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FINANCE DIVISION,
SCHOOL OF ECONOMIC AND BUSINESS SCIENCES
FACULTY OF COMMERCE, LAW AND MANAGEMENT

Master's Research

(50% weighting)

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Definitions of Key Terms & Abbreviations

ALSI: The JSE All Share Index, which is used as the market proxy in this study. The FTSE/JSE All Share Index includes the top 99% of eligible listed companies ranked by full market capitalisation.

BTM: The book value of equity divided by the corresponding market capitalisation.

B - S: Buy minus Sell: the buy portfolio is made up of the portfolio which theory and prior evidence suggests should earn a higher rate of return.

Beta: The sensitivity of a share to changes in the market (proxied by the J203T) portfolio.

CAPI: FTSE/JSE Capped Index, The CAPI index represents all the companies in the ALSI but capped at a maximum of 10% exposure to any one company.

CAPM: The Capital Asset Pricing Model

EGARCH: The exponential GARCH (EGARCH) model is a GARCH variant that models the logarithm of the conditional variance process.

E/P Ratio: Earnings to Price Ratio

Equally Weighted Portfolio: A portfolio where the same weight or importance is given to each share in that portfolio or index fund.

Ex-ante: Phrase meaning "before the event", ex-ante is used most commonly in financial terms where results of a particular action, or series of actions, are forecast in advance i.e. returns in an investment portfolio.

Excess return: The return over and above the risk free rate (proxied by the 3 month Treasury Bill).

FF3: The Fama and French Three Factor Model.

Global financial crisis (GFC): The combined period encompassing the sub-prime mortgage crisis, the liquidity crisis, as well as the European sovereign debt crisis.

HML: The returns of high B/M quintile minus the low B/M quintile.

Idiosyncratic Risk (IdR): Risk that is specific to an asset or a small group of assets also known as unsystematic risk or non-diversifiable risk.

Information Ratio: A ratio of portfolio returns above the returns of a benchmark (usually an index) to the volatility of those returns.

Net International Equity Flows (NIEF): The net purchases of shares of a non-resident on the JSE.

JSE: The Johannesburg Stock Exchange

J203T: The JSE All Share total returns index

Low Beta Anomaly: The Low Beta Anomaly presumes that portfolios of low beta shares have produced higher risk-adjusted returns than portfolios with high beta shares in most markets studied.

Market capitalisation (size): The market price per share multiplied by the number of shares outstanding.

Market Cap Weighted Portfolio: A portfolio where individual components are weighted according to their market capitalisation so that larger components carry a larger percentage weighting.

Market Concentration: Degree to which a relatively small number of firms account for a relatively large percentage of the market

MPT: Modern Portfolio Theory

OLS: Ordinary Least Squares which is a method for estimating the unknown parameters in a linear regression model.

P-value: The probability of committing a Type-1 error, or the probability that the relationship that has been estimated does not exist.

Pre-ranking: Using only historical data to group shares.

Sharpe ratio: The excess return divided by the standard deviation.

SMB: The returns of the small market capitalisation quintile minus the returns of the big market capitalisation quintile.

SWIX: FTSE/JSE Shareholder Weighted Index, the SWIX is similar to the ALSI but excludes the foreign shareholding of listed companies.

Thin Trading: When shares are not traded frequently on a stock exchange.

Tracking Error: A deviation between the price behaviour of a position or a portfolio and the price behaviour of a benchmark.

ZDT: The number of zero daily trades over a particular period.

An Investigation of the Low Beta Anomaly on the JSE

Abstract

This study aims to investigate the presence of the low market risk (beta) anomaly in the Johannesburg Stock Market (JSE). Finance theory suggests that with higher return comes higher risk. However, several studies have reported evidence of low risk anomaly in global markets where portfolios containing low beta shares delivers superior risk adjusted returns compared to market index and high beta shares' portfolio. This study will explore various risk return relationships on the JSE and test a variety of potential explanations of the anomalous behaviour of the low beta premium. Three explanations have been identified as potential factors that contribute to the persistence of the Low Beta Anomaly. These include; Net International Equity flows (NIEF), Idiosyncratic Risk and Market Concentration. The results are consistent with international literature indicating a persistent Low Beta Anomaly on the JSE. However, the results also indicate that in periods of turmoil, high beta shares outperform low beta shares i.e. during the Global Financial Crisis. Although some significant relationships are found between the low minus high beta differential and NIEF. NIEF is unable to suitably explain the anomaly. Idiosyncratic risk results are mixed depending on the model used to calculate the idiosyncratic risk estimates. Despite being a significant issue on the JSE, Market concentration does not explain the Low Beta Anomaly. As the superior performance of the low beta portfolios remains once the portfolios returns have been adjusted for the different variables however magnitude of the outperformance of the low beta portfolio was to a lesser degree.

