-free rate (as per Miller and Scholes, 1972 (quoted in Elton and Gruber, 1995: 346). As stated by Miller and Scholes (1972), if the risk-free rate is constant over the estimation period, no harm is done by omitting it. However, if it fluctuates over time and is correlated to the return on the

market there will be a classic case of missing variable bias (which is especially true as there is a chance of some correlation between the T-bill and the ALBI). This will result in  $\beta_p$  being a biased estimate of the true  $\beta_p$ , and as is shown by figure 4-3 below, the movements of the risk-free rate (3 month Treasury-bill) over the period of estimation are not constant. Therefore showing the importance of including the risk-free rate.

**Figure 4- 3 Movements of the risk-free rate over the period of estimation**



#### 4.3.2.2 Methodology Based on Fama and MacBeth (1973)

Despite the popularity of the study by Black *et al* (1972), Fama and MacBeth's (1973) study appears to be even more popular. This approach is very similar to that of Black *et al* (1972). However, instead of employing one time series regression over the entire period for the first pass regression, Fama and MacBeth (1973) used rolling time series regressions and then averaged the resultant factor loadings to establish the mean factor loading for each portfolio. For the purpose of this study, the first pass regression thus entailed a time series regression over the first 36 months (January 2000 to December 2002), which provided the first beta estimate. After which, a rolling period of one month was used, which meant that the second set of beta estimates were produced over the period February 2000 to January 2003, and the third over the period March 2000 to February 2003, and so on. The issue faced with the Black *et al* (1972) study is that when regressing over the entire period for the first pass regression it is assumed that the betas do not change over time. This change could explain the added popularity of the

Fama and MacBeth (1973) method, as the technique allows for time-variation of the beta estimates (Cochrane, 2001: 228). Another difference from the Black *et al* (1972) study was that instead of using excess returns for the first step of the approach (derived from the CAPM formula) Fama and MacBeth (1973: 616) made use of the market model, and thus total returns, to estimate the betas of the portfolios. This is illustrated in the equations below:

Single factor model:

$$R_{it} = \psi_j + \beta_i R_m + e_{jt} \quad (4.15)$$

Where:

$\psi_j$  is the estimated intercept of the model

$\beta_i$  is the estimated coefficient

(Fama and MacBeth, 1973: 616)

Two-factor model:

$$R_{it} = \psi_j + \beta_{i1} R_{m1} + \beta_{i2} R_{m2} + e_{jt} \quad (4.16)$$

Three-factor model:

$$R_{it} = \psi_j + \beta_{i1} R_{m1} + \beta_{i2} R_{m2} + \beta_{i3} R_{m3} + e_{jt} \quad (4.17)$$

This difference may also explain the added popularity of this method as no risk-free rate is required in the process. Although this may appear contradictory to the previous discussion on omitted variable bias, there is a school of thought that believes that because there is also doubt over the appropriate proxy for the risk-free rate, why risk including an inappropriate proxy when the market model can just be employed (Fama and MacBeth, 1973 :614; Harrington, 1987: 149). Thus it is clear to see that the methodology of Fama and MacBeth (1973) has the added advantages of allowing for time variation of the beta estimates as well as not making use of a potentially inappropriate risk-free rate proxy. Following the first step of their methodology, Fama and MacBeth used their beta estimates in the same way Black *et al* (1972) did in their cross-sectional analysis, to obtain their y-intercept and market risk premium. The major difference between the two methods is that in the Fama and MacBeth method the cross-sectional regression was estimated for each month in the sample (hence the t in the equation)

and then averaged across all months. This is illustrated in the following equation, which is for the single factor model, the two- and three-factor models will follow the same pattern as in the Black *et al* (1972) example:

$$\bar{R}_{pt} = \gamma_0 + \gamma_1 \hat{\beta}_{pt} + \eta_{pt} \quad (4.18)$$

(Fama and MacBeth, 1973: 632)

The standard errors of these estimates were directly observable, as the regression analysis in E-Views computes the standard errors automatically. Thus it was decided that in order for the study to be comprehensive, the regressions were run for both excess and total returns.

#### 4.3.2.3 Methodology Based on a Pooled Regression

Despite the fact that the Fama and MacBeth (1973) method allows for time variation of the beta estimates, Nair *et al* (2009: 200) point out in their study, that the Fama and MacBeth (1973) two pass regression is limited due to the fact that the coefficients of the cross-sectional regression are averaged. Nair *et al* (2009: 200) believed that as a result of averaging the betas across time the Fama and MacBeth method could accept the null hypothesis of no relation between the beta and stock returns even if the underlying model is true. This is because the Fama and MacBeth (1973) method calculates the t-statistic as “a ratio of average cross-sectional regression slope coefficient with the average standard error of the respective coefficient. But, the average of cross-sectional slope coefficients will, by definition, be small relative to the average standard error of the respective coefficient, because while standard errors are always positive the coefficients need not be so. Thus, the t-statistic so calculated will be small and sometime negative” (Nair *et al*, 2009: 200). As a result of this, this study included a pooled approach to avoid such problems.

Essentially the pooled regression is estimated for the cross-sectional regression over the entire period (as in equation 4.12); but takes into account the time-variation in the beta estimates by using all the beta estimates over the various months, for example, all the betas for the ten portfolios in January 2003, all the betas for the ten portfolios in February 2003, then March

2003 and so on are stacked up and used instead of averaged as is the case with the Fama and MacBeth method. That is, to do the pooled approach, the first pass regression results (betas and average returns) of the rolling Fama and MacBeth method are still used, and all these observations are treated as happening at one point in time. Thus at this one point there should be 960 data points (10 portfolios\*12 months in a year\*8 years in the sample). The pooled regression takes a similar form to equations 4.12 and 4.18, depending on whether excess or total returns were used.

Thus the three methods, the Black *et al* (1972), the Fama and MacBeth (1973) and the pooled regression were run for both excess and total returns, to ensure that every base was covered. Once the outputs of the three methodologies had been examined their significance was also scrutinised, this was done by comparing each proxy's t-statistic, the "t-stats" and P-values were evaluated according to whether they were significant at the 5% level of significance. The crucial results here were firstly to find if once the ALBI (debt instruments) had been added to the proxy whether or not its coefficient was found to be positive and significant, as this would illustrate that the market prices the risk associated with debt instruments and is therefore a relevant addition to the proxy. The second crucial result was to find if by creating a proxy comprising of the FINDI and RESI, would also enhance the CAPM (by obtaining a positive and significant coefficient for the two indices), suggesting that there is segmentation on the JSE and that it cannot be ignored. The final crucial result is to see if by combining the two parts of this study (debt instruments and segmentation) would allow for further enhancement of the market proxy in South Africa.

#### **4.3.2.4 Estimation Considerations**

When concerned with the methodologies of both the Black *et al* (1972) and Fama and MacBeth (1973) many considerations that need to be taken into account. Normally when using OLS to estimate linear regressions it is very important to make sure that the sample and models comply with the assumptions of the classical linear regression model (CLRM), this is because any digression from these assumptions could result in inefficient and biased parameter estimates (Brooks, 2008: 145).

Considering that the first stage of the regressions is a time series regression, the areas of concern for violation of the CLRM, are autocorrelation, heteroscedasticity and non-normality of the residual distribution. The first area of concern, autocorrelation, arises when the error terms ( $\bar{e}_j$  and  $e_{jt}$ ) of the regressions are correlated over time resulting in the violation of the assumption that the covariance between error terms is zero (Gujarati, 2003: 442; Brooks, 2008: 139). When autocorrelation is present the beta estimates remain unbiased, meaning that they still provide a reliable estimate of the true parameter, however, the estimates are inefficient, which suggests that the standard errors produced by the regression are biased (Gujarati, 2006: 432; Brooks, 2008: 166).

One of the assumptions of the CLRM is that the variance of the error terms from each of the regressions are constant, this is the second area of concern, the assumption that the terms of the regression are homoscedastic (Brooks, 2008: 132). When the error terms of a regression fluctuate with the explanatory variables of the regression, that is they do not remain constant, it is known as heteroscedasticity (Gujarati, 2006: 169-170; Brooks, 2008: 132). As with autocorrelation, when heteroscedasticity occurs the beta estimates will be unbiased but not minimum-variance.

There are various methods in which these first two areas of concerns can be detected as well as a number of suggested solutions. For example, the Durbin-Watson test, the Breusch-Godfrey test and various graphical tests can all be used to detect autocorrelation (Gujarati, 2006: 434; Brooks, 2008: 140-148), whilst the Cochrane-Orcutt procedure is said to help deal with the problem of autocorrelation. The problem however with the Cochrane-Orcutt procedure is that it does not deal very well with small sample sizes (Gujarati, 2006: 444; Brooks, 2008: 150-151). With regards to heteroscedasticity, it is once again possible to use a graphical method to test if heteroscedasticity is present, as well as other methods such as the Goldfeld-Quandt (1965) test, the White (1980) test, the Park test (Gujarati, 2006: 400-407; Brooks, 2008: 133-136), whilst Wooldridge (2003: 267-270) suggests testing for heteroscedasticity using the Breusch-Godfrey-Koenker, as it does not consume degrees of freedom, thus giving it more power in a study with a smaller sample size. If heteroscedasticity is found to be present a couple of possible remedies are to use methods such as the generalised least squares method (GLS), or the method of weighted least squares (WLS), alternatively the problem could be rectified in EViews using the White (1980) standard error transformation (Gujarati, 2006: 407-408; Brooks, 2008: 136-138).

Despite the numerous ways in which autocorrelation and heteroscedasticity can both be detected and remedied, Brooks (2008: 152) suggests a far simpler approach to tackle both these areas of concern at once. “Newey and West (1987) develop a variance-covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation” (Brooks, 2006: 152). Thus the Newey-West (1987) estimator deals with both residual autocorrelation and heteroscedasticity, by appropriately modifying the standard error estimates.

The third area of concern, as mentioned, is non-normality of the residual distribution. One of the assumptions of the CLRM is that the disturbances, that is the error terms of the regressions have normal distributions, this is known as the normality assumption. If the normality assumption does not hold, as with autocorrelation and heteroscedasticity, the beta estimates will remain unbiased but not minimum-variance (Brooks, 2008: 153). However, the issue of non-normality should not pose any problems, because while share returns are likely to exhibit non-normality, this is less likely to be the case with portfolio returns. Therefore it is reasonable to assume normality due to the formation of portfolios (Brooks, 2008: 164).

#### **4.4 Testing the Explanatory and Forecasting Powers of the Models**

Additional tests were carried out on each of the models in order to further scrutinise their robustness. This was done by having their explanatory powers and forecasting abilities assessed according to their performance in respect to the pre-constructed portfolios. What this means is that each model developed was tested to see how well they explained, and forecasted the excess returns and total returns for each of the pre-constructed portfolios. The steps in which the explanatory powers and forecasting abilities are assessed are now explained.

##### **4.4.1 Testing the Explanatory Power of the Models**

Recently, more and more importance has been placed on model evaluation criteria. When faced with the decision of best approximating model from a class of competing models, these evaluation criteria fulfil an important technical area of any analysis (Bozdogan, 2000: 62). Bozdogan (2000: 62) explains that “model evaluation criteria are figures of merit, or performance measures, for competing models”. Thus in order to properly evaluate which model

is superior from the four models formed in this study each model was tested and ranked based on each of their explanatory powers. In order to evaluate each of these models the explanatory powers of each were tested using two information criteria. The information criteria are obtained by first estimating the models, in the sense that the CAPM model is constructed according the varying inputs, then the models were regressed against the excess returns and total returns of each of the pre-constructed portfolios, one at a time. The information criteria are then calculated using the residual variance estimated from the regression for each of the well diversified portfolios (Brooks 2008: 233). This will be carried out on the time series or first pass regressions of this study. The object of the information criteria, is to choose the model which minimises the value of the information criteria. The three information criteria most commonly used are Akaike's (1974) information criterion (AIC), the Schwarz (1978) Bayesian information criterion (SBIC) and the Hannan-Quinn information criterion (HQIC). Each are represented algebraically below:

$$AIC = \ln(\hat{\sigma}^2) + 2k/T \quad (4.19)$$

Where:

$\hat{\sigma}$  is the residual variance

T is the sample size

k is the total number of parameters estimated

$$SBIC = \ln(\hat{\sigma}^2) + (k/T) \ln T \quad (4.20)$$

$$HQIC = \ln(\hat{\sigma}^2) + (2k/T) \ln(\ln(T)) \quad (4.21)$$

(Brooks 2008: 233)

All the models offered different advantages and disadvantages such as: the SBIC is very consistent but it is inefficient, whilst the AIC is inconsistent but is on average more efficient. For the purpose of this study only the AIC and the SBIC were employed. The rationale behind this decision is because the AIC and SBIC offer two extremes, as shown by their advantages and disadvantages. Furthermore, the SBIC involves a much stiffer penalty term than the AIC while HQIC is somewhere between the two (Brooks 2008: 233). Thus, because the HQIC is



viewed more as an intermediate measure, the other two methods were deemed to suffice. Once the information criteria had been calculated the separate performances of the models were compared, and ranked according to the two measures.

#### 4.4.2 Testing the Forecasting Ability of the Models

Finally the forecasting abilities of each of the models was tested on the time series models (first-pass regressions). Forecasting can be described as the effort to establish “the values that a series is likely to take” (Brooks 2008: 243). As established in the earlier chapters, the CAPM is the most popular model when estimating the cost of equity for firm faced with capital budgeting decisions. Thus, one of the most important purposes of a model such as the CAPM is, to as accurately as possible, forecast the cost of equity of potential projects.

There are a number of ways in which these tests can be carried out, however, for the purpose of this study the in-sample out of sample test was used. This test used a portion of the data obtained from the well diversified portfolios known as the “in-sample” to forecast the remainder of the data known as the “out sample”. The forecasted values were then compared to the actual values from the data set. The time period for this study was January 2000 to December 2010, therefore, all data from January 2000 to December 2009 was collected and used as inputs into the regressions, this data is known as the “in-sample data”. Once the regressions had been run, the estimated models produced “forecasts” for the returns of the 12 months of out-of-sample data (January 2010 to December 2010). The forecasts from the regressions were then compared to the actual returns of the portfolios over the out-of-sample period. The results from the tests were then be ranked and compared according to three criteria, the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE).

$$RMSE = \left[ \frac{1}{T - (T_1 - 1)} \sum_{t=T_1}^T (y_{t+s} - f_{t,s}) \right]^{1/2} \quad (4.22)$$

Where:

T is the total sample size (in-sample + out-sample)

T<sub>1</sub> is the first out of sample observation

$y_{t+s}$  is the actual value

$f_{t,s}$  is the forecasted value

$$MAE = 1/T - (T_1 - 1) \sum_{t=T_1}^T |y_{t+s} - f_{t,s}| \quad (4.23)$$

$$MAPE = 100/T - (T_1 - 1) \sum_{t=T_1}^T |y_{t+s} - f_{t,s}/y_{t+s}| \quad (4.24)$$

(Brooks 2008: 253)

The advantage of the RMSE measure is that it provides a quadratic loss function, which means that it could prove more useful in cases “where large forecast errors are disproportionately more serious than smaller errors” (Brooks, 2008: 252). As a result the RMSE will give a more accurate reflection of the financial markets, especially in times of crisis, such as the Asian or sub-prime crisis, as larger forecasting errors are disproportionately more severe than smaller errors in the financial world. MAE is described as being very consistent, whilst it is also a very commonly used method (Brooks 2008: 253). Dielman (1986) (quoted in Brooks, 2008: 252) believed that when there are outliers present in the data, least absolute errors should be used to decide on model parameters, which again will fit well into the study as the data period could contain a number of outliers. Finally Makridakis (1993: 528) (quoted in Brooks, 2008: 252) argued that the MAPE is “a relative measure that incorporates the best characteristics among the various accuracy criteria”. Thus based on these arguments, it was believed that for the purpose of this study the three methods that will be used are the RMSE, the MAE and the MAPE. The models will help to answer the question of whether the addition of bonds, and the consideration that there is possibly segmentation on the market will enhance the performance of a proxy for the market portfolio.

## **CHAPTER 5**

### **DATA ANALYSIS AND RESULTS**

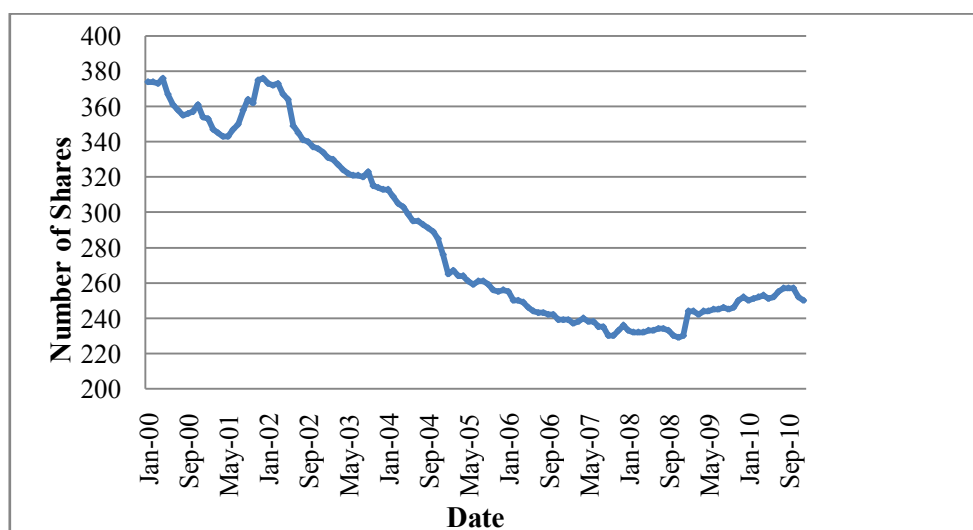
#### **5.1 Overview**

In this chapter, the results of the tests outlined in the previous chapter for determining the most appropriate proxy for the market portfolio are examined. The findings are analysed with reference to the theory set out in chapters 2 and 3, as well as the results of similar international studies. The different models are also examined and compared based on their explanatory powers and forecasting abilities, and the findings are analysed in conjunction with the findings of the earlier tests.

#### **5.2 Preliminary Data Analysis**

##### **5.2.1 Number of Shares included in the Samples**

The number of shares (ordinary and preference) included in the beta-sorted portfolios, in each month of the analysis, are shown in figure 5-1. Due to the fact that the requirements for inclusion are relatively stringent when compared to methods such as industry-sorting, there are fewer shares included than would be expected in industry-sorted portfolios. The general decline in the number of shares included between the period January 2000 to January 2009 is a result of the decrease in the number of shares listed on the JSE over the same period. Similarly, the increase post January 2009 is as a result of an increase in shares listed on the JSE. As discussed in section 4.2.2.1 any shares that were listed after December 2008 did not have adequate trading history to be included in the sample.

**Figure 5- 1      The number of shares included in each sample per month**

### 5.2.2 Formation of Portfolios

As was discussed in section 4.3.1 the ordinary and preference shares were allocated into portfolios based on the method of beta-sorting. Table 5-1 shows the beta values for the portfolios comprising of ordinary and preference shares for the years 2001, 2005 and 2010. These three years were selected in order to get an overview of the relationships from the beginning, middle and end of the period suggested.

**Table 5- 1      Selected portfolio betas**

	<b>Betas 2001</b>	<b>Betas 2005</b>	<b>Betas 2010</b>
<b>Portfolio 1 (Largest)</b>	0.936819093	1.000079727	1.081691409
<b>Portfolio 2</b>	0.567191465	0.715340456	0.447795613
<b>Portfolio 3</b>	0.55721396	0.535263221	0.746218682
<b>Portfolio 4</b>	0.512352974	0.658488097	0.675135103
<b>Portfolio 5</b>	0.541961323	0.474941265	0.465641368
<b>Portfolio 6</b>	0.226350117	0.501335248	0.300983638
<b>Portfolio 7</b>	0.574188081	0.659333675	0.079105141
<b>Portfolio 8</b>	0.063544422	0.122213411	0.174330943
<b>Portfolio 9</b>	0.092033201	0.306819417	0.26922453
<b>Portfolio 10 (Smallest)</b>	0.106000886	0.366172353	0.059750323

As is illustrated in Table 5-1, the estimation period ranking in the beta-sorting method was generally a decent indicator of the actual period risk measures, as the highest beta portfolios in the estimation period generally exhibited the largest betas in the test period and the smallest beta portfolios in the estimation period generally produced the smallest betas in the test period. However, there were a number of discrepancies in this regard, such as portfolio 8 in 2001 and 2005 having the lowest beta. What was also clearly evident was that the beta values had a tendency to cluster together, despite the goal of trying to obtain as much variability as possible in the beta values. The trend of the beta values in the actual period clustering together was also observed in the 2003 study of Van Rensburg and Robertson.