Table of Contents

1. Introduction 12

1.1 Problem Statement 14

2. Literature Review 14

2.1 Capital Asset Pricing Model (CAPM) 14

2.2 Low Beta Share Anomaly 17

2.2.1 Presence of the Low Beta Anomaly – International Evidence 17

2.2.2 Presence of the Low Beta Anomaly – South African Context 20

2.2.3 Explanations of the Low Beta Anomaly 21

2.3 International Equity Flows 26

2.4 Idiosyncratic Risk 27

2.4.1 Studies Finding a Negative Relation between Idiosyncratic Risk and Expected Returns 27

2.4.2 Studies Finding a Positive Relation between Idiosyncratic Risk and Expected Returns 28

2.4.3 Studies Finding No Relation between Idiosyncratic Risk and Expected Returns 28

2.5 Market Concentration 29

3. Methodology 33

3.1 Introduction 33

3.2 Data 33

3.3 Model Construction 35

3.3.1 The Capital Asset Pricing Model (CAPM) 35

3.3.2 The Fama and French Three Factor Model (FF3) 35

3.4 Variables 36

3.4.1 Excess Return 36

3.4.2 Pre-Ranking Market Beta (β_m) *36*

3.4.3 SMB, HML, β_{SMB} and β_{HML} *38*

3.4.4 Net International Equity Flows (NIEF) *38*

3.4.5 Idiosyncratic Risk *39*

3.4.6 Alternative Equity Market Benchmarks *41*

3.5 Constructing Portfolios 41

3.5.1 Portfolio Formation *41*

3.5.2 Transaction Costs: *43*

3.6 Model Analysis 43

3.6.1 Low Beta Anomaly Analysis *43*

3.6.2 Net International Equity Flow Analysis *44*

3.6.3 Idiosyncratic Risk Analysis *45*

3.6.4 Benchmark Analysis (Market Concentration) *45*

3.7 Limitations 47

4. Results 48

4.1 Low Beta Anomaly Analysis 48

4.2 Net International Equity Flows 56

4.3 Idiosyncratic Risk 60

4.3.1 Idiosyncratic Risk Portfolio Performance *60*

4.3.2 Low Beta Anomaly Analysis *62*

4.4 Market Concentration / Alternative Benchmarks 69

4.4.1 Top 5 Constituents *69*

4.4.2 Performance of the Indices *71*

4.4.3 Low Beta Anomaly Analysis *72*

5. Conclusion 79

6. References 82

List of Tables

Table 1: Annualised Returns by beta-sorted quintile equal weighted portfolios (January 1997 – November 2014) 48

Table 2: Annualised Returns by beta-sorted quintile equal weighted portfolios – CAPM Analysis (January 1997 – November 2014) 50

Table 3: Annualised Returns by beta-sorted quintile equal weighted portfolios – Fama and French 3 Factor Model Analysis (January 1997 – November 2014) 50

Table 4: Regression Results – LMH against NIEF (Actual) and NIEF residuals 57

Table 5: Regression Results: Market Portfolio excess Returns against NIEF (actual) and NIEF Residuals 59

Table 6: Annualised Returns of Beta Quintiles (adjusted for NIEF residuals), 1997 - 2014 59

Table 7: Summary of Results for Beta Quintiles Adjusted for CAPM Idiosyncratic Risk Returns, 1997-2014 64

Table 8: Summary of Results for Beta Quintiles Adjusted for CAPM Idiosyncratic Risk Returns - Risk Model Analysis, 1997-2014 66

Table 9: Summary of Results for Beta Quintiles Adjusted for FF3 Factor Model Idiosyncratic Risk Returns, 1997-2014 67

Table 10: Summary of Results for Beta Quintiles Adjusted for FF3 Factor Model Idiosyncratic Risk Returns- Risk Model Analysis, 1997-2014 68

Table 11: Top 5 Constituents of the ALSI (J203), December 2014 69

Table 12: Top 10 Constituents SWIX, December 2014 70

Table 13: Top 10 Constituents CAPI (All share), November 2014 70

Table 14: Annualised Returns by Beta-Sorted Quintile, ALSI 2007-2014 73

Table 15: Annualised Returns by Beta – Sorted Quintiles, SWIX Index, 2007-2014 74

Table 16: Annualised Returns by Beta-Sorted Quintile, CAPI Index 2007-2014 75

Table 17: Annualised Returns by Pre Ranking Beta-Sorted Quintile for EWMP, 2007-2014 .. 75

List of Figures

Figure 1: Option like Manager Compensation 26

Figure 2: Sharpe Ratio (Annualised) by Quintiles of Beta, 1997-2014 49

Figure 3: CAPM Alphas of Beta Quintiles, (1997-2014) 50

Figure 4: Pre-Ranking Beta Sorted Quintiles and Market Portfolio - Cumulative Returns..... 51

Figure 5: Low and High Pre-Ranking Beta Sorted Portfolios - Cumulative Returns during the Period, 1997 - 2014 53

Figure 6: Cumulative Returns of the Pre-Ranking Beta Portfolios during the Period, 1997 – 2007 54

Figure 7: Cumulative Returns of the Pre-Ranking Beta Portfolios during the Period, 2008 -2011 54

Figure 8: Cumulative Returns of the Pre Ranking Beta Portfolios during the Period, 2012 -2014 54

Figure 9: Cumulative Returns of Pre Ranking Beta Quintiles Adjusted for Size, 1997-2014... 55

Figure 10: Cumulative Returns Value Adjusted, 1997-2014 55

Figure 11: Low minus High Beta Return Series (Differential), 1997 – 2014 56

Figure 12: Foreign investors net purchases of JSE shares and the cumulative difference in average return between the high and low beta portfolios, 1997-2014 57

Figure 13: Cumulative Returns of Idiosyncratic Risk Quintiles Calculated Using the CAPM, 1997-2014 60

Figure 14: Cumulative Returns for Idiosyncratic Risk Quintiles calculated using the 3FF, 1997-2014 61

Figure 15: Cumulative Returns for Idiosyncratic Risk Quintiles calculated using the 3FF (All 5 portfolios), 1997-2014 62

Figure 16: Cumulative Returns of Beta Quintiles Adjusted for CAPM Idiosyncratic Risk Returns, 1997-2014 63

Figure 17: Cumulative Returns of Beta Quintiles Adjusted for FF3 Factor Model Idiosyncratic Risk, 1997-2014 67

Figure 18: Cumulative Excess Returns ALSI, SWIX and CAPI Indices and the EWMP, 2004-2014 71

Figure 19: Return Series of the ALSI and EWMP for the period 2004-2014 72

Figure 20: Cumulative Returns for All Share Index, 2007-2014 76

Figure 21: Cumulative Returns for SWIX Index, 2007 – 2014 77

Figure 22: Cumulative Return for CAPI Index, 2007 - 2014 77

Figure 23: Cumulative Return for EWMP, 2007 - 2014 78

1. Introduction

The positive relationship between market risk and expected return is one of the underlying principles of financial theory that has resulted due to the proposition of the Capital Asset Pricing Model (CAPM), presented by Sharpe (1964), Lintner (1965), Mossin (1966) and Treynor (1965). Since its inception, CAPM has been greatly criticised in both theoretical and empirical terms. Nonetheless, CAPM is the most commonly used asset pricing model (Levy, 2012). The linear relationship between a share's expected return and its market beta suggests that investors are compensated for taking non-diversifiable risk. If this relation holds, the riskier the shares are in relation to the market portfolio, the higher the expected return.