### **5.2.3 Estimation Considerations**

As was discussed in section 4.3.2.3, when concerned with the methodologies of Black *et al* (1972), Fama and MacBeth (1973) and the processes of a pooled regression there are a number of considerations that need to be taken into account. The two major concerns that emerged from the discussion in section 4.3.2.3 were autocorrelation and heteroscedasticity. In order to test for autocorrelation a Breusch-Godfrey serial correlation LM test was employed for each of the time series regressions. It was found that at no point could the null hypothesis that there is no autocorrelation be rejected, meaning that no autocorrelation was present (results shown in appendices A and B). Next, the White heteroscedasticity test was conducted to test for evidence of heteroscedasticity in the cross-sectional regressions. Again it was found that at no point could the null hypothesis that there is no heteroscedasticity be rejected, meaning that no heteroscedasticity was present (results shown in appendices C and D). This meant that the tests could be run without any adjustments for autocorrelation or heteroscedasticity being made.

### **5.3 The Suitability of the Proxies for the Market Portfolio**

The purpose of this study is to determine which of the four proposed proxies is best suited to the South African market. As was outlined in section 4.3.2 three tests were used to test the suitability of the various proxies for the market portfolio, namely, the methodology of Black *et al* (1972), the methodology of Fama and MacBeth (1973) and pooled regression. These three tests were conducted on both the excess and total returns of the assets included in the tests. All three of the tests involved using variations of the two pass regression methodology. For

comparison purposes, firstly the results of each of the proxy's for the first pass regressions will be discussed and compared followed by a discussion and comparison of the second pass results.

### **5.3.1 First Pass Regression Results**

Although the first pass regression results are not the crux of this study, some valuable insights on the models and the data can be gained from these results and discussions on them. Therefore the results of the first pass regressions will be discussed in the following sections, beginning with the results of the model containing the ALSI as a proxy.

#### **5.3.1.1 ALSI as the Proxy for the Market Portfolio**

The first pass regression of the Black *et al* (1972) study involved a time series regression of firstly the excess returns of each of the portfolios against, in turn, the excess returns of each of the proposed proxies. This was then repeated on the total returns of the variables. The regression was conducted over the entire period (January 2000 – December 2010). The summary statistics of the time series regression with the ALSI as the explanatory variable are displayed in table 5-2.

Theory predicts that for these time series regressions that the intercept ( $\alpha$ ) is equal to zero, and that the beta coefficient is the correlation of that proxy to the various portfolios. The riskier the portfolio the higher the beta is expected to be (i.e. over 1). From the results it can be seen that with the ALSI as the sole explanatory variable that the intercept is not zero for any of the portfolios. In fact, for the two highest risk portfolios (portfolio 1 and 2) the intercepts are negative suggesting that the high risk portfolios earned less on average than was predicted by the traditional form of the model. Conversely, the lower risk portfolios (portfolios 3 to 10) all have positive intercepts suggesting that these portfolios earned more than was predicted by the traditional form of the asset pricing model. However, as the t-stats and P values of the intercepts for portfolios 1 to 4 suggest, these results were insignificant, and hence not too much should be read into the results of the intercepts for these four portfolios. For the remaining portfolios (5 to 10) the intercepts were found to be significant and hence it can be confirmed that these

portfolios earned more than was predicted by the traditional form of the asset pricing model (as the intercept was greater than 0).

**Table 5- 2 Summary statistics for time series tests with the ALSI as the explanatory variable (excess returns)<sup>3</sup>**

	Portfolio Number									
Item	1	2	3	4	5	6	7	8	9	10
$\alpha$	-0.252	-0.071	0.073	0.471	0.606	1.080	0.949	0.830	1.091	0.734
t-stat ( $\alpha$ )	-0.671	-0.206	0.232	1.549	2.111	3.710	3.317	3.088	4.492	2.081
P Value ( $\alpha$ )	0.503	0.837	0.817	0.124	0.037	0.000	0.001	0.002	0.000	0.039
$\beta$ ALSI	0.857	0.795	0.603	0.573	0.543	0.443	0.448	0.295	0.172	0.248
t-stat ( $\beta$ )	12.743	12.796	10.662	10.482	10.530	8.489	8.716	6.108	3.955	3.923
P value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj R-sq	0.552	0.554	0.462	0.454	0.456	0.352	0.364	0.217	0.101	0.099

Especially when concerned with the ALSI, it is expected that the riskier portfolios would have higher betas, even betas over one. However, from the summary statistics it can be seen that all the coefficients of the ALSI were found to be positive and statistically significant, but none were over one, and also worth noting was that the range of coefficients was found to be very narrow, between 0.857 and 0.172. This illustrated that none of the portfolios that were formed were very risky when compared to the ALSI. This is very a very puzzling result as portfolio 1 is supposedly the riskiest shares on the JSE and yet they still do not have a beta over one, suggesting they were not as risky as the ALSI. When comparing these results with the results of Black *et al* (1972: 14), it was found that the intercepts in both studies followed a similar trend with the riskier portfolios providing negative intercepts, however, again both were found to be insignificant. The difference in the two sets of results came in the betas of the proposed market proxy. Whilst the betas of this study fell in a narrow range (0.857-0.172), the betas of the Black *et al* (1972: 14) study had a broader range, ranging from 1.5614 to 0.4992. Not only was the range broader, it was riskier too. What this means is that on average the ten ordinary share portfolios used in the Black *et al* (1972) study were riskier in comparison to the market proxy than in this study. The betas produced by Black *et al* (1972: 14) are more in line with theory as the riskiest portfolios (1 to 5) all had betas above 1 suggesting that they were riskier than the employed market proxy.

<sup>3</sup> The unit of measurement for this table and the following tables is percent (%)

The adjusted R-squared values for each of the portfolios also supplied a large range of 0.552 to 0.099, with the general trend of decreasing as the portfolios got less and less risky. This statistic describes how much of the movements in the dependant variable can be explained by the explanatory variable, in this case, how much movements in the various portfolios can be described by the ALSI. It was found that at the highest point that 55.4% of the movements of portfolio 2 could be explained by the ALSI, whilst at its lowest 9.9% of the movements of portfolio 10 could be explained by the ALSI. It was found that on average the ALSI could explain 36.1% of the movements of all the shares in the sample. This is a fairly large adjusted R-squared value, illustrating that the ALSI can explain a substantial amount about the movements in the share prices.

**Table 5- 3 Summary statistics for time series tests with the ALSI as the explanatory variable (total returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	-0.141	0.087	0.377	0.795	0.954	1.504	1.369	1.367	1.720	1.307
t-stat ( $\alpha$ )	-0.367	0.246	1.172	2.550	3.244	5.056	4.676	4.994	6.959	3.633
P Value ( $\alpha$ )	0.715	0.806	0.243	0.012	0.002	0.000	0.000	0.000	0.000	0.000
$\beta$ ALSI	0.854	0.791	0.597	0.569	0.538	0.437	0.442	0.286	0.163	0.239
t-stat ( $\beta$ )	12.588	12.626	10.486	10.321	10.355	8.309	8.539	5.909	3.732	3.755
P value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj R-sq	0.546	0.547	0.454	0.446	0.448	0.342	0.354	0.206	0.090	0.091

As table 5-3 illustrates, the results for the time series tests using the total returns of the portfolios and the ALSI produced similar results to the test of excess returns. Theory suggests that the intercept for this test was expected to be 0.745% (the average monthly risk-free rate over the period) and again that the beta values should be positive. To begin with, the three riskiest portfolio produced intercepts less than 0.745, suggesting that the portfolios had not performed as well as predicted by the model, but according to the t-stat and P value the values were insignificant at the 5% level. It was also found that the intercept value for portfolio 4 was insignificant at the same level. However, portfolios 5-10 produced intercepts greater than 0.745 and were found to be statistically significant at the 5% level, which was similar to the results of the test on the excess returns. Next, the betas produced by the time series regression of total returns were very similar to those of excess returns, significant but with a very narrow range. Finally the adjusted R-squared values were also very similar to the adjusted R-squared values



produced by the excess returns, with the value dropping as the portfolios became less and less risky. The average of the R squared values was also very similar, but slightly less, to that of the excess return at 35,2%.

Due to the fact that both the Fama and MacBeth (1973) and the pooled regression methods involved the same first pass method, the following results will apply to both methods and will be presented in the following discussions. The first pass regression of these two methods involved rolling time-series regressions of the excess returns of each of the portfolios to, in turn, the excess returns of each of the proposed proxies for the market portfolio. This was then repeated for the total returns of the variables. The period for the regression was 36 months and the regression was rolled forward monthly. The average intercepts, betas, t-stats and adjusted R-squared values for each of the models are displayed in the following tables. To begin with, table 5-4 and table 5-5 represent the summary statistics for the regression with both excess and total returns being used and with the ALSI as the explanatory variable.

**Table 5- 4 Summary statistics for rolling time series tests with the ALSI as the explanatory variable (excess returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	0.036	0.144	0.226	0.418	0.711	1.123	0.938	0.855	1.001	0.809
t-stat ( $\alpha$ )	0.071	0.427	0.436	0.835	1.249	2.039	1.807	1.653	2.026	1.192
P Value ( $\alpha$ )	0.943	0.672	0.665	0.410	0.220	0.049	0.080	0.108	0.051	0.242
$\beta$ ALSI	0.814	0.782	0.550	0.585	0.516	0.457	0.480	0.319	0.170	0.284
t-stat ( $\beta$ )	5.986	6.711	5.072	5.165	5.024	4.327	5.023	3.348	1.882	2.115
P Value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.068	0.042
Adj R-sq	0.494	0.546	0.408	0.421	0.396	0.334	0.400	0.226	0.072	0.102

As was the case with the Black *et al* (1972) study, theory predicts that the intercept should be zero for excess returns and 0.745% for total returns, whilst the beta coefficient which is the correlation of the proxy to the various portfolios, should be higher (above one) for the riskier portfolios and lower for the less risky portfolios.

**Table 5- 5 Summary statistics for rolling time series tests with the ALSI as the explanatory variable (total returns)**

	Portfolio Number									
Item	1	2	3	4	5	6	7	8	9	10
$\alpha$	0.184	0.313	0.571	0.740	1.080	1.544	1.339	1.379	1.637	1.369
t-stat ( $\alpha$ )	0.247	0.665	0.961	1.343	1.856	2.701	2.505	2.595	3.252	1.939
P Value ( $\alpha$ )	0.807	0.510	0.343	0.188	0.072	0.011	0.017	0.014	0.003	0.061
$\beta$ ALSI	0.812	0.779	0.545	0.582	0.511	0.451	0.474	0.312	0.161	0.277
t-stat ( $\beta$ )	5.924	6.636	4.997	5.096	4.947	4.247	4.944	3.263	1.781	2.044
P Value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.084	0.049
Adj R-sq	0.488	0.541	0.401	0.414	0.389	0.326	0.393	0.217	0.063	0.096

As with Black *et al* (1972) it was found that none of the coefficients in the excess returns regression were found to equal zero, all were found to be positive. However, the intercepts for portfolios 1-5 were found to be insignificant at the 5% level, whilst for portfolios 6-10 the coefficients were all found to be significant and positive, suggesting that these lower risk portfolios outperformed the model's expectations. It was a similar story for the total returns results, the intercepts for the higher risk portfolios (1-4) were found to be insignificant, however there after the intercepts (portfolios 5-10) were found to be significant and above 0.745% illustrating that lower risk portfolios, also according to the total returns regression, outperformed the expectations of the model.

The beta coefficients for the ALSI in both the excess returns regressions and the total returns regressions produced very similar results. It was found that all the coefficients were significant and positive. Again it was found that the coefficients displayed a very narrow range, with none of the coefficients found to be over one. This shows, as was the case with the Black *et al* (1972) study that none of the portfolios were found to be more risky than the ALSI.

Finally the adjusted R squared estimates spiked for both the regressions at portfolio 2, however the general trend was that the adjusted R squared values decreased as the portfolios became less and less risky. The average adjusted R squared for the excess return regressions was found to be 34.0% and the R squared for the total return regressions was found to be 33.3%, illustrating that the ALSI had relatively high explanatory power for the portfolios.

### 5.3.1.2 ALSI and ALBI as the Proxies for the Market Portfolio

Table 5-6 illustrates the summary statistics of the first pass Black *et al* (1972) regression using the ALSI and the ALBI as explanatory variables. As can be seen from the intercept statistics, as was the case when the ALSI was the proxy, the regression produced negative intercepts for the three riskiest portfolios. However, these values were found to be insignificant at the 5% level. This was found to be the case with the intercepts for portfolios 4 and 5 too. The intercepts for portfolios 6-10 were all found to be significant, and as was the case with the ALSI, the intercepts for the lower risk shares were positive, suggesting that these portfolios outperformed the model's expectations.

The betas for the ALSI were also similar to the tests on the model with the ALSI as the sole proxy. All were found to be significant at the 5% level, the betas generally decreased as the portfolios became less risky. As with the test on the first model, all the values were found to be in a narrow range (0.855-0.171), in fact the range is exactly the same as the range obtained from the time series regression of the excess returns of the ALSI and the portfolios. Again none of the betas of the ALSI were found to be above one. Next, the betas for the ALBI, the second explanatory variable, were all found to be significant at the 5% level except for portfolios 7, 8 and 9. The other coefficients (for portfolios 1-6 and 10) generally got larger as the portfolios became less risky, as would be expected because the ALBI is a lower risk index than the ALSI and is therefore more likely to have a correlation with lower risk portfolios.

Finally the adjusted R-squared values for every portfolio increased when compared with the first test, suggesting that the addition of the ALBI improved the explanatory power of the model for every variation of risk. The average adjusted R-squared value was found to be 39.8%, which was an increase of 3.7% when compared to the first test, again showing the improvement of the model as a whole.

**Table 5- 6 Summary statistics for time series tests with the ALSI and ALBI as the explanatory variables (excess returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
<b><math>\alpha</math></b>	-0.331	-0.216	-0.101	0.308	0.450	0.949	0.903	0.803	1.060	0.639
<b>t-stat (<math>\alpha</math>)</b>	-0.884	-0.646	-0.345	1.083	1.680	3.402	3.141	2.963	4.335	1.826
<b>P Value (<math>\alpha</math>)</b>	0.378	0.520	0.731	0.281	0.095	0.001	0.002	0.004	0.000	0.070
<b><math>\beta</math> ALSI</b>	0.855	0.791	0.597	0.567	0.538	0.439	0.446	0.294	0.171	0.245
<b>t-stat (<math>\beta</math>)</b>	12.801	13.268	11.442	11.190	11.270	8.839	8.709	6.080	3.932	3.932
<b>P value (<math>\beta</math>)</b>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
<b><math>\beta</math> ALBI</b>	0.326	0.590	0.711	0.667	0.639	0.534	0.189	0.108	0.125	0.386
<b>t-stat (<math>\beta</math>)</b>	1.741	3.531	4.855	4.687	4.768	3.833	1.316	0.794	1.018	2.208
<b>P value (<math>\beta</math>)</b>	0.084	0.001	0.000	0.000	0.000	0.000	0.190	0.429	0.311	0.029
<b>Adj R-sq</b>	0.559	0.590	0.542	0.530	0.534	0.413	0.368	0.215	0.101	0.125

The equivalent test was run on the total returns of each of the parameters and again similar results were obtained as can be seen in table 5-7. The intercepts for the five riskiest portfolios were found to be insignificant, whilst the last five were found to be significant at the 5% level. Of the significant results only portfolio 6 was found to have an intercept of less than 0.745%, suggesting that it earned less than was predicted by the model. Whilst the last four portfolios all had intercepts greater than 0.745% meaning that they exceeded the expectations of the model. The betas for the ALSI and ALBI were all found to be similar in values and significance. This was also the case with the adjusted R-squared values as both tests produced very similar results in this regard, although on average the adjusted R-squared values were slightly lower as compared to when excess returns were utilised. This was displayed in the average R-squared value which was 38.7%.

**Table 5- 7 Summary statistics for time series tests with the ALSI and ALBI as the explanatory variables (total returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
<b><math>\alpha</math></b>	-0.445	-0.472	-0.300	0.141	0.333	0.991	1.187	1.275	1.607	0.945
<b>t-stat (<math>\alpha</math>)</b>	-1.050	-1.244	-0.905	0.437	1.098	3.144	3.659	4.182	5.848	2.394
<b>P Value (<math>\alpha</math>)</b>	0.296	0.216	0.367	0.663	0.274	0.002	0.000	0.000	0.000	0.018
<b><math>\beta</math> ALSI</b>	0.854	0.791	0.597	0.569	0.538	0.436	0.442	0.286	0.163	0.239
<b>t-stat (<math>\beta</math>)</b>	12.670	13.122	11.297	11.113	11.161	8.712	8.560	5.897	3.731	3.804
<b>P value (<math>\beta</math>)</b>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
<b><math>\beta</math> ALBI</b>	0.306	0.562	0.682	0.658	0.624	0.516	0.183	0.093	0.114	0.364
<b>t-stat (<math>\beta</math>)</b>	1.646	3.381	4.680	4.665	4.698	3.733	1.283	0.695	0.946	2.105
<b>P value (<math>\beta</math>)</b>	0.102	0.001	0.000	0.000	0.000	0.000	0.202	0.488	0.346	0.037
<b>Adj R-sq</b>	0.552	0.581	0.530	0.522	0.525	0.401	0.358	0.202	0.089	0.114

The rolling time series regressions of Fama and MacBeth (1973) produced very similar results to the time series regression of Black *et al* (1972). For both the excess and total returns a few of the intercepts for the riskier portfolios were found to be negative, however as was the case with the Black *et al* (1972) results, these intercepts were insignificant at the 5% level. The difference in the results of the two, came in the number of significant intercepts obtained. Whilst the Black *et al* (1972) study found 6 significant intercepts (portfolios 5-10) for excess returns and 5 (portfolios 6-10) for total returns, the Fama MacBeth (1973) study produced only 3 (portfolios 6, 7 and 9) for excess returns and 3 (portfolios 7-9) for total returns. Of these significant intercepts, they were all positive again suggesting, as these were lower risk portfolios, that the less risky portfolios exceeded the expectations of the model when the ALSI and ALBI are employed as market proxies.

The beta coefficients of the two explanatory variables followed a similar trend to those of the Black *et al* (1972) tests. The betas of the ALSI were all positive and significant with the coefficient generally decreasing from portfolio 1 to portfolio 10, as would be expected. However, as was found with the previous results and as was the case with the Black *et al* (1972) results, the coefficients were found to be in a narrow range, with none over the value of one. The coefficients for the ALBI were found to be insignificant for portfolio 1 and 7-10, the remainder were all significant and positive, with the value of the coefficient at its highest in

portfolios 3, 4 and 5, suggesting that the shares in these portfolios were fairly correlated with the ALBI.

**Table 5- 8 Summary statistics for rolling time series tests with the ALSI and ALBI as the explanatory variables (excess returns)**

	Portfolio Number									
Item	1	2	3	4	5	6	7	8	9	10
$\alpha$	-0.006	0.053	0.130	0.394	0.631	1.092	0.993	0.891	1.048	0.796
t-stat ( $\alpha$ )	0.027	0.292	0.263	0.742	1.142	1.986	1.908	1.670	2.069	1.138
P Value ( $\alpha$ )	0.979	0.772	0.794	0.463	0.262	0.055	0.065	0.104	0.046	0.263
$\beta$ ALSI	0.834	0.783	0.556	0.577	0.509	0.451	0.469	0.318	0.169	0.282
t-stat ( $\beta$ )	6.165	7.058	5.616	5.491	5.443	4.513	5.075	3.310	1.849	2.109
P Value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.073	0.043
$\beta$ ALBI	0.167	0.657	0.698	0.718	0.718	0.594	0.278	0.079	0.051	0.388
t-stat ( $\beta$ )	0.514	2.180	2.589	2.434	2.660	2.125	1.125	0.331	0.273	1.111
P Value ( $\beta$ )	0.611	0.036	0.014	0.020	0.012	0.041	0.269	0.743	0.787	0.274
Adj R-sq	0.509	0.602	0.503	0.500	0.486	0.401	0.425	0.215	0.070	0.116

**Table 5- 9 Summary statistics for rolling time series tests with the ALSI and ALBI as the explanatory variables (total returns)**

	Portfolio Number									
Item	1	2	3	4	5	6	7	8	9	10
$\alpha$	-0.044	-0.273	-0.061	0.183	0.485	1.091	1.217	1.372	1.662	1.076
t-stat ( $\alpha$ )	-0.015	-0.240	-0.135	0.283	0.686	1.683	1.968	2.253	2.897	1.338
P Value ( $\alpha$ )	0.988	0.812	0.894	0.779	0.498	0.102	0.057	0.031	0.007	0.190
$\beta$ ALSI	0.833	0.784	0.556	0.579	0.508	0.449	0.465	0.312	0.160	0.277
t-stat ( $\beta$ )	6.114	6.996	5.551	5.461	5.389	4.452	4.998	3.226	1.754	2.056
P Value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.089	0.048
$\beta$ ALBI	0.159	0.640	0.677	0.718	0.702	0.572	0.268	0.064	0.033	0.371
t-stat ( $\beta$ )	0.492	2.128	2.513	2.437	2.612	2.057	1.076	0.270	0.198	1.067
P Value ( $\beta$ )	0.626	0.041	0.017	0.020	0.013	0.048	0.290	0.789	0.845	0.294
Adj R-sq	0.504	0.595	0.493	0.494	0.477	0.389	0.417	0.205	0.059	0.106

The adjusted R-squared values for the Fama MacBeth tests with the ALSI and ALBI as explanatory variables remained fairly consistent over the first five portfolios, with a spike at portfolio 2, however thereafter they generally decreased from portfolio 6-10. On average the adjusted R-squared values increased as compared to the model with only the ALSI as the explanatory variable, the average for the excess returns test was 38.3%, whilst for the total returns test it was 37.4%.