However, a discrepancy exists between theoretical predictions and the empirical studies regarding the risk-return relationship. Black, Jensen, & Scholes (1972) and Miller & Scholes, (1972) discovered that the security market line for US shares was flatter than predicted by the CAPM. Haugen and Heins (1972) was the first paper to suggest that the relationship was not merely flat but inverted. The seminal paper by Fama and French (1992) extended the analysis of Haugen and Heins (1972) and found that, after adjusting for size effects, the relation between CAPM beta and return is flat over the period from 1963 to 1990. Recently this anomaly has been found across international markets in papers such as Blitz & van Vliet (2007), Frazzini & Pederson (2014); Baker, Bradley, & Wurgler (2011) and Baker and Haugen (1996, 2010, 2012). This finding holds true in South Africa, as several papers including Van Rensburg and Robertson (2003a), Strugnell, Gilbert and Kruger (2011) and McClelland (2013) examined the relationship between market beta and share returns and have also found that an inverse relationship between beta and returns exists on the JSE. McClelland (2013) found that low beta shares significantly outperformed high beta shares, even when size, value and liquidity were taken into account. Baker *et al.* (2011) suggested that this anomaly is potentially the greatest financial anomaly in capital markets.

This study will explore various risk return relationships on the JSE and test a variety of potential explanations of the anomalous behaviour of the low beta premium. Although this anomaly has been thoroughly researched across the world's markets, there is no consensus as to the reason why the phenomenon exits. Various explanations have been suggested and can be broadly grouped into those based on behavioural demand and those based on limits

to arbitrage. This research aims to add to the literature by examining the persistence of the Low Beta Anomaly and exploring three potential explanations for this anomaly. This research seeks to determine whether these three potential explanations have a significant relationship with the Low Beta Anomaly on the JSE. Firstly, the potential causal link between net international equity flows and the Low Beta Anomaly is investigated. Secondly, this research will determine whether investors in fact do require additional compensation for idiosyncratic risk as they are unable to costlessly fully diversify their portfolios. Lastly, Kruger and Van Rensburg (2008) found that market concentration on the JSE had a major effect on benchmarks and the valuation of shares. Through the use of alternative equity benchmarks as proxies for the market portfolio, it is investigated whether the anomaly still exists. It is important to note that this study is not exhaustive and primarily aims to determine the significance of the identified explanations. Numerous other reasons have been studied within the academic literature and many other explanations of the Low Beta Anomaly may exist.

The paper is structured into five sections. Following the introduction, the second section presents a review on the relevant existing literature on CAPM, Low Beta Anomaly, Idiosyncratic Risk, International Trade flows and Market Concentration. Section three describes the methodology and data used to complete the empirical analysis. In section four, the results of the analysis and their possible implications are discussed. Finally, Section five presents the conclusions of this research generated by a consolidated view of the results and the existing literature.

1.1 Problem Statement

This study aims to investigate the presence of the low market risk (beta) anomaly in the Johannesburg Stock Exchange (JSE). This study will explore various risk return relationships on the JSE and test a variety of potential explanations of the anomalous behaviour of the low beta premium. Three explanations have been identified as potential factors that contribute to the persistence of the Low Beta Anomaly. These include Net International Equity flows (NIEF), Idiosyncratic Risk and Market Concentration.

2. Literature Review

2.1 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model, attributed to Sharpe (1964) Lintner (1965), Mossin (1966) and Treynor (1965) is an ex-ante static, one period asset pricing model. The model is premised on the fundamental relationship between systematic risk and share returns (Fama & French, 1992). The CAPM draws on the portfolio theory as developed by Markowitz (1959), where investors are assumed to be risk averse, profit maximising agents that operate in a frictionless market environment, free from taxes. Therefore, investors are expected to choose portfolios based on the mean and variance of their one period investment return.

It has been well documented that total risk consists of two components when evaluating the volatility of an individual share; systematic risk and idiosyncratic risk. Systematic risk (beta) is simply the variability that is derived from exposure to non-diversifiable risk factors. These can be macro-economic factors like interest rates or, if the CAPM holds true, they can be fully captured by the sensitivity to market movements. The second risk is unsystematic risk, also known as idiosyncratic, it is the risk specific to individuals' shares. Modern Portfolio Theory (MPT) indicates that the relevant risk of a share is the risk added by the individual share to the investor's portfolio i.e. systematic risk (Simon, Zani, Morias & Costa, 2013). Whereby in an efficient market, idiosyncratic risk can be eliminated through holding a diversified portfolio and therefore is not relevant when pricing individual shares.