### **5.3.1.3 FINDI and RESI as the Proxies for the Market Portfolio**

The next time series and rolling time series tests to be run were with the FINDI and the RESI as the explanatory variables. The results of the Black *et al* (1972) tests on the excess returns of the parameters are shown in table 5-10. As with the previous two Black *et al* (1972) tests on excess returns the riskier portfolios provided intercepts that were not statistically significant at the 5% level. Portfolios 4 to 10 produced intercepts that were significant, and as was the case with the previous tests the intercepts were not equal to zero and were positive, which yet again suggests that the portfolios with lower risk were found to outperform the expectations of the model.

The coefficients of the explanatory variables proved to be very interesting. The betas for the FINDI were all found to be significant at the 5% level and all were found to be positive. This was not the case however, for the RESI. Firstly the beta for portfolio 4 was found to be negative, however portfolio 4, along with portfolios 3,5,6,9 and 10 produced betas for the RESI that were not significant at the 5% level. The remaining betas were found to be significant and all were positive values. For both explanatory variables the betas produced were found to be in a small range, as was the case in the first two models.

The adjusted R-squared values produced by this model differed from the previous models. Instead of the adjusted R-squared generally decreasing as the portfolios became less risky they tended to fluctuate until portfolio 5, after which they steadily decreased. The average adjusted R-squared value for the model was 39.0% which was higher than the adjusted R-squared of the model involving excess returns of the ALSI, but lower than the adjusted R-squared of the model involving the excess returns of the ALSI and ALBI. Despite the fact that this model produced a lower average adjusted R-squared value than the model involving the ALSI and ALBI, what is worth noting is that for portfolios 3 and 4 the adjusted R-squared of the FINDI, RESI model

significantly outperforms the ALSI, ALBI model. A possible explanation for this is that there could be a large number of financial and industrial or resource shares in those particular portfolios. With regards to adjusted R-squared and explanatory powers, in no other portfolio did this model outperform the ALSI, ALBI model.

**Table 5- 10 Summary statistics for time series tests with the FINDI and RESI as the explanatory variables (excess returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
<b><math>\alpha</math></b>	-0.231	0.007	0.182	0.589	0.687	1.149	0.998	0.852	1.105	0.766
<b>t-stat (<math>\alpha</math>)</b>	-0.600	0.019	0.635	2.276	2.483	4.028	3.455	3.137	4.510	2.173
<b>P Value (<math>\alpha</math>)</b>	0.549	0.985	0.526	0.024	0.014	0.000	0.001	0.002	0.000	0.032
<b><math>\beta</math> FINDI</b>										
	0.548	0.702	0.674	0.705	0.542	0.446	0.378	0.224	0.130	0.242
<b>t-stat (<math>\beta</math>)</b>	6.478	9.463	10.645	12.355	8.892	7.085	5.941	3.743	2.412	3.118
<b>P value (<math>\beta</math>)</b>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.017	0.002
<b><math>\beta</math> RESI</b>										
	0.300	0.157	0.023	-0.013	0.060	0.044	0.090	0.077	0.044	0.034
<b>t-stat (<math>\beta</math>)</b>	5.493	3.278	0.573	-0.348	1.529	1.096	2.192	1.999	1.278	0.678
<b>P value (<math>\beta</math>)</b>	0.000	0.001	0.568	0.728	0.129	0.275	0.030	0.048	0.204	0.499
<b>Adj R-sq</b>										
	0.531	0.580	0.555	0.607	0.497	0.379	0.355	0.204	0.088	0.103

Table 5-11 displays the results of the time series tests with total returns and the FINDI and RESI as the proxies. The results for the intercept are very similar to the equivalent model with excess returns. Portfolios 1-3 all produce insignificant intercepts, with portfolios 4-10 producing significant estimates which are all above 0.745%, suggesting that these seven portfolios earned more than the model predicted.

The betas of the FINDI were all found to be significant and positive. The betas of the RESI for portfolio 3,4,5 and 6 were also found to be insignificant in line with the excess returns model, and the remaining betas were found to be positive and significant. The adjusted R-squared values were very similar to those of the excess returns model, with fluctuation in the first five, then a steady decline thereafter. The adjusted R-squared values outperformed the equivalent ALSI and ALBI model for portfolios 3 and 4. The average adjusted R-squared value was found to be 38.1%, less than the equivalent ALSI, ALBI model but higher than the ALSI model.



**Table 5- 11 Summary statistics for time series tests with the FINDI and RESI as the explanatory variables (total returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	-0.113	0.116	0.414	0.821	0.988	1.537	1.402	1.384	1.732	1.317
t-stat ( $\alpha$ )	-0.288	0.336	1.411	3.098	3.494	5.278	4.751	5.013	6.961	3.668
P Value ( $\alpha$ )	0.774	0.737	0.161	0.002	0.001	0.000	0.000	0.000	0.000	0.000
$\beta$ FINDI	0.545	0.699	0.669	0.703	0.538	0.439	0.372	0.215	0.120	0.233
t-stat ( $\beta$ )	6.399	9.365	10.522	12.231	8.773	6.956	5.819	3.588	2.230	2.988
P value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.027	0.003
$\beta$ RESI	0.299	0.156	0.023	-0.013	0.060	0.044	0.089	0.076	0.044	0.033
t-stat ( $\beta$ )	5.488	3.273	0.563	-0.350	1.521	1.085	2.182	1.990	1.262	0.664
P value ( $\beta$ )	0.000	0.001	0.574	0.727	0.131	0.280	0.031	0.049	0.209	0.508
Adj R-sq	0.525	0.573	0.547	0.600	0.489	0.368	0.344	0.192	0.077	0.094

The results of both the excess and total return rolling time series regressions with the FINDI and RESI as explanatory variables are illustrated in tables 5-12 and 5-13. The results of the intercepts proved to be very different not only from each other but from the results of the Black *et al* (1972) tests. Firstly the excess returns tests produced only two significant intercepts (portfolios 6 and 9) whilst the equivalent Black *et al* (1972) test produced 7. Of the significant intercepts, as was the case with the Black *et al* (1972) tests, all were positive. The total returns regressions provided 6 significant intercepts (portfolios 5-10) which was one less than the equivalent Black *et al* (1972) tests produced. Again it was found that these significant intercepts were found to be above 0.745% meaning that the model underestimated the returns of the lower risk portfolios.

Discrepancies between the Black *et al* (1972) tests and the Fama MacBeth (1973) study were also found with the beta coefficients of the FINDI and RESI. To begin with, eight coefficients (portfolios 1-8) of the FINDI were found to be significant for both excess and total returns. All these coefficients were positive, suggesting that the majority of financial and industrial shares are in the riskier portfolios, and not many in the least risky portfolios (portfolios 9 and 10). The Black *et al* (1972) tests had different results when concerned with the FINDI, where both excess and total returns produced ten significant betas versus the eight of the Fama and MacBeth (1973) tests. However, in line with the Fama and MacBeth (1973) tests, all the significant coefficients were positive. Only two coefficients (portfolios 1 and 2) for the RESI were found to

be significant in the Fama and Macbeth (1973) tests (both total and excess returns), the equivalent Black *et al* (1972) tests produced four significant coefficients. However in both tests the coefficients were found to be positive.

**Table 5- 12 Summary statistics for rolling time series tests with the FINDI and RESI as the explanatory variables (excess returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	0.204	0.270	0.287	0.432	0.700	1.086	0.839	0.800	0.894	0.842
t-stat ( $\alpha$ )	0.279	0.533	0.425	0.896	1.371	1.929	1.634	1.504	1.784	1.179
P Value ( $\alpha$ )	0.782	0.597	0.673	0.376	0.180	0.062	0.112	0.142	0.084	0.247
$\beta$ FINDI	0.442	0.678	0.637	0.749	0.609	0.520	0.470	0.257	0.173	0.252
t-stat ( $\beta$ )	2.680	4.951	5.498	6.541	5.186	4.442	4.277	2.262	1.590	1.631
P Value ( $\beta$ )	0.011	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.121	0.112
$\beta$ RESI	0.340	0.170	0.019	-0.017	0.013	0.019	0.074	0.082	0.022	0.058
t-stat ( $\beta$ )	3.327	2.039	0.271	-0.232	0.253	0.274	1.070	1.175	0.286	0.567
P Value ( $\beta$ )	0.002	0.050	0.788	0.818	0.802	0.785	0.292	0.248	0.777	0.574
Adj R-sq	0.500	0.573	0.517	0.596	0.500	0.422	0.462	0.231	0.094	0.100

**Table 5- 13 Summary statistics for rolling time series tests with the FINDI and RESI as the explanatory variables (total returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	0.370	0.388	0.555	0.648	0.993	1.451	1.198	1.314	1.518	1.384
t-stat ( $\alpha$ )	0.474	0.691	0.856	1.300	1.892	2.522	2.277	2.407	2.972	1.880
P Value ( $\alpha$ )	0.638	0.494	0.398	0.202	0.067	0.017	0.029	0.022	0.005	0.069
$\beta$ FINDI	0.439	0.675	0.633	0.747	0.606	0.516	0.465	0.251	0.166	0.245
t-stat ( $\beta$ )	2.654	4.913	5.454	6.498	5.144	4.396	4.231	2.209	1.528	1.587
P Value ( $\beta$ )	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.136	0.122
$\beta$ RESI	0.339	0.170	0.018	-0.018	0.012	0.018	0.072	0.080	0.020	0.056
t-stat ( $\beta$ )	3.320	2.032	0.258	-0.242	0.240	0.255	1.057	1.157	0.251	0.548
P Value ( $\beta$ )	0.002	0.050	0.798	0.811	0.812	0.800	0.298	0.255	0.803	0.587
Adj R-sq	0.496	0.568	0.511	0.591	0.494	0.414	0.455	0.222	0.084	0.093

When concerned with the adjusted R-squared values of the rolling time series regressions, it was found that the model with the FINDI and RESI as the proxy for the market portfolio outperformed the model with the ALSI and ALBI as the market proxy for portfolios 3-9, this difference was especially significant in portfolio 4 (as was the case with the Black *et al* (1972) tests) suggesting that it is likely that this portfolio has a larger number of financial, industrial or resource shares in it. The average adjusted R-squared values for the excess and total returns were 40.0% and 39.3% respectively, which is higher than the model with the ALSI as the market proxy and the model with the ALSI and the ALBI as the market proxy.

#### **5.3.1.4 ALBI, FINDI and RESI as the Proxies for the Market Portfolio**

Table 5-14 displays the results of the time series tests involving excess returns of the ALBI, FINDI and RESI. As has been the trend with all the models thus far the riskier portfolios produced negative intercepts, however portfolios 1-3 were found to be statistically insignificant at the 5% level. The intercepts of the remaining portfolios, once again not bucking the trend, were all found to be significant and positive suggesting that this model underestimated the portfolios with lower risk.

The coefficients of the ALBI were all found to be positive, however, the betas for portfolios 1, 7,8 and 9 were all found to be insignificant. This is interesting because when the ALBI was combined in a model with the ALSI only the betas for portfolio 7,8 and 9 were found to be insignificant, however since the formation of this model (i.e. involving the FINDI and RESI in place of the ALSI) another beta has become insignificant which could be explained by omitted variable bias. The omission of important variables can result in the estimated coefficients on the variables to be biased and inconsistent, possibly explaining this result (Gujarati, 2003: 521). The betas of the FINDI were all found to be significant at the 5% level of significance, and all were positive as was the case with the previous model with FINDI and RESI as the explanatory variables. Lastly, the coefficients of the RESI were all found to be positive. However, the betas for portfolios 3, 4, 9 and 10 were all insignificant. This was an improvement on the previous model (FINDI and RESI as proxies), as by adding the ALBI to the model the betas for portfolios 5 and 6 which were previously insignificant, become significant.

The adjusted R-squared values produced by this model fluctuated up to portfolio 5, thereafter they steadily dropped. There was once again relatively high adjusted R-squared results for portfolios 3 and 4, these adjusted R-squared values were even higher than the previous model which in turn was significantly higher than those produced by the first two models. Again the ALSI, ALBI model performed better in the majority of the remaining R-squared values. However, it appears that the addition of the ALBI to the previous model strengthened its explanatory powers in the lower risk portfolios. This has resulted in a higher average adjusted R-squared value than the previous model of 40.0%. This adjusted R-squared value is the highest of the four models suggesting that this model of the four, on average, best explains the movements of share prices on the JSE.

**Table 5- 14 Summary statistics for time series tests with the ALBI, FINDI and RESI as the explanatory variables (excess returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	-0.320	-0.104	0.062	0.501	0.554	1.038	0.983	0.837	1.074	0.668
t-stat ( $\alpha$ )	-0.826	-0.308	0.216	1.937	2.037	3.657	3.346	3.034	4.321	1.884
P Value ( $\alpha$ )	0.410	0.758	0.829	0.055	0.044	0.000	0.001	0.003	0.000	0.062
$\beta$ ALBI	0.305	0.376	0.411	0.298	0.453	0.380	0.052	0.049	0.104	0.332
t-stat ( $\beta$ )	1.437	2.032	2.636	2.104	3.042	2.440	0.320	0.322	0.761	1.712
P value ( $\beta$ )	0.153	0.044	0.009	0.037	0.003	0.016	0.749	0.748	0.448	0.089
$\beta$ FINDI	0.497	0.639	0.604	0.654	0.465	0.381	0.369	0.216	0.113	0.186
t-stat ( $\beta$ )	5.415	8.006	8.974	10.681	7.237	5.678	5.317	3.302	1.914	2.215
P value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.058	0.029
$\beta$ RESI	0.330	0.194	0.064	0.017	0.105	0.082	0.095	0.082	0.055	0.067
t-stat ( $\beta$ )	5.660	3.830	1.504	0.436	2.575	1.928	2.151	1.973	1.465	1.258
P value ( $\beta$ )	0.000	0.000	0.135	0.663	0.011	0.056	0.033	0.051	0.145	0.211
Adj R-sq	0.535	0.590	0.574	0.617	0.528	0.402	0.350	0.198	0.085	0.116

Table 5-15 illustrates the summary statistics of the equivalent time series test with total returns. The intercepts provided some interesting results, as has been the case in the previous tests the higher risk portfolios provided intercepts that were negative, however, unlike the previous tests the intercepts for portfolios 1, 2 and 3 were found to be significant at the 5% level, suggesting that it is safe to say that these portfolios earned less than the model predicted. Portfolios 4,5, 6 and 9 provided insignificant intercepts, whilst portfolio 7, 8 and 9 produced significant

estimates that were positive meaning that these portfolio earned more than the model expected. As was the trend in the previous models, these were lower risk models that performed better than the model predicted.

As found in the equivalent test with excess returns the betas of the ALBI for portfolios 1,7,8,9 and 10 were found to be insignificant, whilst the remaining portfolios were found to be significant and positive. The betas for the FINDI were all significant and positive as was the case with the excess returns. In line with the tests on excess returns the betas of the RESI were found to all be positive, but insignificant for portfolios 3,4,9 and 10.

Lastly, the adjusted R-squared values followed the same trend as the equivalent excess return model, however the adjusted R-squared values were slightly lower for most of the portfolios, resulting in a lower average adjusted R-squared value of 39.5%, the highest of all the models.

**Table 5- 15 Summary statistics for time series tests with the ALBI, FINDI and RESI as the explanatory variables (total returns)**

Item	Portfolio Number									
	1	2	3	4	5	6	7	8	9	10
$\alpha$	-1.129	-0.970	-0.711	-0.220	-0.190	0.437	0.613	0.609	0.899	0.269
t-stat ( $\alpha$ )	-2.534	-2.498	-2.165	-0.743	-0.610	1.339	1.822	1.924	3.153	0.662
P Value ( $\alpha$ )	0.012	0.014	0.032	0.459	0.543	0.183	0.071	0.057	0.002	0.509
$\beta$ ALBI	0.261	0.331	0.370	0.286	0.424	0.346	0.033	0.019	0.077	0.293
t-stat ( $\beta$ )	1.242	1.806	2.387	2.046	2.879	2.243	0.205	0.125	0.576	1.525
P value ( $\beta$ )	0.216	0.073	0.018	0.043	0.005	0.027	0.838	0.900	0.566	0.130
$\beta$ FINDI	0.511	0.654	0.618	0.665	0.478	0.392	0.376	0.221	0.117	0.194
t-stat ( $\beta$ )	5.565	8.169	9.132	10.918	7.427	5.828	5.421	3.384	1.988	2.314
P value ( $\beta$ )	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.049	0.022
$\beta$ RESI	0.326	0.190	0.061	0.016	0.103	0.079	0.093	0.079	0.052	0.063
t-stat ( $\beta$ )	5.570	3.729	1.407	0.423	2.509	1.847	2.112	1.895	1.390	1.181
P value ( $\beta$ )	0.000	0.000	0.162	0.673	0.013	0.067	0.037	0.060	0.167	0.240
Adj R-sq	0.53	0.584	0.567	0.618	0.523	0.39	0.35	0.19	0.08	0.11

Finally, the first pass rolling time series regression results for both the excess and total returns with the ALBI, FINDI and RESI are displayed in the following two tables. In the tests only two and three intercepts were found to be significant for the excess and total returns respectively. For excess returns these intercepts were for portfolio 6 and 9, and both these intercepts were positive. Whilst for the total returns, the significant intercepts were for portfolios 7, 8 and 9, again these intercepts were found to be above 0.745%, meaning that for all the significant intercepts the portfolios outperformed the expectations of the model. These results are quite different from the results of the Black *et al* (1972) tests, where for the equivalent excess returns tests it was found that seven intercepts were significant, whilst the equivalent total returns test produces six significant intercepts.

**Table 5- 16 Summary statistics for rolling time series tests with the ALBI, FINDI and RESI as the explanatory variables (excess returns)**

	Portfolio Number									
Item	1	2	3	4	5	6	7	8	9	10
$\alpha$	0.168	0.109	0.133	0.423	0.608	1.005	0.886	0.792	0.911	0.795
t-stat ( $\alpha$ )	0.234	0.325	0.218	0.808	1.166	1.755	1.676	1.448	1.792	1.086
P Value ( $\alpha$ )	0.816	0.747	0.829	0.425	0.252	0.089	0.104	0.157	0.083	0.286
$\beta$ ALBI	0.307	0.441	0.394	0.299	0.441	0.353	0.084	-0.014	-0.002	0.360
t-stat ( $\beta$ )	0.753	1.308	1.275	0.952	1.479	1.127	0.308	-0.029	-0.015	0.865
P Value ( $\beta$ )	0.457	0.200	0.211	0.348	0.149	0.268	0.760	0.977	0.988	0.393
$\beta$ FINDI	0.380	0.606	0.568	0.694	0.530	0.458	0.450	0.259	0.164	0.188
t-stat ( $\beta$ )	2.092	4.031	4.494	5.500	4.166	3.527	3.704	1.994	1.385	1.082
P Value ( $\beta$ )	0.044	0.000	0.000	0.000	0.000	0.001	0.001	0.055	0.175	0.288
$\beta$ RESI	0.386	0.216	0.068	0.013	0.058	0.057	0.083	0.083	0.029	0.096
t-stat ( $\beta$ )	3.491	2.428	0.841	0.148	0.780	0.696	1.045	1.050	0.306	0.876
P Value ( $\beta$ )	0.001	0.021	0.406	0.883	0.441	0.491	0.304	0.301	0.761	0.388
Adj R-sq	0.511	0.600	0.545	0.598	0.522	0.433	0.464	0.214	0.098	0.095

For both excess and total returns tests it was found that none of the coefficients for the ALBI were found to be relevant. This is of particular interest because with the same dependant variables the ALSI, ALBI proxy produced significant coefficients for the ALBI, however when it is grouped with the FINDI and RESI none of the coefficients are significant. This was also found to be the case in the equivalent Black *et al* (1972) tests, a possible explanation for this is omitted variable bias. The coefficients of the FINDI for portfolios 1-8 were found to be

significant in both tests, and all the coefficients were positive, which is slightly different to the findings of the Black *et al* (1972) tests, where all the coefficients were found to be significant and positive. The coefficients of the RESI were only found to be significant for portfolios 1 and 2, again it was found that these coefficients were positive. Again this result differed from the result of the equivalent Black *et al* (1972) tests, where it was found that six coefficient were significant and positive.

The adjusted R-squared values increased from portfolio to portfolio when compared with the model using only the FINDI and the RESI as the proxy for the market portfolio, this is illustrated by the increase in average adjusted R-squared values for the two models. The average adjusted R-squared value for the excess return model was 40.8%, whilst the average adjusted R-squared value for the total returns model was 40.0%.

**Table 5- 17 Summary statistics for rolling time series tests with the ALBI, FINDI and RESI as the explanatory variables (total returns)**

	Portfolio Number									
Item	1	2	3	4	5	6	7	8	9	10
<b><math>\alpha</math></b>	0.091	-0.080	0.108	0.424	0.605	1.131	1.203	1.324	1.541	1.099
<b>t-stat (<math>\alpha</math>)</b>	0.098	-0.006	0.133	0.649	0.957	1.691	1.909	2.112	2.671	1.299
<b>P Value (<math>\alpha</math>)</b>	0.922	0.996	0.895	0.521	0.346	0.101	0.065	0.043	0.012	0.203
<b><math>\beta</math> ALBI</b>	0.293	0.421	0.372	0.305	0.429	0.332	0.077	-0.031	-0.018	0.340
<b>t-stat (<math>\beta</math>)</b>	0.722	1.256	1.209	0.973	1.445	1.068	0.272	-0.086	-0.081	0.824
<b>P Value (<math>\beta</math>)</b>	0.476	0.218	0.236	0.338	0.158	0.294	0.787	0.932	0.936	0.416
<b><math>\beta</math> FINDI</b>	0.384	0.609	0.570	0.694	0.530	0.458	0.448	0.255	0.160	0.187
<b>t-stat (<math>\beta</math>)</b>	2.112	4.054	4.516	5.503	4.175	3.541	3.695	1.980	1.360	1.079
<b>P Value (<math>\beta</math>)</b>	0.043	0.000	0.000	0.000	0.000	0.001	0.001	0.056	0.183	0.289
<b><math>\beta</math> RESI</b>	0.384	0.214	0.066	0.014	0.056	0.054	0.081	0.079	0.026	0.092
<b>t-stat (<math>\beta</math>)</b>	3.455	2.401	0.806	0.153	0.760	0.663	1.017	1.009	0.253	0.842
<b>P Value (<math>\beta</math>)</b>	0.002	0.022	0.426	0.880	0.453	0.512	0.317	0.320	0.802	0.406
<b>Adj R-sq</b>	0.504	0.595	0.537	0.593	0.515	0.423	0.455	0.204	0.087	0.086

Thus in conclusion of this section of the first pass regression results it can be seen that at no point were any of the intercepts of any of the models equal to 0 or 0.745% (for total returns). Throughout the models the intercepts for the riskier portfolios were found to be either negative

or insignificant, whilst the intercepts for the less risky portfolios across the four models were consistently found to be positive and significant. These results were similar to the results obtained by Black *et al* (1972: 14), who found that “the intercepts  $\hat{\alpha}$  are consistently negative for high-risk portfolios... and consistently positive for low-risk portfolios”. These results suggest that the high risk portfolios generally earned less on average than was predicted by the various CAPM and market models, whilst the low risk portfolios on average earned more than was predicted by the various CAPM and market models.

The betas for the explanatory variables produced interesting reading. The betas are essentially the correlation of the portfolios to the various proxies. Black *et al* (1972: 14) and Fama and MacBeth (1973: 621) obtained large ranges in their betas, with values of over 1.5 to values below 0.4, however, the betas of this study were found to have a very narrow range. At no point was a beta value obtained that was over one. This is particularly strange when considering that portfolio one contains the riskiest shares on the JSE and yet it still does not obtain a beta over one, meaning that it is not riskier than the ALSI, or the FINDI, or the RESI. However, in a similar study conducted by Van Rensburg and Robertson (2003: 11) on the JSE, the betas for their explanatory variables when using the ALSI or FINDI as the proxy were also found to be in a narrow range, with none of their beta sorted portfolios having a beta over one. This shows that the results obtained in this study were not the first of their kind, and suggesting that on average the portfolios of South African shares were less risky than the U.S. ones. Nevertheless the betas for the various dependant variables were mainly significant and positive. The only additional variable that appeared to have insignificant betas on a regular basis was the RESI.

When concerned with the adjusted R-squared values for each of the models, it was found that the final model which included the RESI, as well as the FINDI and ALBI was the best performing model in this regard. The Black *et al* (1972) regressions found that the second best model based on the adjusted R-squared criteria was the second model which contained the ALSI and the ALBI as the proxy for the market portfolio, whilst the Fama and MacBeth (1973) study found the model with the FINDI and RESI to be the second best. Therefore the results obtained from the first pass regression were not always in line with theory, however they appear consistent with past studies especially South African studies. The major finding for practitioners was that the lower risk portfolios were outperforming the various models expectations whilst the higher risk portfolios generally were underperforming compared to the expectations of the



models. When concerned with the explanatory powers of the models the final model comprising of the ALBI, FINDI and RESI was found to be the strongest.

### 5.3.2 Second Pass Regression Results

The second pass CAPM and market model are displayed by formulas 5.1 and 5.2 respectively.

CAPM:

$$\bar{R}_p - \bar{R}_f = \gamma_0 + \gamma_1 \beta_m + \bar{e} \quad (5.1)$$

Market model:

$$\bar{R}_{pt} = \gamma_0 + \gamma_1 \hat{\beta}_{pt} + \eta_{pt} \quad (5.2)$$

According to Black *et al* (1972: 22) the CAPM implies that the intercept ( $\gamma_0$ ) should be equal to zero and the slope ( $\gamma_1$ ) should be equal to the  $\bar{R}_M$  which is the average monthly excess return of the proxy over the period of the study. Building on from this, and as was discussed in section 4.3.2.1, if the intercept is statistically significant and different from zero, it implies that the model is insufficient for pricing assets as there are other factors which have an influence on returns which are not accounted for in the model. Whilst the values for  $\gamma_1$ ,  $\gamma_2$ , and  $\gamma_3$  are expected to be significant and positive, as this would illustrate that the market prices the risk associated with the various proxies. The market model predicts that the intercept ( $\gamma_0$ ) should be equal to the average risk-free rate over the period (0.745%) and the slope ( $\gamma_1$ ) should be equal to the  $\bar{R}_M$  which is the average monthly return of the proxy over the period. The interpretations of the various parameters are the same as the CAPM.

The statistical significance of each of the values were also assessed, this is because if a variable is statistically significant then it suggests that it is a relevant factor in the estimation of expected returns, whilst if the variable was found to be insignificant then it could be eliminated from the proxy and thus the model.

### 5.3.2.1 ALSI as the Proxy for the Market Portfolio

To begin with, the results for the model with the ALSI as the sole proxy is discussed for both excess and total returns. This model is essentially the control or benchmark for this study as this is the method used by the majority of practitioners in South Africa (PriceWaterhouseCoopers, 2009: 31), and the model to which the remaining three models were compared. The results of the various cross-sectional regressions with the ALSI as the sole proxy for both excess and total returns are illustrated in tables 5-18 and 5-19 below.

**Table 5- 18 Summary statistics of the various cross-sectional regressions with the ALSI as the proxy (excess returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.492578283	7.457514	0.0001
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.238955	-3.349902	0.0101
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.390818	3.659568	0.0064
	$\beta_{\text{ALSI}}(\gamma_1)$	-0.782873	-1.218883	0.2576
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.599103	17.44483	0.0000
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.178863	-6.992307	0.0000

**Table 5- 19 Summary statistics of the various cross-sectional regressions with the ALSI as the proxy (total returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.222567	11.27956	0.0000
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.22511	-3.333263	0.0103
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.136379	5.885632	0.0000
	$\beta_{\text{ALSI}}(\gamma_1)$	-0.778942	-1.225239	0.2289
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.357203	27.0914	0.0000
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.205187	-7.469544	0.0000

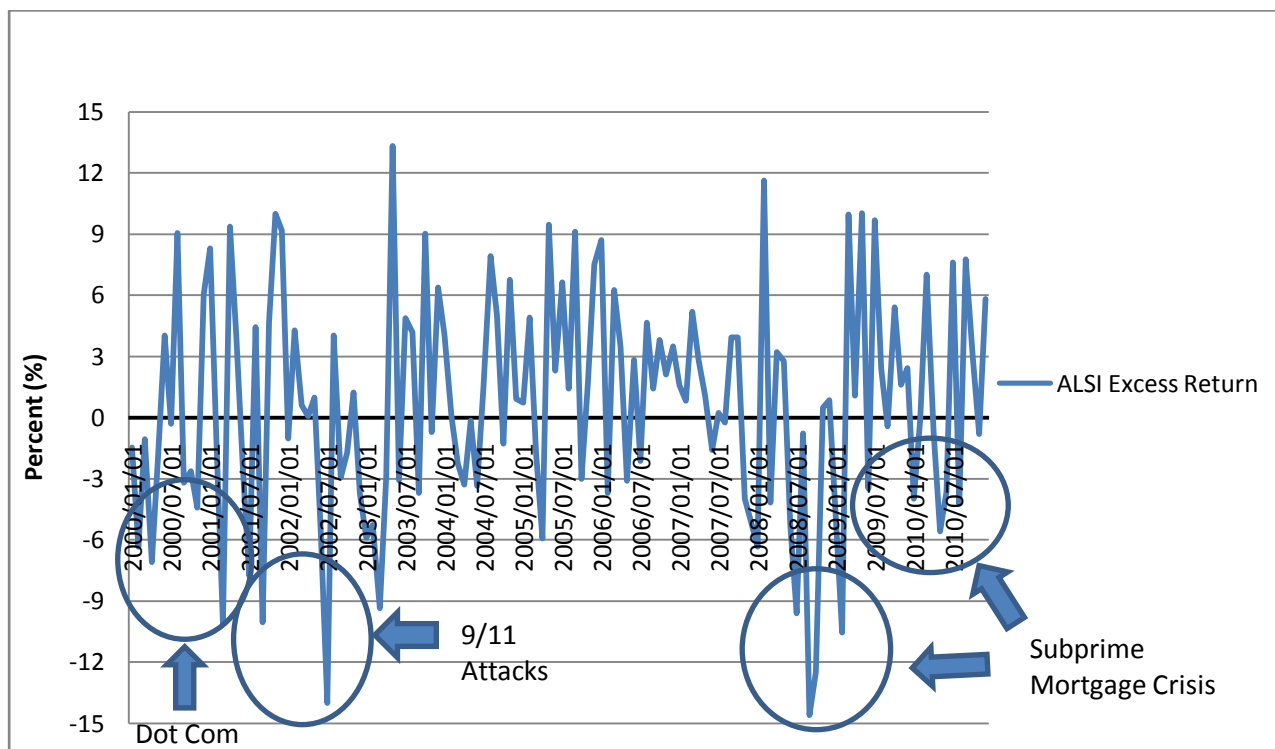
Immediately it can be seen that these results are not in line with theory. To begin with, the Black *et al* (1972) cross-sectional regression produced both a significant intercept and a significant coefficient for the beta of the ALSI. However, the intercept was found to be substantially different from zero suggesting that the model was missing influential factors. Furthermore, the coefficient ( $\gamma_1$ ) although significant, was not found to be positive or anywhere near the average excess return of the ALSI which was 0.653%, illustrating that firstly the ALSI is a relevant factor to the model and secondly that the market prices the risk associated with the ALSI inversely, i.e. an investor will obtain a higher return for less risk. This result is not what was expected of the model, in fact the result goes against everything discussed in chapters two and three.

Expectations for the results of the Fama and MacBeth (1973) tests are no different to the expectations of the Black *et al* (1972) tests, the only difference between the two models, as explained in section 4.3.2, is the way in which the tests are run. As can be seen from the results of the first cross-sectional analysis where the ALSI was used as the sole proxy, the intercept was found to be significant. The coefficient was very different from zero with a positive figure 1.391 being obtained. This trend was consistent with the Black *et al* (1972) result and suggests that the model was not accounting for all of the risk factors. Where the results differed to those obtained by the Black *et al* (1972) test was that the coefficient for the beta of the ALSI was insignificant, suggesting that the excess returns on the ALSI are not priced as a risk factor and thus irrelevant to the excess returns of the various portfolios. This is a particularly puzzling result as the ALSI, especially with how much it is used in practice, should be significant.

Finally, the expectations for the results of the pooled regression tests are the same as the first two sets of tests. As was found in the first two tests, the first model, with the ALSI as the market proxy, produced a significant and positive intercept. The difference between the pooled regression results and the previous tests is the level of significance, the pooled regression suggested that the intercept was more significant than any of the other models found. The coefficient for the beta of the ALSI was also found to be very significant, more significant than the other two tests, but the coefficient was still found to be negative as was the case with the first two results.

When comparing this set of results to the result of Black *et al* (1972), Black *et al* (1972) did obtain an intercept of much closer to zero as well as a positive figure for the slope ( $\gamma_1$ ), which was in line with theory that an investor can expect a higher return for bearing higher risk. Although having said this, in one of the sub periods that Black *et al* (1972) examined (1957-1965) the slope was found to be negative and the intercept a bit further from zero. Pettengill, Sundaram and Mathur (1995: 101), try and explain any negative slope obtained in these tests by stating that “the positive relationship between returns and beta predicted by the Sharpe-Lintner-Black model is based on expected rather than realized returns. In periods where excess market returns are negative, an inverse relationship between beta and portfolio returns should exist”. The time period of this study was limited by the availability of data on the ALBI, hence the time period is only eleven years. Within the eleven years of this study many financial events have occurred that could have caused such results, such as, the Asian crisis, the dot com bubble burst, the 9/11 attacks and the subprime mortgage crisis. These are possible reasons for the negative relationship between risk and return, as it was found that the excess returns of the ALSI were negative for 60 of the 132 months of the period used in this study. A number of these downturns and the events that caused them are displayed in the following figure.

**Figure 5-2 Market downturns over the period of the study (ALSI excess returns)**



The first event that could have affected the results of this study is the Asian crisis. Despite the fact that this crisis occurred in 1997/1998 which is outside the period of this study, beta sorting took place from 1997 onwards and thus was affected by this event. As a result of the crisis investor confidence all around the world dipped and caused equities to slump quite dramatically. As South Africa has status as an emerging market, it is also regarded as a riskier market, and thus when there is a slump in equities, no matter where in the world, generally investors liquidate their riskier positions such as investments in emerging markets, and thus countries like South Africa can be hardest hit. Thus the Asian crisis could have impacted on South African equities causing negative returns. The dot com bubble burst occurred in 2000 and thus also falls within the sample period of this study. The dot com bust had quite an impact on the world's economy, and thus caused investors to liquidate risky positions they held and hence the South African market, as an emerging market, was affected. Another event in the sample period that would have impacted negatively on South African equities was the advent of 9/11, once again this event caused investor confidence to drop causing liquidation of stocks and a decrease in the price of stocks. This event was particularly hard on the South African as the Rand plummeted to all time lows against the world's major currencies for some time after the actual event. There was even an official enquiry into the behaviour of the rand, illustrating the severity of the depreciation. The final event that could have caused the average return of equities to drop and standard deviation to increase, was the advent of the sub-prime crisis at the end of 2007. When the housing bubble burst in the United States and millions of people began to default on the mortgages, it sent shock waves through the country. People were in a frenzy for liquidity, which caused a rippling effect across all the markets in the world, South Africa was not spared. World markets slumped to some of the lowest levels experienced since the great depression, the crisis is still being felt around the world today, more than four years since it started. There is no doubt that this adversely affected equities.

These four events could possibly explain the inverse relationship between risk and return. Furthermore, the Black *et al* (1972) study was conducted over 35 years versus the 11 year period of this study, and hence any down turn in the market could have been averaged out by the upturns and thus resulting in a positive relationship between risk and return. This is evident in the Black *et al* (1972) study where the one sub period has a negative slope, but the remainder are positive and hence over the entire period the slope generated is also positive. Despite the possible explanations for these unexpected results, it is very important that they are not simply accepted at face-value. Thus a number of further tests were performed on the dataset to ensure the robustness of the earlier results. To begin with, although there were a number of downturns in the market, it was decided that an analysis would be conducted on a period in the study that

displayed a general upturn. This would show if the economic downturns discussed earlier can explain the odd results obtained. The period decided upon was from January 2003 to December 2007 (60 months) and the results of the cross-sectional regressions with the ALSI as the sole proxy for the market portfolio are displayed in the following tables.

**Table 5- 20 Sub period analysis of the cross-sectional results obtained using the ALSI as the proxy (excess returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.034642	1.666188	0.1342
	<b><math>\beta_{\text{ALSI}}(\gamma_1)</math></b>	1.076007	1.210993	0.2605
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.124023	6.961507	0.0001
	<b><math>\beta_{\text{ALSI}}(\gamma_1)</math></b>	-0.298815	-0.345825	0.7384
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.997052	20.73893	0.0000
	<b><math>\beta_{\text{ALSI}}(\gamma_1)</math></b>	-0.00726	-0.03739	0.9702

As can be seen from the results displayed in tables 5-20 and 5-21, altering the period of the tests did make a difference when compared to the results obtained in the previous tests. The Black *et al* (1972) results had some of the biggest changes, in the previous test it was found that the intercept was positive and highly significant, although the sub period produced a positive intercept, it was closer to zero. In a change from the previous test, this statistic was found to be insignificant at the 5% level. The other difference between the two results was that the previous Black *et al* (1972) results produced a negative beta coefficient for the ALSI, whilst the sub period produced a positive coefficient, however, this statistic was found to be insignificant, unlike the first test.

The Fama and MacBeth (1973) tests also produced slightly different results for the sub period. The intercept of the test actually got larger, and remained significant. Whilst the beta of the ALSI for the sub period was found to be a smaller negative than the previous test, but became more insignificant. The pooled regression test of the sub period produced an intercept closer to zero than the previous test, which was found to be significant, as was the case with the first test. The beta of the ALSI in the sub period pooled regression was found to be a much smaller negative value, however this statistic went from being highly significant in the first test to

highly insignificant in the sub period test. The results of the total returns tests were very similar to the excess returns model. As was the case with the excess returns models, the betas got less negative, and all three models found these betas to be insignificant. The major difference between the two tests was that intercepts for the sub period analysis actually got larger for each of the tests. Therefore it can be seen that the period does affect the results of the cross-sectional regressions, however it does not solve the problem.

**Table 5- 21 Sub period analysis of the cross-sectional regressions obtained using the ALSI as the proxy (total returns)**

<b>Methodology</b>	<b>Variable</b>	<b>Coefficient</b>	<b>t Statistic</b>	<b>P Value</b>
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.604436	8.67994	0.0000
	$\beta_{ALSI}(\gamma_1)$	-0.21118	-0.335443	0.7459
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.822733	9.271564	0.0000
	$\beta_{ALSI}(\gamma_1)$	-0.302100	-0.355864	0.7311
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.712477	31.27792	0.0000
	$\beta_{ALSI}(\gamma_1)$	-0.041689	-0.23652	0.8132

The fact that even in the sub period the results of the cross-sectional regression were not in line with theory casts serious doubts over the validity of the CAPM in the South African context. Once again however, it is not wise to just accept such a result. Thus a further robustness check of the results was performed through the use of a dummy variable. Dummy variables are described by Brooks (2008: 113) as qualitative variables as the majority of the time they are “used to numerically represent a qualitative entity”. In this case the qualitative entity was whether or not the market was in a bull or bear market. Thus the dummy variable employed in the regression was assigned a value of 1 if the return on the ALSI is negative, and a value of 0 if the return is positive. This allows for the isolation of whether or not bad news, or a market downturn, had a different effect on the portfolios that was not captured by the CAPM. If the dummy variable is found to be significant it indicates that the dummy variable and thus the downward movements of the market are relevant to the returns on the portfolios, and therefore would confirm that the model is *not* capturing some influencing factor on the portfolios. Due to the nature of the data, this test could only be run on the pooled regression. The test was run on the excess returns, as any negative return or return less than the risk-free rate was considered to

be “bad news”. The cross-sectional regression output involving the dummy variable is displayed in the following table.

As is illustrated in the table, the dummy variable was found to be insignificant. This result confirms that market downturns do not have a separate effect on the portfolios. This means that the suggestion that bad news has a separate effect on the portfolios that is not being captured by the models can be rejected.