The CAPM equation is presented as follows:

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f], \quad (1)$$

And Beta as:

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}, \quad (2)$$

where $E(r_i)$ is the expected return on the share, r_f is the risk-free rate, β_i is the beta coefficient representative of a share's systematic risk, $E(r_m)$ is the expected market return, and $[E(r_m) - r_f]$ is the market premium - the difference between the expected market return and the risk-free rate. Beta is the covariance of the returns of a particular share with the market, divided by the variance of the market portfolio. The CAPM assumes a linear relationship between the risky asset's expected excess returns and its beta. Beta is the systematic risk which captures the cross section of average returns. Therefore suggesting that beta captures all systematic risks, making it the only risk necessary to describe return. The relationship implies that assets can only earn a high average return if they have a high beta.

Since its proposition, the CAPM has been the subject of much criticism. Literature has revealed three dominant tests of the CAPM specifically regarding the relationship between expected return and beta (Fama & French, 2004). The first aspect tests whether cross-sectional and time series regression, are able to accurately reflect the risk free rate as the intercept term and the excess return of the market over the risk free rate as the slope. The second aspect of the CAPM that is often tested, is whether the assumption that beta is the only risk factor that can explain the actual return on an investment holds true. Suggesting that the expected returns on all assets are fairly close to the actual return generated as well as whether any other measure can describe returns once Beta is accounted for. The final aspect of CAPM that is usually examined is whether the beta premium is always positive, whereby the risky asset should always have a return that is higher that the risk free rate. This research focuses on the last test of CAPM.

Extensive research on CAPM has resulted in the identification of additional variables / factors that provide explanatory power other than the beta for average share returns. Fama and French (1993, 1996) referred to these additional variables as anomalies. Fama and French (2004) provide a summary of the various empirical studies testing the CAPM, mostly with negative results regarding the explanatory power of share's betas in explaining share returns. Basu (1983) finds that the earnings-prices ratio (E/P) helps to explain the cross-section of US shares whereby high E/P shares experienced on average higher risk adjusted returns

compared to low E/P shares. Banz (1984) identifies that smaller companies have higher risk adjusted returns, on average, than larger firms. Bhandari (1988) identifies a positive relationship between leverage and the cross-section of average returns. Rosenberg, Reid and Lanstien (1985) find a positive relationship between average return and the ratio of a firm's book-to-market equity. Fama and French (1992) through cross-section regressions conclude that factors such as size and earnings-to-price ratio, debt-to-equity ratio and book-to-market ratio substantially increase the explanatory power of the model. The Low Beta Anomaly is just one of many anomalies identified within the asset pricing literature.

South African studies on the CAPM have produced similar results to the US and other international markets. There has been research on identifying additional individual factors that may better predict the return that an investor will obtain by investing shares. These include: Van Rensburg and Robertson, (2003a), Basiewicz and Auret (2009), and Hoffman (2012). Whilst other research has focused on the actual asset pricing model and the theory behind the assumptions etc. such as Ward and Muller (2012).

On the other hand, studies such as Black (1972), Chen, Roll and Ross (1986) or Campbell, Giglio, Polk and Turley (2012) and Merton (1973) argue that CAPM still has a place in financial practice and can arguably be salvaged. Although these studies are motivated by the observation that the basic CAPM does not work, they argue that this can be resolved by extending the model, without the need to abandon the fundamental notion of a positive risk–return relation.

Black (1972) developed another version of CAPM called the zero-beta CAPM, where it is not assumed that a risk free asset exists. Black's findings show that the model fits the data better. Similarly, the model presumes that there is higher return for higher beta. Merton (1973) introduced the ICAPM, whereby investors are not only concerned with the return on a portfolio at the end of the period, but also the opportunities that will be available for them to invest the return. The ICAPM assumes that an investor will be interested in how their wealth varies with certain state variables, including earnings from labour activities, inflation and investment opportunities. Therefore, the optimal investment portfolio is multifactor efficient and other variables are required over and above the market beta in order to explain expected returns (Merton, 1973).