**Table 5- 22 Cross-sectional output involving a dummy variable**

Dependent Variable: AVERAGE_RETURN				
Method: Panel Least Squares				
Date: 11/18/11 Time: 07:51				
Sample: 2002M12 2010M12				
Periods included: 97				
Cross-sections included: 10				
Total panel (balanced) observations: 970				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.573863	0.093373	16.85566	0.0000
BETA_ALSI	-1.104546	0.176652	-6.252649	0.0000
DUMMY	-0.274619	0.195895	-1.401867	0.1613
R-squared	0.050011	Mean dependent var		1.014598
Adjusted R-squared	0.048046	S.D. dependent var		1.200154
S.E. of regression	1.170967	Akaike info criterion		3.156625
Sum squared resid	1325.916	Schwarz criterion		3.171710
Log likelihood	-1527.963	F-statistic		25.45317
Durbin-Watson stat	0.024312	Prob(F-statistic)		0.000000

Once again the result of the dummy variable test questions the use of the CAPM in South Africa. Initially it was suggested that the reason for the poor results was due to the crises in and around the period of this study, however, the results of the sub period analysis and the dummy variable analysis have indicated that this may not be an excuse. Nevertheless, the CAPM remains the most popular equity valuation tool in South Africa and thus results like these need to be scrutinised over and over. The next robustness test performed involved the pooled regression.



One of the disadvantages of pooling data is that it assumes that the average values of the parameters and the relationships between them are fixed over time and across all the cross-sectional units of the sample (Gujarati, 2003: 365; Brooks, 2008: 488). Two of the techniques available to remedy such a problem are known as the fixed effects model and the random effects model, and Brooks (2008: 490) suggests that these two models are particularly relevant to financial data. Essentially, the fixed effects model allows the y-intercept (in this case the risk-free rate) to vary over time or cross-sectional units, depending on whether it is a time-fixed effects model or an entity-fixed effects model. Whilst the random effects model, also allows the y-intercept to vary over time or cross-sectionally (depending on the model), the difference lies in the fact that the intercepts for each of the cross-sectional units of the random effects model are assumed to result from a common intercept (Brooks, 2008: 490-498). Thus the random effects model looks for an underlying value of commonality for the y-intercepts of the model. When deciding upon which model to use on the pooled data, there are various hypothesis tests which help establish which is the most appropriate. For the fixed effects model, the redundant fixed effects tests were run, whilst for the random effects model, the correlated random effects or Hausman test was run. The results of the tests are displayed in the following table.

**Table 5- 23 Summary statistics of Fixed and Random effects tests on the pooled data**

	<b>EXCESS RETURNS</b>		<b>TOTAL RETURNS</b>	
<b>Redundant Fixed Effects Tests</b>				
Effects Test	Statistic	P-Value	Statistic	P-Value
Cross-section F	24.628324	0.0000	24.578201	0.0000
Cross-section Chi-square	221.744397	0.0000	221.340894	0.0000
Period F	57.315108	0.0000	52.276343	0.0000
Period Chi-square	1938.248335	0.0000	1861.582611	0.0000
Cross-Section/Period F	54.871691	0.0000	50.422989	0.0000
Cross-Section/Period Chi-square	1976.976059	0.0000	1906.047526	0.0000
<b>Correlated Random Effects - Hausman Test</b>				
Test Summary	Chi-Sq. Statistic	P-Value	Chi-Sq. Statistic	P-Value
Cross-section random	0.938276	0.3327	0.753584	0.3853
Period random	5.797572	0.0160	8.985732	0.0027
Cross-section and period random	2.349975	0.1253	2.405325	0.1209

The results of the tests illustrated that all of the models, except for the period random model, were deemed to be appropriate for the data. In this case, Brooks (2008: 500) suggests theoretically deciding on which model is the most appropriate. For this study it was decided that

the risk-free rate (y-intercept) is expected to vary over time, as is the case with the rate of return on the three month T-bill. However the risk-free rate should not vary cross-sectionally, as the risk-free rate (three month T-bill) should be the same for every portfolio and will not vary depending on the risk levels of a portfolio, and thus a “time” model was deemed appropriate. When deciding between a time-fixed effects model or a time-random effects model, the decision was simple as the period random effects model was found to be insignificant in the above tests. Thus it was decided that a time-fixed effects model would be used. Further to these theoretical arguments, in a study by Esterer and Shroder (2010: 17), a fixed time-effects model was employed so as to capture any variation in share returns which are the result of influences other than firm risk, such as during a financial crises. During financial crises Esterer and Shroder (2010: 17) mention that it is considered more important to allow intercepts to vary across time, rather than cross-sectionally. As was discussed earlier, a number of financial crises occurred throughout the time period of this study and thus it is deemed appropriate to employ a time-fixed effects model. The results are displayed in the following table.

**Table 5- 24 Summary statistics of the pooled cross-sectional regressions after employing a time-fixed effects model**

<b>Model</b>	<b>Variable</b>	<b>Coefficient</b>	<b>t Statistic</b>	<b>P Value</b>
<b>Excess Returns</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.449178	35.26105	0.0000
	<b><math>\beta_{\text{ALSI}}(\gamma_1)</math></b>	-0.876485	-11.48451	0.0000
<b>Total Returns</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.194196	54.382540	0.0000
	<b><math>\beta_{\text{ALSI}}(\gamma_1)</math></b>	-0.872692	-11.554240	0.0000

Despite the fact that the coefficients of the ALSI were found to improve after employing the time-fixed effects model, the results were still contradictory to theory, as the slopes were still found to be significant and negative, whilst the intercepts were again significantly different from zero.

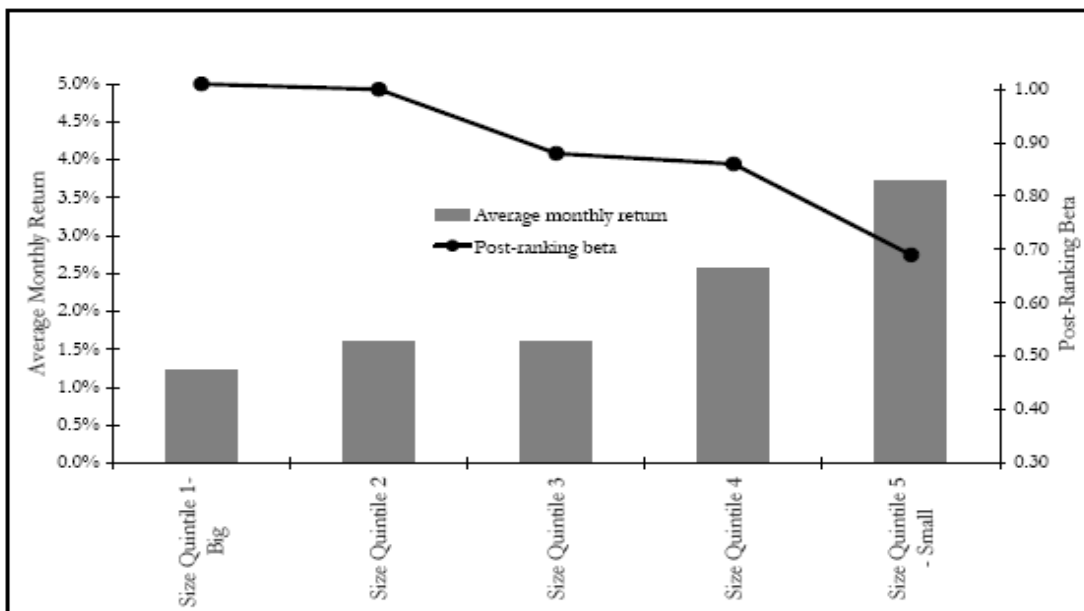
All these results, as has been mentioned, provide quite damning evidence against the CAPM, and the practices of many practitioners around South Africa. What these results suggest is that there is a negative relationship between beta (risk) and return. However, on closer inspection of South African research this result is not unprecedented. Van Rensburg and Robertson (2003: 7-14) in using a two-pass regression method, examined the CAPM based portfolios that are

sorted on the criteria of price-to-earnings, size and betas over the period July 1990 to June 2000 (eleven years – the same length as this study). Van Rensburg and Robertson (2003:14) found that smaller sized firms earn a higher return on the JSE, despite their lower betas. Van Rensburg and Robertson (2003) also found that the firms with the lowest price-to-earnings ratios earned the highest average returns again despite having the lowest betas. However, when discussing the results of the beta-sorted portfolios Van Rensburg and Robertson (2003: 14) made a statement that enforces the results of this study; they stated that “taken together the results based on sorting by pre-ranking betas this study finds for the first time on the JSE that, if anything, beta is inversely related to returns”. Basically the results of the Van Rensburg and Robertson (2003) study support the findings of this study as the shares with the lowest betas were obtaining the highest returns. The results of the Van Rensburg and Robertson (2003) study are illustrated in figure 5-3.

More recently Strugnell, Gilbert and Kruger (2011) obtained results that supported both the results of Van Rensburg and Robertson (2003) and this study. The study by Strugnell *et al* (2011: 1) was conducted over the period January 1994 to October 2007 (178 months) and was also a portfolio based study similar to Van Rensburg and Robertson (2003) where the portfolios were sorted according to beta, size and price-to-earnings. Based on the results of their study Strugnell *et al* (2011: 1) found that “beta has no predictive power for returns on the JSE, invalidating the CAPM, at least as it is commonly applied, based on a market proxy of the All Share Index”. This statement is particularly profound for this study, as it supports the earlier findings. Along with the results of Van Rensburg and Robertson (2003), the results of the beta sorted portfolios from the Strugnell *et al* (2011: 10) study are illustrated by the scatter plot over page, and the two sets of results are compared to a scatter plot produced by this study, all with the ALSI as the proxy for the market portfolio.

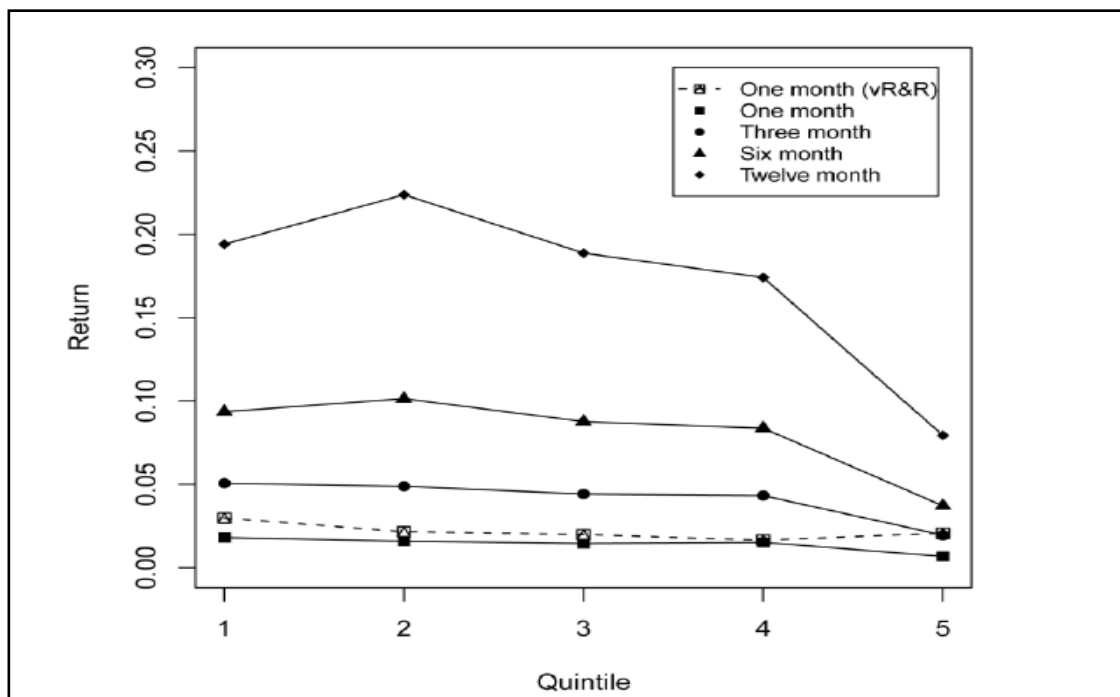
The quintiles from the Van Rensburg and Robertson (2003) study are organised so that the shares with the highest betas are in quintile 1, down to the shares with the lowest betas in quintile 5. Whilst the Strugnell *et al* (2011: 10) quintiles are the opposite, they are arranged such that the shares with the lowest beta are organised into quintile 1, up to the shares with the highest betas in quintile 5. Based on this, it can be seen from the three diagrams, that they all produce negative sloping SMLs, and show that the results obtained in this study are feasible. The initial belief that the inverse relationship between beta and return might be sample-specific is clearly not applicable, as these studies by Van Rensburg and Robertson (2003) and Strugnell *et al* (2011) cover different periods, whilst Strugnell *et al* (2011) even cover a longer period.

**Figure 5-3 Results of the Van Rensburg and Robertson (2003) study illustrating a downward sloping SML**



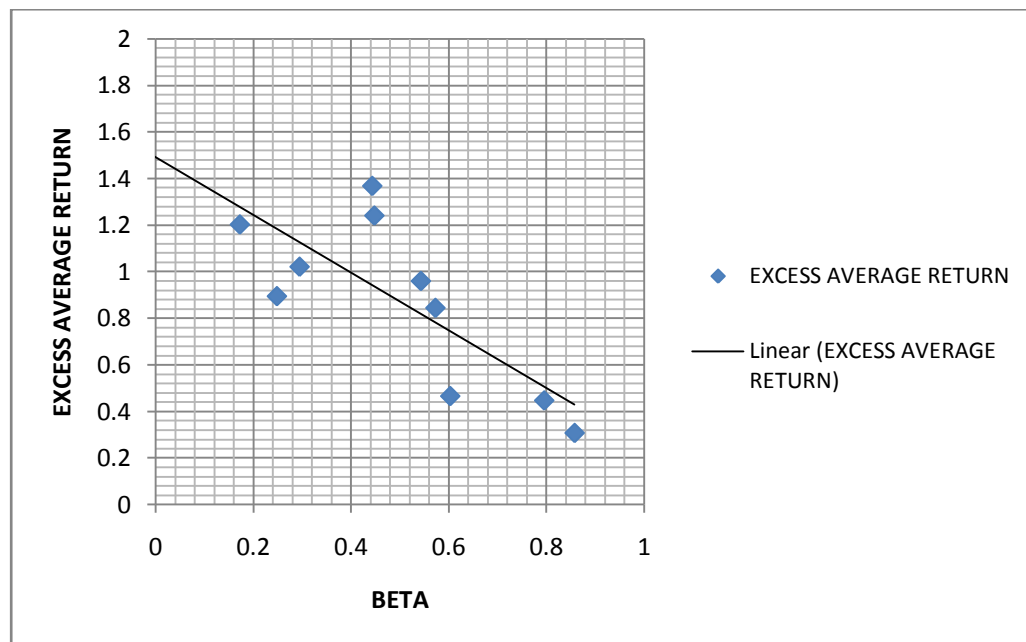
(Source: Van Rensburg and Robertson, 2003: 12)

**Figure 5-4 Results of the Strugnell *et al* (2011) study illustrating a downward sloping SML**



(Source: Strugnell *et al*, 2011: 10)

**Figure 5- 5** Scatter plot of average excess returns to portfolio betas from this study, illustrating a downward sloping SML



Strugnell *et al* (2011: 14) conclude their study by stating that an important extension of their research would be the formation of multifactor pricing models to further test the implications of the CAPM. As discussed in section 4.2.2.3 this study provides that by looking at multifactor CAPMs made up of the ALSI and the ALBI, then the FINDI and the RESI, and lastly the ALBI, FINDI and RESI. To begin with, the cross-sectional results of the models containing the ALSI and ALBI as proxies for the market portfolio will be presented and discussed.

### 5.3.2.2 ALSI and ALBI as Proxies for the Market Portfolio

Going back to the discussion on the cross-sectional results of this study, the next model examined was the model with both the ALSI and ALBI as proxies for the market portfolio. The results for the tests with the excess and total returns are displayed in the following two tables.

**Table 5- 25 Summary statistics of the cross-sectional regressions using the ALSI and the ALBI as proxies (excess returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.488226	6.621525	0.0003
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.254697	-2.684116	0.0314
	$\beta_{\text{ALBI}}(\gamma_2)$	0.018751	0.04167	0.9679
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.542292	3.435249	0.0109
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.037929	-1.425652	0.1970
	$\beta_{\text{ALBI}}(\gamma_2)$	-0.027345	0.395840	0.7040
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.788342	19.76138	0.0000
	$\beta_{\text{ALSI}}(\gamma_1)$	-1.134449	-6.628195	0.0000
	$\beta_{\text{ALBI}}(\gamma_2)$	-0.488448	-5.01936	0.0000

As was the case when the ALSI was used as the proxy in the Black *et al* (1972) tests, it was found that the intercept was significant and positive meaning that the model, even with the addition of the ALBI, was still missing influential explanatory variables. It was also found that the coefficient for the beta of the ALSI was significant at the 5% level, however, again it was found to be negative suggesting the inverse relationship between risk and return. The coefficient for the beta of the ALSI was actually found to be more negative than when it was the sole proxy, it was also found to be less significant than when it was the sole proxy. The intercept was found to get slightly closer to zero, however, it was still a very high positive figure. The coefficient for the beta of the ALBI was found to be insignificant, suggesting that it was not a valuable addition to the proxy for the market portfolio, and does not have a significant impact on the returns of the various portfolios.

The results of the Fama and Macbeth (1973) tests followed a similar pattern to the first model, with the intercept found to be significant and positive. However, the addition of the ALBI to the proxy for the market portfolio resulted in the intercept becoming smaller, meaning that the explanatory variables (the ALSI and ALBI) for this model accounted for slightly more of the movement of the portfolio returns than the first model (ALSI alone). Conversely, the coefficients for both explanatory variables were found to be insignificant. However, not too much should be read into this, because as was pointed in section 4.3.2.3, because of how the values are averaged in this method, often the t-stats are found to be very low. Finally the pooled

regression produced different results for the second model when compared to the first two tests. As was the case with the previous two tests, it was found that the intercept was significant and positive and it was found to be more significant than the other tests. In line with the Black *et al* (1972) test it was found that the ALSI was significant (although again in this case more significant), however the difference came when concerned with the significance of the beta for the ALBI. In the previous two tests, both revealed that the ALBI was insignificant, however the pooled regression found that the ALBI was highly significant. However, the coefficient was negative suggesting an inverse relationship between the risk associated with the ALBI and the returns of the portfolios.

**Table 5- 26 Summary statistics of the cross-sectional regressions using the ALSI and ALBI as proxies (total returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.214518	10.01454	0.0000
	$\beta_{\text{ALSI}} (\gamma_1)$	-1.254013	-2.713464	0.0300
	$\beta_{\text{ALBI}} (\gamma_2)$	0.054115	0.118211	0.9092
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.154222	5.929253	0.0000
	$\beta_{\text{ALSI}} (\gamma_1)$	-0.365522	-0.723813	0.4743
	$\beta_{\text{ALBI}} (\gamma_2)$	-0.313297	-0.285505	0.7770
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.52439	29.4215	0.0000
	$\beta_{\text{ALSI}} (\gamma_1)$	-1.150962	-7.035781	0.0000
	$\beta_{\text{ALBI}} (\gamma_2)$	-0.455204	-4.827165	0.0000

The tests on the total returns produced a few slightly different results. The intercepts produced by the Fama and MacBeth (1973) and pooled regression test produced significant intercepts that were slightly larger than the equivalent tests with the ALSI. However as in line with the excess returns tests, the coefficients for the ALSI in the separate tests were all found to be significant at the 5% level. The coefficients of the ALBI also followed a similar trend to the excess returns tests, with the Black *et al* (1972) and Fama and MacBeth tests producing insignificant coefficients, whilst the pooled regression produced a significant, yet negative coefficient. The results of these tests are very mixed and thus shed little light as to whether a multifactor CAPM will enhance the standard model. However, a further model as was discussed in section 4.2.2.3, which comprised the FINDI and the RESI was employed to test whether the issue of market

segmentation on the JSE should be acknowledged by practitioners. The results of the cross-sectional regressions on this model are presented and discussed in the following section.

### 5.3.2.3 FINDI and RESI as Proxies for the Market Portfolio

The results of the excess and total return tests are displayed in tables 5-27 and 5-28. Across all three tests for both excess and total returns it was found that the intercepts remained significant and positive, suggesting missing explanatory variables. The intercepts for each of the tests were found to be the lowest of all the models thus far, across both excess and total returns. The coefficients produced for the FINDI and the RESI by the Black *et al* (1972) and the pooled regression methods were found to be significant and as has been the case in the past models, negative. Although it is worth noting that the FINDI was found to be more significant than the RESI in the Black *et al* (1972) test. The coefficients produced by the Fama and MacBeth (1973) tests for excess and total returns were found to be insignificant (as was expected). Thus again it was found that neither of the proposed factors were found to be priced as risk factors by the market, and in fact these results again suggest that an investor will be rewarded for bearing less risk – contradictory to the CAPM theory.

**Table 5- 27 Summary statistics of the cross-sectional regressions using the FINDI and the RESI as proxies (excess returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.472452	6.925618	0.0002
	<b><math>\beta_{\text{FINDI}}(\gamma_1)</math></b>	-0.955286	-2.29988	0.055
	<b><math>\beta_{\text{RESI}}(\gamma_2)</math></b>	-1.932725	-1.96791	0.0898
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.257933	2.979200	0.0205
	<b><math>\beta_{\text{FINDI}}(\gamma_1)</math></b>	-0.466399	-0.803438	0.4481
	<b><math>\beta_{\text{RESI}}(\gamma_2)</math></b>	-0.144118	-0.507237	0.6276
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.670664	17.74155	0.0000
	<b><math>\beta_{\text{FINDI}}(\gamma_1)</math></b>	-1.112596	-6.95799	0.0000
	<b><math>\beta_{\text{RESI}}(\gamma_2)</math></b>	-1.586983	-5.27568	0.0000



**Table 5- 28 Summary statistics of the cross-sectional regressions using the FINDI and the RESI as proxies (total returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.202815	10.54994	0.0000
	<b><math>\beta_{\text{FINDI}}(\gamma_1)</math></b>	-0.938761	-2.282193	0.0565
	<b><math>\beta_{\text{RESI}}(\gamma_2)</math></b>	-1.928684	-1.958427	0.0910
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.011500	4.990798	0.0000
	<b><math>\beta_{\text{FINDI}}(\gamma_1)</math></b>	-0.469819	-0.811653	0.4228
	<b><math>\beta_{\text{RESI}}(\gamma_2)</math></b>	-0.148879	-0.509978	0.6135
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.444747	27.39816	0.0000
	<b><math>\beta_{\text{FINDI}}(\gamma_1)</math></b>	-1.184534	-7.758144	0.0000
	<b><math>\beta_{\text{RESI}}(\gamma_2)</math></b>	-1.519947	-5.260846	0.0000

The final model to be run was the three three-factor CAPM, with the ALBI, FINDI and RESI as explanatory variables. This model essentially combined the two aspects of this study, the addition of debt instruments and the acknowledgement of market segmentation on the South African market.

#### 5.3.2.4 ALBI, FINDI and RESI as Proxies for the Market Portfolio

The Black *et al* (1972) tests produced an intercept that was significant and positive again, and surprisingly, was actually found to be the furthest away from zero of the four models (again not by much). The interesting thing about the Black *et al* (1972) results for this model was that it was found that when combining these three explanatory variables it resulted in all three of them being insignificant. Although the finding for the ALBI is in line with the finding on the second model, the significances of the FINDI and RESI found in the third model were reversed in the fourth. Possible explanation of this is near multicollinearity, which is the presence of a correlated relationship (not perfect) between two or more variables, in this case the FINDI and the RESI. In the presence of near multicollinearity a regression can become very sensitive to small changes in its specification, and by adding or subtracting an explanatory variable (in this case adding the ALBI) can result in large changes in the coefficient values or significances of these coefficients (Brooks, 2008: 172). Similar results were obtained from the Fama and MacBeth (1973) tests, with a positive and significant intercept, but all the explanatory variables

were found to be negative and insignificant (although this was the case with the previous two models too).

The pooled regression however, produced some very interesting results, as with the previous two tests the intercept was found to be significant and positive. The interesting result was that the coefficient for the beta of the ALBI, which was found to be highly significant in the second model (combined with the ALSI) was actually found to be highly insignificant in this model (combined with the FINDI and RESI). A possible explanation for this again is near multicollinearity. The last two coefficients for the model (FINDI and RESI) as was found with the Black *et al* (1972) and Fama and MacBeth (1973) tests were found to be significant and negative.

**Table 5- 29 Summary statistics of the cross-sectional regressions using the ALBI, FINDI and RESI as proxies (excess returns)**

<b>Methodology</b>	<b>Variable</b>	<b>Coefficient</b>	<b>t Statistic</b>	<b>P Value</b>
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.495233	6.429891	0.0007
	$\beta_{ALBI}(\gamma_1)$	-0.282839	-0.376538	0.7195
	$\beta_{FINDI}(\gamma_1)$	-0.784335	-1.311775	0.2375
	$\beta_{RESI}(\gamma_2)$	-1.99424	-1.889886	0.1077
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.277478	3.062655	0.0221
	$\beta_{ALBI}(\gamma_1)$	-0.157090	0.080024	0.9388
	$\beta_{FINDI}(\gamma_1)$	-0.402443	-0.665979	0.5302
	$\beta_{RESI}(\gamma_2)$	-0.037794	-0.421244	0.6883
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	1.708227	18.09841	0.0000
	$\beta_{ALBI}(\gamma_1)$	0.006154	0.054385	0.9566
	$\beta_{FINDI}(\gamma_1)$	-1.133979	-6.87006	0.0000
	$\beta_{RESI}(\gamma_2)$	-1.909948	-6.493671	0.0000

**Table 5- 30 Summary statistics of the cross-sectional regressions using the ALBI, FINDI and RESI as proxies (total returns)**

Methodology	Variable	Coefficient	t Statistic	P Value
<b>Black <i>et al</i> (1972)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.225123	9.682287	0.0001
	$\beta_{ALBI}(\gamma_1)$	-0.227289	-0.285652	0.7848
	$\beta_{FINDI}(\gamma_1)$	-0.795413	-1.308614	0.2386
	$\beta_{RESI}(\gamma_2)$	-2.000703	-1.86222	0.1119
<b>Fama and MacBeth (1973)</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.035818	4.910736	0.0000
	$\beta_{ALBI}(\gamma_1)$	-0.172789	0.032196	0.9745
	$\beta_{FINDI}(\gamma_1)$	-0.402746	-0.679611	0.5016
	$\beta_{RESI}(\gamma_2)$	-0.032208	-0.428180	0.6714
<b>Pooled Regression</b>				
	<b>Intercept (<math>\gamma_0</math>)</b>	2.470266	27.62745	0.0000
	$\beta_{ALBI}(\gamma_1)$	0.076326	0.69097	0.4898
	$\beta_{FINDI}(\gamma_1)$	-1.234901	-7.835916	0.0000
	$\beta_{RESI}(\gamma_2)$	-1.810129	-6.40767	0.0000

Table 5-30, illustrates that the results for the tests with total returns are very similar to those with excess returns, hence the above discussions also apply to the results of the total returns tests.

In summary of the results for the cross-sectional tests, the intercepts for the CAPM models were expected to be equal to zero, whilst the market models according to theory should have produced intercepts equal to 0.745%. It was found that none of the proposed models produced intercepts that were predicted by theory. All of the models produced intercepts much larger than what was predicted, and all of the statistics were found to be significant. These results suggest that all of the models were missing factors that had influences on the returns of the portfolios.

The coefficients for any explanatory variables were expected to be positive and significant, as this would indicate that the explanatory variable had an impact on the returns of the various portfolios, and that the market prices the risk associated with the explanatory variable. Once again none of the models produced results that were in line with theory, as almost all of the explanatory variables were found to have negative coefficients. The majority of the tests produced significant coefficients (apart from the Fama and MacBeth (1973) tests) which

suggested that the market did price the risk associated with the explanatory variables, however it suggested a negative relationship between the risk of these variables and returns of the portfolios. These results were again not predicted by theory, as this model basically suggested that there is a negative relationship between risk and return on the JSE, which contradicts everything discussed in chapters two and three and everything the CAPM stands for.

An initial explanation for the results was the fact that over the period employed in the study there were several significant market downturns and thus the negative relationship between risk and return. However, robustness tests such as sub period analysis, dummy variable analysis and fixed effects models were carried out on the data and it was found that although the robustness tests made a difference to the results, they did not solve the problem. On closer inspection of literature it was found that results of this nature were not unprecedented, suggesting that perhaps the CAPM is irrelevant in the South African context. Despite these results it is still of importance, especially considering how often the CAPM is employed in practice, that the best of these four models is established. One way of doing this is through testing the explanatory powers and forecasting abilities of the four models and then comparing their separate performances, thus establishing which is the best performing.

### **5.3.3 The Explanatory Powers of the Four Models**

As outlined in section 4.4.1 the explanatory powers of each of the models will be tested. For the purpose of this study the information criteria used were the AIC and the SBIC. The proxy with the lowest AIC and SBIC values for these tests is considered to have the best explanatory powers. The results for each of the information criteria for the Black *et al* (1972) are displayed in the following tables, tables 5-31 and 5-32. The proxy with the lowest AIC and SBIC value for a given portfolio are highlighted.

**Table 5- 31 The explanatory powers of the four models according to AIC and SBIC, based on the Black *et al* (1972) test (excess returns)**

Portfolio	AIC				SBIC			
	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI
1	5.7600	5.7519	5.8122	5.8113	5.8037	5.8174	5.8777	5.8987
2	5.6010	5.5239	5.5488	5.5321	5.6447	5.5894	5.6143	5.6195
3	5.4121	5.2594	5.2308	5.1931	5.4557	5.3249	5.2963	5.2805
4	5.3429	5.2008	5.0219	5.0030	5.3866	5.2663	5.0874	5.0904
5	5.2272	5.0800	5.1556	5.1010	5.2709	5.1455	5.2211	5.1884
6	5.2532	5.1605	5.2175	5.1872	5.2969	5.2260	5.2830	5.2745
7	5.2197	5.2215	5.2418	5.2561	5.2634	5.2870	5.3073	5.3435
8	5.0935	5.1038	5.1174	5.1318	5.1372	5.1693	5.1830	5.2192
9	4.8912	4.8984	4.9121	4.9227	4.9349	4.9639	4.9776	5.0101
10	5.6362	5.6142	5.6390	5.6315	5.6798	5.6797	5.7045	5.7189
Ave	5.3437	5.2814	5.2897	5.2770	5.3874	5.3470	5.3552	5.3643

As can be seen from the statistics in tables 5-30 and 5-31, both excess and total returns have similar winners (i.e. lowest score on the criterion). The only difference between the two sets of winners is the result of the SBIC for portfolio 10, where in the excess returns tests it was found that for this portfolio the second model with the ALSI and the ALBI as the proxies had the highest explanatory power, whilst for total returns it was found to be the first model with the ALSI as the sole proxy. The results of these tests suggest that according to AIC that the model containing the ALBI, FINDI and RESI had on average the best explanatory power over the ten portfolios, despite only being the strongest for two of the ten portfolios it was very consistent for the remaining eight, being the second strongest model for four of the eight. Although the model containing the ALSI and the ALBI appeared the best performing as it was the strongest model for five and the second strongest for three, because of its lack of consistency it was found on average to be second strongest. The next strongest on average, was surprisingly the model containing the FINDI and RESI as explanatory variables, despite the fact this model was not found to be the strongest for any of the portfolios, it was only the weakest for one of the ten portfolios, illustrating that it was fairly consistent and thus its strong average performance. The weakest on average was the model containing the ALSI which was surprising as it produced the best results for three of the portfolios, however for six of the remaining seven portfolios it was one of the weakest. What is interesting to note is that for this information criterion, it was found that the two models containing the ALBI were the best at explaining the returns of the first six portfolios, meaning that models containing debt instruments explained the returns of the higher risk portfolios. Proxies such as the FINDI and the RESI, or the ALSI were expected to explain

the higher risk portfolios better, as they too are more risky than the ALBI. In fact the ALSI accounted for the movements of three of the four least risky portfolios, which was not expected.

**Table 5- 32 The explanatory powers of the four models according to AIC and SBIC, based on the Black *et al* (1972) test (total returns)**

Portfolio	AIC				SBIC			
	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI
1	5.7590	5.7534	5.8111	5.8123	5.8027	5.8189	5.8766	5.8997
2	5.5989	5.5291	5.5476	5.5343	5.6425	5.5946	5.6131	5.6216
3	5.4068	5.2651	5.2278	5.1941	5.4505	5.3307	5.2934	5.2815
4	5.3427	5.2020	5.0245	5.0031	5.3864	5.2675	5.0900	5.0905
5	5.2247	5.0819	5.1550	5.1011	5.2684	5.1474	5.2205	5.1885
6	5.2473	5.1599	5.2135	5.1852	5.2910	5.2254	5.2790	5.2725
7	5.2163	5.2187	5.2393	5.2537	5.2600	5.2843	5.3049	5.3410
8	5.0820	5.0934	5.1066	5.1212	5.1257	5.1589	5.1721	5.2085
9	4.8776	4.8858	4.8988	4.9099	4.9213	4.9514	4.9644	4.9972
10	5.6279	5.6092	5.6318	5.6262	5.6715	5.6748	5.6973	5.7136
Ave	5.3383	5.2799	5.2856	5.2741	5.3820	5.3454	5.3511	5.3615

Moving onto the results of the SBIC, it is important to note that this criterion has a much stiffer penalty for adding extra variables to any model. Thus it was expected that the model containing only the ALSI was expected to have better results based on this criterion.

However, the model containing the ALSI did not end up displaying better results based on the SBIC. For excess returns the model was found to be the strongest for four of the ten portfolios, whilst for total returns it was found to be the strongest for five. However, consistency was not this model's greatest strength as it was found to be the weakest for all except one of the remaining portfolios resulting in it being the weakest model on average at explaining the movements of the portfolios. Once again the model containing the ALSI and the ALBI performed well, displaying the best results for four of the excess portfolio and three of the total portfolios, and second for the majority of the remaining. This consistency resulted in it being the best at explaining the returns of the ten portfolios according to SBIC. Both the models containing the FINDI and the RESI, and the ALBI, FINDI and RESI were the strongest for only one of the portfolios, but despite this remained fairly consistent and thus on average were the mid-performing models.

Due to the fact that the first pass regressions of the Fama and MacBeth (1973) tests and the pooled regression are the same, the following information criteria represents both. The results are displayed in tables 5-33 and 5-34.

**Table 5- 33 The explanatory powers of the four models according to AIC and SBIC, based on the Fama and MacBeth (1973) and the pooled regression tests (excess returns)**

Portfolio	AIC				SBIC			
	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI
1	5.8002	5.7992	5.8156	5.8187	5.8881	5.9312	5.9475	5.9947
2	5.4823	5.3869	5.4402	5.4095	5.5703	5.5189	5.5722	5.5855
3	5.3589	5.2016	5.1604	5.1336	5.4469	5.3335	5.2924	5.3096
4	5.4122	5.2890	5.0661	5.0858	5.5001	5.4209	5.1981	5.2618
5	5.2785	5.1320	5.1265	5.1052	5.3665	5.2639	5.2584	5.2812
6	5.2830	5.2006	5.1481	5.1580	5.3710	5.3326	5.2800	5.3340
7	5.0889	5.0551	5.0019	5.0196	5.1769	5.1870	5.1339	5.1956
8	5.0527	5.0887	5.0654	5.1135	5.1407	5.2206	5.1974	5.2895
9	4.9583	4.9861	4.9583	4.9768	5.0463	5.1181	5.0903	5.1528
10	5.6501	5.6598	5.6792	5.7089	5.7381	5.7917	5.8112	5.8848
Ave	5.3365	5.2799	5.2462	5.2530	5.4245	5.4118	5.3781	5.4289

The “winners” for the two criteria were found to be exactly the same for both total and excess returns. The AIC results had the model with the ALSI as the best at explaining three of the ten portfolios. Again these three were the portfolios with the least amount of risk, which as discussed earlier is a puzzling result. As was the case with the information criteria produced by the Black *et al* (1972) tests, the model with the ALSI was very inconsistent as it was found to be the weakest model in explaining the returns of six of the remaining seven portfolios and thus was the weakest model on average. The model with the ALSI and ALBI as the proxies, was found to be far more consistent, even though it was the best at explaining the returns of only two of the portfolios, it was only once the weakest and thus was the third strongest portfolio on average. The big difference between the Black *et al* (1972) results and these, was the performance of the model with the FINDI and the RESI as explanatory variables. These results showed that this model had the strongest explanatory power for three of the portfolios, and was never found to be the weakest for any of the portfolios, resulting in it being found the strongest model on average. Finally the model containing the ALBI, FINDI and RESI, was found to have the strongest explanatory power for two of the portfolios, whilst it was fairly inconsistent being the weakest for three of the remaining portfolios, however it was still found to be on average the second strongest model.

**Table 5- 34 The explanatory powers of the four models according to AIC and SBIC, based on the Fama and MacBeth (1973) and the pooled regression tests (total returns)**

Portfolio	AIC				SBIC			
	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI
1	5.8035	5.7994	5.8147	5.8217	5.8914	5.9313	5.9466	5.9976
2	5.4816	5.3912	5.4401	5.4116	5.5696	5.5231	5.5720	5.5875
3	5.3540	5.2056	5.1562	5.1335	5.4420	5.3375	5.2882	5.3095
4	5.4134	5.2912	5.0686	5.0878	5.5014	5.4232	5.2005	5.2638
5	5.2741	5.1327	5.1232	5.1039	5.3621	5.2646	5.2552	5.2799
6	5.2769	5.2017	5.1427	5.1555	5.3648	5.3336	5.2746	5.3314
7	5.0823	5.0524	4.9966	5.0167	5.1703	5.1844	5.1286	5.1926
8	5.0410	5.0788	5.0541	5.1025	5.1290	5.2108	5.1861	5.2784
9	4.9388	4.9687	4.9403	4.9600	5.0268	5.1006	5.0722	5.1360
10	5.6440	5.6577	5.6738	5.7059	5.7320	5.7897	5.8057	5.8819
Ave	5.3310	5.2779	5.2410	5.2499	5.4189	5.4099	5.3730	5.4259

The model containing the ALSI was again found to be inconsistent across the ten portfolios, according the SBIC, as it was found to have the strongest explanatory power for four portfolios and the weakest for four, despite this it was the second weakest proxy on average. Despite the fact that the model with the ALSI and ALBI as proxies was only found to have the best explanatory powers for one models, it remained very consistent, and was not found to be the weakest for any of the portfolios, and it ended up being the second strongest model on average. Again the model containing the FINDI and the RESI was found to be the strongest, as it had the best explanatory power for five portfolios, and was not found to be the worst at explaining any of the portfolios. Finally the poorest performing model according to SBIC was the model containing the ALBI, FINDI and RESI, (not surprising considering the stiffer penalty the model employs) this model was not found to be the strongest for any of the portfolios, whilst at the same time was found to be the weakest for six of the ten portfolios.

Thus over the two tests, the two most consistent models were the models containing the ALSI and the ALBI, and the FINDI and the RESI. The model containing the ALSI, although the strongest at explaining the returns on several of the portfolios lacked consistency for the remaining portfolios and thus was found on average to be the weakest model of the four.



### 5.3.4 The Forecasting Abilities of the Four Models

The next, and final step in this study was to test the forecasting abilities of each of the models. As outlined in section 4.4.2 for the purpose of this study the RMSE, the MAE and the MAPE were used to assess the forecasting abilities of each of the models. The better the model is at forecasting the lower the values for RMSE, MAE and MAPE will be. Due to the large number of regressions required for the rolling time series tests of Fama and MacBeth (1973) and the pooled regression (as their time series tests are the same), which was in excess of 15 000 regressions, the time series tests for these methods were run in excel. As a result of these tests being run in excel it unfortunately meant that forecasting tests could not be run on these first pass results. This meant that the only method that could have its first pass results tested for their forecasting ability was the first pass of Black *et al* (1972). The results of the forecasting tests with the period January 2000 to December 2009 as the in sample data and January 2010 to December 2010 as out-of-sample data are shown in Tables 5-35 and 5-36 below, where model with the lowest RMSE, MAE and MAPE is highlighted.

**Table 5- 35 The forecasting abilities of the CAPM with various proxies based on RMSE, MAE and MAPE (in sample: Jan 2000 to Dec 2009, out-of-sample: Jan 2010 to Dec 2010)**

EXCESS RETURNS												
Proxy:	RMSE				MAE				MAPE			
	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI
Portfolio 1	3.3171	3.2345	3.2872	3.2065	2.7243	2.6583	2.7758	2.6726	130.4188	130.4200	123.5973	125.9512
Portfolio 2	2.7726	3.3291	3.2639	3.4895	2.3538	2.5891	2.4575	2.5470	255.3624	306.8892	291.9069	313.9334
Portfolio 3	2.5029	2.0350	2.1561	1.9363	1.9702	1.6935	1.7078	1.5062	79.9814	65.6828	58.9480	42.7015
Portfolio 4	1.7536	2.0402	1.5834	1.7586	1.1767	1.6460	1.3066	1.4629	44.1994	87.3658	45.1038	66.8320
Portfolio 5	2.0628	2.4770	2.4856	2.6347	1.6436	2.1574	1.9226	2.2088	97.1198	142.3002	94.0318	125.2018
Portfolio 6	1.3791	1.9340	1.8102	2.0423	1.0831	1.5042	1.3333	1.5264	65.1843	107.6486	76.9660	106.6534
Portfolio 7	2.8206	2.9782	3.0891	3.1123	1.9807	2.0670	2.0075	2.0189	675.4985	744.6137	732.1552	747.5025
Portfolio 8	2.2923	2.2938	2.2438	2.2487	1.7881	1.8210	1.7546	1.7704	14614.53	15322.07	14510.28	14827.7700
Portfolio 9	1.9004	1.8597	1.8846	1.8489	1.5472	1.5205	1.5399	1.5134	26.2981	75.5587	77.0314	75.6125
Portfolio 10	1.9134	2.0064	1.8928	1.9748	1.6409	1.6258	1.6082	1.5994	157.7421	175.4033	169.3921	176.7954
Average	2.2715	2.4188	2.3697	2.4253	1.7909	1.9283	1.8414	1.8826	1614.6335	1715.7952	1617.9413	1660.8954

**Table 5- 36 The forecasting abilities of the market model with the various proxies based on RMSE, MAE and MAPE (in sample: Jan 2000 to Dec 2009, out-of-sample: Jan 2010 to Dec 2010)**

TOTAL RETURNS												
Portfolio	RMSE				MAE				MAPE			
	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI	ALSI	ALSI, ALBI	FINDI, RESI	ALBI, FINDI, RESI
Portfolio 1	3.3216	3.2390	3.2909	3.2132	2.7284	2.6618	2.7787	2.6801	79.5641	76.8066	76.8464	74.8364
Portfolio 2	2.7622	3.2917	3.2548	3.4649	2.3423	2.5797	2.4431	2.5496	643.0257	784.1033	755.9260	819.7150
Portfolio 3	2.4898	2.0595	2.1498	1.9475	1.9804	1.7002	1.7041	1.5189	63.3561	49.6936	51.5789	38.8448
Portfolio 4	1.7402	2.0386	1.5822	1.7634	1.1869	1.6384	1.3175	1.4658	73.1995	169.9188	53.3584	112.2886
Portfolio 5	2.0402	2.4675	2.4705	2.6282	1.6322	2.1390	1.9109	2.1997	103.0755	161.6706	109.5287	146.1804
Portfolio 6	1.3708	1.9050	1.8046	2.0236	1.0275	1.4819	1.3135	1.5099	73.6198	253.6551	112.0605	255.2427
Portfolio 7	2.8238	2.9730	3.0886	3.1111	1.9709	2.0561	1.9742	1.9924	309.6233	317.2302	332.7344	332.9929
Portfolio 8	2.3089	2.3070	2.2639	2.2661	1.8249	1.8488	1.7924	1.8030	124.5990	127.3343	124.2646	125.2401
Portfolio 9	1.9102	1.8719	1.8962	1.8612	1.5197	1.4993	1.5124	1.4909	90.5763	88.2128	89.9775	87.6101
Portfolio 10	1.9215	1.9959	1.9044	1.9674	1.6525	1.6276	1.6214	1.6046	639.0030	194.1107	583.7795	216.2948
Average	2.2689	2.4149	2.3706	2.4247	1.7866	1.9233	1.8368	1.8815	219.9642	222.2736	229.0055	220.9246

The forecasting test (in sample: January 2003 to December 2009, out-of-sample: January to December 2010), found that according to RMSE, MAE and MAPE that the CAPM and market model using the ALSI as the proxy were more accurate (had a lower forecasting error) than any of the other models employed in this study for both total and excess returns. For all three of the measures; RMSE, MAE and MAPE, across both excess and total returns, this model was found to be the strongest model by some distance. The model employing the FINDI and RESI as the market proxy was found to be the second strongest model in all of the measures except for the results of MAPE where the model using the ALBI, FINDI and RESI was found to be the second strongest. The weakest models at forecasting were found to be the models with the ALSI and the ALBI as the proxies, which after their strong performance on the information criteria was surprising. Despite the fact that the models with the ALSI as the proxy had performed poorly when concerned with the information criteria, the forecasting test is probably the most important test for practitioners. Practitioners when using the CAPM, will be attempting to predict the cost of equity the majority of the time, although the ability of the model to explain the returns of a portfolio is important, the ability to forecast is vital. Aside from this, the additional effort required to run a two or three factor model needs to be justified by a distinct improvement in the results from the single factor model to the multifactor models, which is not found in this study. Therefore although the results of the two-pass regression tests suggest that the CAPM is an inappropriate model for the South African market, if it is to be used, the ALSI should be employed as the proxy for the market portfolio.

#### **5.4 Chapter Summary**

In this chapter, the results of the both the first-pass and second-pass regressions for each of the four proposed models were presented and discussed, followed by the presentation and discussion of the explanatory powers and forecasting abilities of the models.

The results of the first pass regression, were not what were predicted by theory. The models never produced intercepts equal to zero or 0.745% (for total returns), however in line with the results of Black *et al* (1972), the portfolios with higher risk produced negative intercepts, whilst the lower risk portfolios produced positive intercepts. These results suggest that the high risk portfolios generally earned less on average than was predicted by the various CAPM and market models, whilst the low risk portfolios on average earned more than was predicted by the various CAPM and market models. The betas produced for the explanatory variables were

found to be in a narrow range, where the Studies of Black *et al* (1972) and Fama and MacBeth (1973) obtained larger ranges in their betas, however a South African study by Van Rensburg and Robertson (2003) also obtained a narrow range for the betas of their explanatory variables, somewhat validating these results. Finally according to the adjusted R-squared value, the model with the ALBI, FINDI and RESI as the proxies had the strongest explanatory power, whilst the model with the ALSI as the sole proxy was found to have the weakest explanatory power.

The results of the second pass regression were of particular interest. When testing the first model, which was a CAPM with the ALSI as the market proxy, it was found that the intercept was statistically significant and very positive, which is contradictory to CAPM theory. These results suggested that there was an inverse relationship between risk and return. On initial inspection it was believed that the results were possibly due to the time period selected for this study, and that the numerous market downturns in and around the period could have caused such results. However through various robustness checks it was found that this was not the case. Following closer analysis of various South African literature it was found that such results were not a first. Studies by both Van Rensburg and Robertson (2003) and Strugnell *et al* (2011) had produced similar results, leading the authors to believe that the CAPM was invalid in South Africa. Strugnell *et al* (2011) suggested that one extension of their study was to test multi-factor CAPMs, and that was the next step of the analysis. However, the various methods employed all produced similar results for the remaining three models; a positive and significant intercept, and negative or insignificant coefficients for all the explanatory variables. Casting serious doubt over the validity of the CAPM in a South African context.

Finally the explanatory power and forecasting abilities of the four models were tested, because despite these results the CAPM is still the most popular equity valuation tool in South Africa, and any improvement on the model could be of help to practitioners. It was found that the models containing the ALSI and the ALBI, and the FINDI and the RESI as explanatory variables were the two strongest at explaining the returns of the portfolios used. The conventional CAPM with the ALSI as the market proxy was the worst performing in this regard. There was a complete turnaround when concerned with the forecasting abilities of the models as it was found that by far and away the conventional CAPM with the ALSI as proxy was the best model, Whilst the CAPM with the ALSI and the ALBI was found to be the weakest. In chapter six of this study the conclusions are presented as well as recommendations for future research.

## CHAPTER 6

### CONCLUSIONS AND RECOMMENDATIONS

#### 6.1 Review of Research Objectives

The CAPM, despite its numerous critics and the arguments surrounding its validity, is still the most popular model used to estimate the cost of equity for use in capital budgeting decisions, in both the U.S. and South Africa (Graham and Harvey, 201: 203; Correia and Cramer, 2008: 41; PriceWaterhouseCoopers, 2009: 26). The parameters of the CAPM are notoriously hard to compute as they are all theoretical constructs that need to be estimated. The theoretical market portfolio as discussed in section 2.4.1, is impossible to form in practice, and as a result proxies are used in its place. As was highlighted in section 2.5.4, the two important factors that need to be considered when finding a proxy for the market portfolio is firstly, that it is mean-variance efficient and secondly, that according to theory it contains all risky assets. Studies in the U.S., as shown in section 3.4, have attempted to comply with these two factors by adding assets such as real estate, and more specifically for this study, bonds. These studies had varying success.

Despite the attempts in U.S. studies to add assets to the proxy for the market portfolio, very little research of this nature has been conducted in South Africa. Most studies on the market proxy in South Africa focus on the issue of market segmentation. Although the studies in the U.S. concerning the addition of bonds to the market portfolio had varying levels of success, there is no guarantee that that would be the case in South Africa due to the dissimilarities between the two markets. Given the importance of the CAPM in ensuring that resources are allocated efficiently, it is vital that the parameters such as the market portfolio are accurately estimated. Consequently, the research question for this study was whether or not the incorporation of a bond index into the proxy for the market portfolio will enhance the use of the CAPM in South Africa. In answering this question, the following three objectives were also considered:

- Does the common trend of using the ALSI as a market portfolio suffice in the South African context?

- To test whether a portfolio synthesized from the market and bond indices will enhance the proxy i.e. are bonds priced as a risk factor?
- Does the existence of market segmentation on the JSE allow for further enhancements of the proxy? i.e. are the separate indices priced as separate risk factors?

As can be seen from the objectives, the issue of market segmentation was also addressed. It was decided that because the majority of South African research on the proxy for the market portfolio is focused on the segmentation of the JSE, it illustrated the importance of this issue when investigating a market proxy in the South African context. Therefore, it was believed that the topic could not be ignored and would be included in the study to enhance its results.

The degree to which each of the objectives were dealt with is best understood by considering a summary of each of the specific findings. As each of these objectives help address the research question of this study, they will be discussed first, followed by the overall conclusion based on the research question.

## **6.2 Summary of Study Findings**

### **6.2.1 The use of the ALSI as the Market Proxy in South Africa**

The common trend of using a broad-based equity index such as the ALSI as a proxy for the market portfolio has been debated for some time now. Researchers around the world question the use of such indices because they ignore large asset classes such as real estate and bonds. Further to this is the South African specific problem of market segmentation of the JSE, and as a result of this problem numerous researchers have questioned the trend of using the ALSI. In light of these arguments, a set of theoretical requirements that an index or portfolio should comply with in order to be considered an appropriate market proxy for the South African market were set out. Firstly, it was acknowledged that estimating the market portfolio is a very intricate process. To begin with, when calculating the returns of the portfolio, it was established that a researcher or practitioner should use arithmetic returns of a value-weighted index over a time period that should reflect the best judgement as to what the forecasting period will resemble. However, the most important decision when estimating the market portfolio is the

choice of proxy. It was found that there were two key criteria which a proxy for the market portfolio should meet in order to be an adequate proxy. These were first, that the portfolio should be mean-variance efficient, and secondly, that theory states that the market portfolio contains all risky assets held in proportion to their market value. Research of literature concerned with whether or not the ALSI was an adequate mean-variance proxy for the market portfolio, produced mixed results. However, it was established that, by using the ALSI as a proxy for the market portfolio, a number of assets were excluded. Suggesting that, theoretically, there was room for improvement in the trend of using the ALSI as a market proxy.

Empirically, the second pass regression results when using the ALSI as the proxy for the market portfolio were very interesting. Whilst theory suggested that the intercept of the model should be zero and statistically significant and that the coefficient of the explanatory variable (in this case the beta of the ALSI) positive and significant, the results proved to be the opposite. The intercepts for the models with both total and excess returns across all three tests, were found to be significantly different from zero (and very positive) and the coefficients of the explanatory variable were all found to be either insignificant or negative. This was a startling result as this suggested that either the risk associated with the ALSI was not priced or the common method of using the ALSI as the portfolio for the market proxy resulted in a negative sloping SML – essentially meaning that there is an inverse relationship between risk and return on the JSE. Initially it was believed that these findings came as a result of the period over which the analysis was conducted, as there were considerable market downturns in and around the data period, including the Asian crisis, the dotcom bubble burst, the 9/11 attacks and the subprime mortgage crisis. However, it was deemed necessary to perform robustness checks on these findings. Three tests were performed, firstly, a sub period analysis was conducted on a period in the study that was believed to be a general bull market. Secondly, a dummy variable analysis was performed in an attempt to pin point whether bad news or market downturns had an effect on returns that was not captured by the model. Finally, fixed and random effects models were discussed and employed to see if these models would improve the results. Although the robustness tests did have an impact on the results of the cross-sectional analysis, they did not solve the problem. Upon closer analysis of South African literature it was found that these results were not the first of their kind in South Africa, as Van Rensburg and Robertson (2003) and more recently Strugnell *et al* (2011) obtained similar findings. Due to the fact that these studies were conducted over different and longer periods it again suggested that the results of this study were not down to the period used.



Thus overall the empirical research of the CAPM or market model employing the ALSI as a proxy, were fairly damning of the use of the CAPM or market model in South Africa, as the results suggested that the CAPM was invalid in the South African context. One of the suggestions of Strugnell *et al* (2011: 14) which coincided with the research questions of this study was that they believed that a possible enhancement of their study was to employ multifactor asset pricing models. Appropriately that was the next step of the study. The first multifactor model reviewed was one that employed the ALSI and ALBI as proxies for the market portfolio.

### **6.2.2 The Addition of Bonds to the Market Proxy**

As mentioned earlier, it was discussed on numerous occasions that the two criteria that the market proxy should adhere to was that it was mean-variance efficient and that it contained all risky assets held in proportion to their market value. It was argued that these two criteria could complement each other, i.e. by adding extra assets that have been ignored in the past, such as bonds, this could in turn assist in obtaining a portfolio that was mean-variance efficient. Bonds were found to be a large asset class on the South African market as they accounted for 23 percent of the market capitalisation on the JSE in 2009. Based on the theoretical argument being that all risky assets should be included in the proxy for the market portfolio, it appeared flawed to ignore such a large asset class. However, a review of studies that had incorporated bonds into the market index showed that varying results had been produced. What was found to be interesting was that tests of incorporating a debt instrument into the proxy for the market portfolio had been conducted in the U.S. and not South Africa. Thus despite the mixed results obtained in these U.S. studies, it was argued that due to the dissimilarities between the two markets, that bonds were still a plausible addition to the market proxy.

It was suggested by Strugnell *et al* (2011: 14) that the use of multifactor models could possibly enhance the poor performances of the CAPM with the ALSI as a proxy. Empirically it was found that the addition of the ALBI to the proxy for the market portfolio did little to improve the results of both the CAPM and the market model. The intercepts for each of the cross-sectional regressions were again found to be positive and significant, and as was the case with the ALSI as a sole proxy, it was found that the coefficients for all the explanatory variables were either found to be insignificant or negative. These results again suggested that either the proposed proxies were not priced as risk factors by the market or were negatively priced,

meaning that an investor would be rewarded for holding less risk. However, the intercepts for most of the tests were found to be slightly closer to zero, suggesting that the proxy containing the ALSI and the ALBI, accounted for more of the returns of the portfolios than the proxy with only the ALSI. However, this was a minor improvement and thus these results still cast doubt over the validity of the CAPM in the South African market.

### **6.2.3 Incorporating the Issue of Market Segmentation into the Market Proxy**

The next multifactor model to be proposed contained the FINDI and RESI as proxies for the market portfolio. The logic behind this model was brought about by the theoretical argument that the JSE is heavily segmented towards the Financial and Industrial and the Resource sectors. This theoretical argument was supported by the finding that in January 2010, the Financial and Industrial and the Resources sectors made up nearly 90 percent of the total capitalization of the JSE. The majority of research on the market proxy in South Africa has centred around the debate of market segmentation. Numerous authors tested using the indices of these two sectors (FINDI and RESI) as proxies for the market portfolio, with mixed results. Whilst a number of researchers found the use of these sectorial indices an improvement on the proxy, there were also those that concluded that the ALSI was a sufficient proxy. Despite these mixed results, it was important not to ignore such an important characteristic of the South African market, especially when attempting to establish an adequate proxy for it. Therefore, models with the FINDI and RESI as proxies were included in the empirical research of this study.

As was the case with the first two proposed models it was found that the intercepts of the cross-sectional regressions were positive and significant for each of the tests, which suggested that the models were missing explanatory variables. Although the intercepts for these models were found to be the lowest of all the models tested, suggesting that these models accounted for more of the movements in the portfolios than any other proposed models. Like the first two models it was found that the proxies were either found to be insignificant or negative. These results further enhanced the argument that the CAPM may be an inappropriate model in the South African market.

#### **6.2.4 Three Factor Model Combining the Two Aspects of the Study**

The final multifactor model that was proposed combined the two aspects of this study, the addition of bonds to the market proxy and the appreciation of the market segmentation on the JSE. The model made use of the ALBI, FINDI and RESI as proxies for the market portfolio. The theoretical argument behind including this model was that if these two aspects each separately enhanced the CAPM, then by combining them it could result in a further enhancement.

Empirically, the results were not very different than the first three models. The cross-sectional tests all produced positive and significant intercepts, which were further from zero than the model containing only the FINDI and RESI. In one of the tests, the coefficient for the FINDI even became insignificant after adding the ALBI to the model, when it had previously been significant in the third model – a possible case of near multicollinearity. Nevertheless as was the trend with the first three models, all the proxies were insignificant or negative. Based on these results, the addition of a bond index to the third model (FINDI and RESI as proxies) was found to be to that models detriment. However, these results again cast a shadow over the use of the CAPM.

Despite the fact that the cross-sectional results had provided such damning results for the CAPM, there is no escaping the fact that the CAPM is still the most popular equity valuation tool in South Africa. Therefore, because the CAPM is being used regardless, it was important to test the explanatory powers and forecasting abilities of the four proposed models to find which was, in a sense, the best of the worst.

#### **6.2.5 The Explanatory Powers of the Models**

The two criteria used for testing the explanatory powers of the models were Akaike's information criterion (AIC) and Schwartz Bayesian information criterion (SBIC). The models produced slightly different results but it was found that overall, the models containing the ALSI and ALBI, and the FINDI and RESI as proxies were the best at explaining the returns of the portfolios. Whilst the model containing the ALBI, FINDI and RESI as proxies was a strong

performer for the AIC tests on excess returns, it was found to be fairly inconsistent for the remaining tests. The worst performing model over the various tests was found to be the model with the ALSI as the sole proxy. Although the model was found to be the strongest at explaining the returns on several portfolios, it lacked consistency and was often found to be the weakest at explaining the movements of other portfolios.

Therefore the results of the explanatory power tests did not support the trend of using the ALSI as a proxy, however, the reason most practitioners need an accurate estimation of the market portfolio, is so that they can use the CAPM to forecast the returns of either single shares or portfolios. Thus the forecasting ability of the four models was also tested.

### **6.2.6 The Forecasting Ability of the Models**

The three criteria used to test the forecasting abilities of the four models were the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). Despite the fact that, according to the results of the cross-sectional and explanatory power tests, the model with the ALSI as the proxy appeared to be the weakest of the four. However based on all the forecasting tests, it was the strongest and by some distance. The next strongest model was found to be model three, which employed the FINDI and RESI as proxies. The weakest of the four models when concerned with forecasting was found to be the CAPM and market model with the ALSI and ALBI as proxies. Thus, according to the forecasting results, the ALSI was the best proxy for the market portfolio.

### **6.3 Limitations of this study**

Despite the best efforts to make this study as thorough as possible, there were a number of limitations that this study faced that were unavoidable.

### **6.3.1 Time Period**

Due to the limited availability of data on the ALBI, this study could only be conducted over an eleven year period. Studies conducted by Black *et al* (1972) and Fama and MacBeth (1973) were conducted over periods of more than thirty years. As a result of the short time period of this study, market irregularities like the subprime mortgage crisis have a larger effect on the overall results of the various models because the effects of such a period do not get smoothed out. However, having mentioned this, it is noted that studies by Van Rensburg and Robertson (2003: 8) and Strugnell *et al* (2011: 1) used different and slightly longer time periods (July 1990 to June 2000 and January 1994 to October 2007 respectively), but still obtained similar results. Despite this, it would still be worth running the tests over much longer periods, periods in excess of thirty years. Conducting these tests over an extended time period would ensure that market fluctuations are smoothed out and thus provide more robust results.

### **6.3.2 Implications of the Fama and MacBeth (1973) Two-Pass Method**

One of the limitations of the study was that due to the nature of the Fama and MacBeth two-pass regression technique, the t-stats that it produced were very low, and as a result most of the coefficients it produced were found to be insignificant. This was due to the fact that, as there were only ten cross-sections in the study, it resulted in increased variation of the estimates and therefore increased standard errors. These larger standard errors result in lower t-stats meaning that the coefficients are deemed insignificant. A way in which future studies can remedy this, is to run the cross-sectional analysis on the average return of individual shares, whilst assigning each share a portfolio beta. So in a sense twenty of the shares could have the same beta (according to their pre-sorted betas) based on which portfolio they are assigned to, and this way it allows for more estimates to be included in the cross-sectional analysis and thus decreasing the variation and standard errors.

## **6.4 Opportunities for Future Research**

This study, by attempting to enhance the proxy for the market portfolio for applications of the CAPM in South Africa, has contributed to the knowledge of this parameter and the model as a whole. However, there are a number of opportunities for future research on this topic.

### **6.4.1 Testing the Mean-variance Efficiency of the Proposed Proxies**

In chapter three of this study, a lot of emphasis was placed on the importance of a proxy being mean-variance efficient. However, the scope of this study was to compare the various single and multifactor CAPM and market models. This comparison was based on their two-pass regression, explanatory and forecasting outputs. The natural progression of this, and thus an opportunity for future research would be to test the mean-variance efficiency of the four models.

### **6.4.2 Industry Sorted Portfolios**

Despite the fact that beta sorted portfolios have been used in studies for years, a further robustness test of these results would be to use industry sorted portfolios as the dependant variables of this study. Stambaugh (1982) made use of industry sorted portfolios, and with the segmented nature of the South African market, the use of such portfolios could provide valuable insights into uses of market proxies on a market such as the JSE.

### **6.4.3 Equal Weighted Proxies**

In section 2.5.3, the debate between the use of a value- or equal weighted index as the proxy for the market portfolio was highlighted. As was discussed, the choice between the two can make a large difference. Although the proxies used in this study were all value-weighted indices, academics such as Van Rensburg and Slaney (1997: 1-2) and Raubenheimer (2010: 1) suggest that the use of equal weighted indices could be superior. They argue that due to the segmented nature of the JSE, value-weighted indices such as the ALSI are made up of predominantly 4 or 5 companies. This argument was supported by table 2-2, where it was illustrated that the five largest firms on the JSE make up over 43% of the ALSI, and with the segmentation on the JSE, these five companies could come from only two or three sectors which is hardly representative. An equal weighted index ensures diversification, the index does not overweight overpriced stocks and underweight underpriced stocks, the index is easy to construct and manage, and based on returns an equal weighted index often outperforms the equivalent value weighted index (Reilly and Brown, 1997: 156; Bodie *et al*, 2007: 48; Hawkins, 2010). Therefore the use of such an index would be a natural progression of this study.

#### **6.4.4 Tests of the CAPM**

There is always a possibility that the results obtained by this study could be due to the fact that inappropriate tests of the model were employed. As discussed earlier in section 4.3.2.3, one of the assumptions made when using OLS to estimate linear regressions is that the dependant and independent variables are normally distributed and as a result the residuals of the regression are also normally distributed - known as the normality assumption (Brooks, 2008: 153). If this assumption is violated it is not easily resolved with OLS, however, the problem was assumed to be irrelevant in this study due to the formation of the pre-constructed portfolios. Despite this, another way in which the problem can be avoided is through the use of an estimation procedure such as Generalised Method of Moments (GMM). This estimation procedure does not require the specification of any distributional properties, and as a result can acceptably be used to estimate the CAPM or market model (Hall, 2005: 1-2). Jagannathan, Skoulakis and Wang (2002: 470) state that the GMM has become popular for this very reason. However, this method has not been employed on the CAPM in South Africa. Therefore employing such a method would improve the reliability of the results of any study when compared to using an OLS estimation.

#### **6.4.5 The Proxy for the Risk-Free Asset**

The results of this study, and in particular the results of the tests on the CAPM could be particularly susceptible to an incorrect specification of the risk-free rate proxy. Strydom and Charteris (2009) suggest that the most appropriate risk-free asset proxy in South Africa is the T-Bond, however the issue with the use of such a proxy is that it would be correlated to the ALBI as it contains government bonds. Despite this, the fact remains that the 3 month T-bill could be an inappropriate proxy for the risk-free asset, and thus could be a possible advancement of future studies.

### **6.5 Conclusion**

The primary objective of this study was to determine whether the addition of a bond index to the proxy for the market portfolio would enhance the use of the CAPM in South Africa. In answering such a question, the use of the ALSI as the proxy and the issue of market

segmentation on the JSE were also addressed. Despite the attempts of this study to improve the proxy, the results obtained call into question the CAPM as a whole. It was found that when using the ALSI as a proxy in both the CAPM and the market model, that both models predicted a downward sloping SML, i.e. an inverse relationship between risk and return. This finding is completely contrary to theory as it suggests that the less risk an investor takes the higher the return that will be obtained. Due to the nature of these results, a number of robustness tests were performed on this model, and despite the results improving, these tests did not solve the problems faced by the original model. As mentioned, in an attempt to enhance the market proxy and thus the CAPM, multifactor models which included, the ALSI and ALBI, the FINDI and RESI, and the ALBI, FINDI and RESI as proxies for the market portfolio were employed. None of these proposed models reversed the results of the first model as all suggested an inverse relationship between risk and return. On review of South African literature, it was found that these results were not unprecedented, as similar studies by Van Rensburg and Robertson (2003) and Strugnell *et al* (2011) had also obtained negative sloping SMLs. Thus on this evidence the CAPM appears to be an inappropriate model in the South African context.

Despite these results, the CAPM is still the most popular tool for estimating the cost of equity in South Africa, and is widely used throughout the world. Thus it is important to establish which of the models is best at explaining and forecasting returns. It was found that the two factor models, with the ALSI and ALBI, and the FINDI and RESI had the strongest explanatory powers, whilst the single factor CAPM with the ALSI as proxy was the strongest at forecasting. Suggesting that if the CAPM is to be employed, the decision as to which proxies should be used is not clear cut. Based on the fact that the majority of practitioners use the CAPM to forecast the cost of equity, it is recommended that the single factor with the ALSI is the best model to employ in practice. However due to the results produced by this study, it is not recommended that the CAPM is used in practice.

The recent survey conducted by PWC (2009: 26) suggests that practitioners are beginning to acknowledge the shortcomings of the CAPM. The equivalent surveys run in 2005 and 2007 found that all of the respondents of the survey, always or almost always used the CAPM to estimate the cost of equity. However, in 2009 the survey found that although the CAPM was still the most popular approach, practitioners are increasingly exploring alternative approaches – a step in the right direction. A recent study by Basiewicz and Auret (2010: 13) tested the feasibility of the Fama and French three factor model in explaining returns on the JSE, and came to the conclusion that it would be an appropriate model to use on the JSE. This finding



coincides with the results of the PWC (2009) survey, where the survey showed that of the “alternative approaches” being explored, the Fama and French three factor model was the most popular, and was growing in popularity. A growing body of evidence thus seems to question the validity of the CAPM in a South African context, a possible reason for this is if the market proxy is misspecified. This study set out to test if the performance of the CAPM could be enhanced by adding a bond index to the market portfolio. The results however were still not found to be in line with the theoretical relationship. The results of this study therefore indicate that adding a bond index does not significantly improve the results of the CAPM in South Africa.

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## APPENDICES

**Appendix A – Test results for autocorrelation in the Black, Jensen and Scholes (1972) time series regressions using the Breusch-Godfrey serial correlation LM test (both excess and total returns).**

### Excess Returns

Proxy:	ALSI		ALSI, ALBI		FINDI,RESI		ALBI,FINDI, RESI	
	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square
<b>Portfolio 1</b>	0.332165	0.316725	0.27722	0.259067	0.445046	0.415522	0.344758	0.314304
<b>Portfolio 2</b>	0.91963	0.904858	0.910056	0.8912	0.888139	0.866446	0.87216	0.844722
<b>Portfolio 3</b>	0.788321	0.763223	0.435754	0.406713	0.208611	0.196408	0.215588	0.196962
<b>Portfolio 4</b>	0.206875	0.200543	0.748346	0.715921	0.660041	0.625486	0.907219	0.884861
<b>Portfolio 5</b>	0.22259	0.215058	0.785117	0.754512	0.251497	0.235508	0.453755	0.416252
<b>Portfolio 6</b>	0.134197	0.13335	0.138599	0.140847	0.186175	0.17602	0.1288	0.119628
<b>Portfolio 7</b>	0.514083	0.489086	0.454984	0.424965	0.268094	0.250698	0.270168	0.246142
<b>Portfolio 8</b>	0.129432	0.128928	0.108861	0.105823	0.148574	0.141901	0.141356	0.130777
<b>Portfolio 9</b>	0.338229	0.322387	0.378385	0.352735	0.406208	0.378828	0.421444	0.385716
<b>Portfolio 10</b>	0.131627	0.130966	0.145715	0.147594	0.060401	0.061339	0.097465	0.097861

**Total Returns**

<b>Proxy:</b>	<b>ALSI</b>		<b>ALSI, ALBI</b>		<b>FINDI,RESI</b>		<b>ALBI,FINDI, RESI</b>	
	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>
<b>Portfolio 1</b>	0.337405	0.321617	0.277708	0.259514	0.449588	0.419836	0.348168	0.317449
<b>Portfolio 2</b>	0.915435	0.900156	0.910746	0.891986	0.886328	0.864418	0.870998	0.843409
<b>Portfolio 3</b>	0.800794	0.776283	0.435126	0.406119	0.217414	0.204418	0.215304	0.196707
<b>Portfolio 4</b>	0.2098	0.203244	0.737878	0.705042	0.651033	0.616418	0.909961	0.888049
<b>Portfolio 5</b>	0.221846	0.214371	0.770811	0.739426	0.246086	0.230563	0.446759	0.409616
<b>Portfolio 6</b>	0.145923	0.144218	0.13925	0.141467	0.195012	0.184046	0.131953	0.122428
<b>Portfolio 7</b>	0.513644	0.488662	0.458625	0.428431	0.26939	0.251886	0.272679	0.248418
<b>Portfolio 8</b>	0.150122	0.148105	0.130039	0.125079	0.170038	0.161373	0.164925	0.151726
<b>Portfolio 9</b>	0.358259	0.341124	0.390026	0.363633	0.423406	0.395037	0.433137	0.396734
<b>Portfolio 10</b>	0.1435	0.141973	0.151926	0.153432	0.067653	0.068061	0.082492	0.082469

**Appendix B – Summary test results for autocorrelation in the Fama and MacBeth (1973) and Pooled Regression time series regressions using the Breusch-Godfrey serial correlation LM test (selected regressions for excess returns).**

**ALSI as proxy**

Proxy:	ALSI									
	Jan 2000 - Dec 2002		Jan 2002 - Dec 2004		Jan 2004 - Dec 2006		Jan 2006 - Dec 2008		Jan 2008 - Dec 2010	
	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square
<b>Portfolio 1</b>	0.52821	0.430017	0.667012	0.55298	0.929609	0.861413	0.598434	0.490134	0.912104	0.834893
<b>Portfolio 2</b>	0.777692	0.665965	0.935059	0.870015	0.218569	0.197066	0.713862	0.598801	0.888626	0.801525
<b>Portfolio 3</b>	0.714333	0.599275	0.974308	0.938983	0.893341	0.80805	0.962004	0.915707	0.871516	0.778499
<b>Portfolio 4</b>	0.125953	0.149669	0.612909	0.503028	0.855047	0.757202	0.726686	0.61182	0.917469	0.842855
<b>Portfolio 5</b>	0.732341	0.617632	0.507408	0.412903	0.246977	0.217169	0.882123	0.792657	0.955694	0.904452
<b>Portfolio 6</b>	0.957564	0.907746	0.934542	0.86919	0.428523	0.350432	0.82405	0.719077	0.80606	0.697962
<b>Portfolio 7</b>	0.989447	0.97128	0.20923	0.190467	0.098406	0.110709	0.703107	0.588047	0.91703	0.842198
<b>Portfolio 8</b>	0.865054	0.770048	0.152265	0.150055	0.974272	0.938912	0.578308	0.472507	0.519496	0.422813
<b>Portfolio 9</b>	0.084991	0.100493	0.421376	0.344942	0.844153	0.74353	0.246238	0.216645	0.089879	0.063173
<b>Portfolio 10</b>	0.479742	0.390579	0.609773	0.500218	0.869068	0.775283	0.380009	0.313637	0.997605	0.992195

## ALSI, ALBI as Proxies

Proxy:	ALSI, ALBI									
	Jan 2000 - Dec 2002		Jan 2002 - Dec 2004		Jan 2004 - Dec 2006		Jan 2006 - Dec 2008		Jan 2008 - Dec 2010	
	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square
<b>Portfolio 1</b>	0.59743	0.458723	0.523038	0.395758	0.960509	0.90148	0.497104	0.374923	0.902025	0.800711
<b>Portfolio 2</b>	0.976993	0.936319	0.903539	0.803033	0.922831	0.833723	0.08417	0.087238	0.811189	0.677695
<b>Portfolio 3</b>	0.859488	0.73959	0.914909	0.820862	0.868636	0.752133	0.336154	0.255684	0.911973	0.816189
<b>Portfolio 4</b>	0.157947	0.136593	0.435684	0.327551	0.77543	0.635702	0.420951	0.31656	0.987518	0.961646
<b>Portfolio 5</b>	0.840386	0.7143	0.532256	0.403293	0.488355	0.368012	0.629823	0.488837	0.995881	0.985149
<b>Portfolio 6</b>	0.79414	0.657318	0.613782	0.473279	0.47216	0.355367	0.420612	0.316309	0.909509	0.812306
<b>Portfolio 7</b>	0.98608	0.957978	0.070759	0.077792	0.287417	0.222234	0.471977	0.355225	0.951627	0.884305
<b>Portfolio 8</b>	0.822847	0.692037	0.178813	0.150261	0.976056	0.934207	0.56582	0.431349	0.574359	0.438649
<b>Portfolio 9</b>	0.096023	0.095399	0.418247	0.314558	0.82159	0.690475	0.431964	0.324763	0.059702	0.069767
<b>Portfolio 10</b>	0.526205	0.398339	0.427228	0.321226	0.782468	0.643746	0.33237	0.253051	0.921002	0.83072

**FINDI, RESI as proxies**

Proxy:	FINDI, RESI									
	Jan 2000 - Dec 2002		Jan 2002 - Dec 2004		Jan 2004 - Dec 2006		Jan 2006 - Dec 2008		Jan 2008 - Dec 2010	
	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square
<b>Portfolio 1</b>	0.669802	0.525424	0.882174	0.771261	0.922016	0.832382	0.852874	0.730702	0.9076	0.80932
<b>Portfolio 2</b>	0.948752	0.878932	0.582512	0.445683	0.891358	0.784664	0.353365	0.267741	0.86798	0.751223
<b>Portfolio 3</b>	0.686467	0.541688	0.671222	0.526796	0.606058	0.466368	0.920846	0.830465	0.911923	0.816109
<b>Portfolio 4</b>	0.375436	0.283413	0.557637	0.424416	0.321403	0.245457	0.311636	0.238736	0.969889	0.920744
<b>Portfolio 5</b>	0.860475	0.74093	0.142845	0.126672	0.184203	0.15379	0.836478	0.709264	0.90515	0.805516
<b>Portfolio 6</b>	0.953599	0.88804	0.97271	0.926812	0.424475	0.319177	0.84511	0.720449	0.576435	0.440433
<b>Portfolio 7</b>	0.990202	0.968731	0.237011	0.188514	0.366612	0.277118	0.382294	0.288334	0.944744	0.871577
<b>Portfolio 8</b>	0.769916	0.62947	0.185253	0.154477	0.975575	0.933129	0.942636	0.867768	0.808177	0.674046
<b>Portfolio 9</b>	0.133776	0.12069	0.46691	0.351308	0.149083	0.130775	0.547662	0.416047	0.44066	0.331294
<b>Portfolio 10</b>	0.419085	0.315178	0.497959	0.375602	0.883422	0.773062	0.147047	0.129437	0.889942	0.782574

## ALBI, FINDI and RESI as proxies

Proxy:	ALBI, FINDI, RESI									
	Jan 2000 - Dec 2002		Jan 2002 - Dec 2004		Jan 2004 - Dec 2006		Jan 2006 - Dec 2008		Jan 2008 - Dec 2010	
	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square	Prob. F	Prob. Chi-Square
<b>Portfolio 1</b>	0.833929	0.678781	0.679672	0.50335	0.970521	0.911076	0.868727	0.727385	0.939242	0.844683
<b>Portfolio 2</b>	0.997639	0.989175	0.923891	0.816237	0.980242	0.935353	0.404708	0.276942	0.829407	0.672785
<b>Portfolio 3</b>	0.782235	0.613882	0.85579	0.708771	0.513149	0.357307	0.940554	0.847215	0.836455	0.682159
<b>Portfolio 4</b>	0.292301	0.202078	0.49603	0.34398	0.644464	0.469588	0.537382	0.376637	0.97431	0.920249
<b>Portfolio 5</b>	0.834869	0.680035	0.071806	0.074784	0.334926	0.229625	0.80196	0.637757	0.889327	0.75857
<b>Portfolio 6</b>	0.809816	0.647556	0.777038	0.607755	0.631522	0.457617	0.876261	0.738555	0.643169	0.46838
<b>Portfolio 7</b>	0.990255	0.963751	0.081729	0.073957	0.472742	0.32626	0.412466	0.282395	0.909374	0.791077
<b>Portfolio 8</b>	0.781565	0.613089	0.206237	0.148855	0.982088	0.940273	0.948316	0.862585	0.808072	0.645366
<b>Portfolio 9</b>	0.065913	0.067508	0.646762	0.471737	0.143352	0.111201	0.526221	0.367665	0.468868	0.323356
<b>Portfolio 10</b>	0.411619	0.281798	0.46272	0.318772	0.781292	0.612766	0.167214	0.125437	0.846257	0.695479

**Appendix C – Test results for heteroscedasticity using the White heteroscedasticity test in the Black, Jensen and Scholes (1972) cross section regressions (both excess and total returns).**

**Excess Returns**

	<b>Heteroscedasticity Test: White Test</b>	
<b>Proxy:</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>
<b>ALSI</b>	0.382959	0.301424
<b>ALSI, ALBI</b>	0.303926	0.228536
<b>FINDI, RESI</b>	0.387678	0.280661
<b>ALBI, FINDI RESI</b>	0.580496	0.374296

**Total Returns**

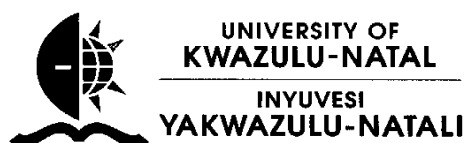
	<b>Heteroskedasticity Test: White Test</b>	
<b>Proxy:</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>
<b>ALSI</b>	0.380053	0.298944
<b>ALSI, ALBI</b>	0.23005	0.186387
<b>FINDI, RESI</b>	0.380015	0.275668
<b>ALBI, FINDI RESI</b>	0.531064	0.344534



**Appendix D – Summary test results for heteroscedasticity using the White heteroscedasticity test in the Fama and MacBeth (1973) cross section regressions (for excess returns of various proxies).**

	<b>Heteroscedasticity Test: White Test</b>									
<b>Date:</b>	<b>Dec-02</b>		<b>Dec-04</b>		<b>Dec-06</b>		<b>Dec-08</b>		<b>Dec-10</b>	
<b>Proxy:</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>	<b>Prob. F</b>	<b>Prob. Chi-Square</b>
<b>ALSI</b>	0.849235	0.796053	0.603195	0.510464	0.844962	0.790601	0.584838	0.491409	0.936442	0.911251
<b>ALSI, ALBI</b>	0.350451	0.256844	0.287905	0.219126	0.423305	0.304537	0.516913	0.373092	0.372863	0.27105
<b>FINDI, RESI</b>	0.346417	0.254328	0.461485	0.331417	0.979624	0.950389	0.535172	0.387574	0.962978	0.914768
<b>ALBI, FINDI RESI</b>	0.192418	0.197292	0.50885	0.332117	0.964455	0.853917	0.82691	0.59455	0.780893	0.539908

## Appendix E – Ethical Clearance



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26 May 2011

**Mr DC Baines (206506888)**  
School of Economics and Finance  
Faculty of Management Studies  
Pietermaritzburg Campus

Dear Mr Baines

**PROTOCOL REFERENCE NUMBER: HSS/0263/011M**

**PROJECT TITLE: The Impact of Incorporating a Bond Index into the Proxy for the Market Portfolio**

In response to your application dated 23 May 2011, the Humanities & Social Sciences Research Ethics Committee has considered the abovementioned application and the protocol has been granted **FULL APPROVAL**.

**Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.**

**PLEASE NOTE: Research data should be securely stored in the school/department for a period of 5 years.**

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

.....  
**Professor Steven Collings (Chair)**  
**HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS COMMITTEE**

cc. Supervisors: Mr B Strydom & Mr A Christison

cc. Prof D Vigar-Ellis: Post Graduate Centre, School of Management Studies



Founding Campuses: ■ Edgewood ■ Howard College ■ Medical School ■ Pietermaritzburg ■ Westville