Consolidated views regarding the CAPM seem to suggest that the model is flawed and is unable to accurately estimate a cost of equity that reliably reflects the return that can be expected by an investor. However, Levy (2012) suggests that the CAPM and its alpha and beta coefficients are still the financial measures most widely used by academic researchers and are even more heavily adopted by investment and corporate finance practitioners. Similarly, a survey conducted by Graham and Harvey (2001) with CFOs of US and Canadian companies indicated that 73.5 % of respondents always or almost always use the CAPM.

This research focuses on the fundamental relationship between market risk (beta) and return, which CAPM predicts to be linear. The next section will provide an overview on the existing literature regarding this relationship.

2.2 Low Beta Share Anomaly

The literature regarding the low risk effect can be divided in terms of the type of risk measurement. The types of risk include; a total risk measure in terms of volatility, market risk (beta) and the unsystematic risk (idiosyncratic risk, which traditional finance suggests to be diversified away in an efficient market). This research focuses on the "Low Beta Anomaly" however, some of the literature regarding the total variance and idiosyncratic risk has been summarised. The anomaly is investigated within the framework of the CAPM, as these limitations of risk only work in a CAPM framework.

2.2.1 Presence of the Low Beta Anomaly - International Evidence

The recognition of the low-beta anomaly dates back to Black (1972) and Black, Jensen, and Scholes (1972). For the period between 1931 and 1965, Black (1993) reports that the study conducted by Black *et al.* (1972) showed that low-beta shares in the US performed better than predicted by the CAPM model, while high-beta shares performed worse than expected. Black (1972) highlights that if investors wish to take on more risk than the market, they can leverage up the market portfolio. However if leverage is unavailable or costly, they may decide to buy high risk (high beta) shares instead, leaving low beta shares undersubscribed and under-priced. Black expressed this concept by stating that the CAPM line should appear flatter under conditions of restricted leverage than it would be otherwise (Black *et al.* 1972). Haugen and Heins (1975) found the relationship between risk and return to not merely be flatter than predicted by the CAPM, but in their sample period it was found to be negative.

The Low Beta Anomaly has attracted a vast amount of attention. The majority of the findings contradict CAPM's underlying principle.

Fama and French (1992) popularised the idea that value shares and small cap shares generate out-sized returns, which has become known as the size and value effects. What is less well-known is that their research also found that shares with low beta tend to outperform high beta stocks (Fama & French 1992):

"...funds that concentrate on low beta stocks, small stocks, or value stocks will tend to produce positive risk adjusted returns ...even when the fund managers have no special talent for picking winners."

Through their assessment of the US, European and Japanese markets, Blitz and van Vliet (2007) present evidence of more significant positive risk adjusted returns in shares with low volatility. They found this to be true even against the FTSE World Development Index. They provide a detailed analysis of the volatility anomaly and demonstrate the robustness of their findings even after size, value and momentum effects have been taken into account. Another important finding of this research is that shares with high volatility exhibited high betas and similarly, low volatility shares exhibit low betas. Therefore suggesting that using beta or variance as a measure of volatility should produce a similar impact on the portfolio's return and risk profile. Blitz and Van Vliet (2007), similar to Black (1972), believes that the low volatility performance is due to restricted borrowing and behavioural biases such as the "preference for lotteries".

Chouefaty and Coignard (2008) proposed that using the maximization of the diversification ratio as a way to achieve superior risk-adjusted return over that of the market cap-weighted benchmark. The diversification ratio is the weighted average of the shares volatility divided by the portfolios volatility. They observed that the minimum variance and the maximum diversification portfolios outperformed the market cap indices with lower volatility.

Ang, Hodrick, Xing and Zhang (2009) analysed 23 markets of the MSCI Developed Country Index during the period of 1980 to 2003. The authors used Fama and French's (1993) three Factor Model to measure idiosyncratic volatility. They found that within the countries investigated, shares that had previously high idiosyncratic volatility tended to significantly

offer lower returns in comparison with low idiosyncratic volatility. They concluded that the anomaly with better performing low idiosyncratic shares was a global phenomenon.

Baker *et al.* (2011) research data of all US listed shares for January 1968 to December 2008. They sort shares into five groups for each month according to five-year trailing beta (or at least 24 months trailing beta if the history of data is less than 60 months), and track the returns on these portfolios. They then repeat the task and calculate the cumulative returns of each group. The authors illustrate that no matter how risk is defined (i.e. beta or volatility) or whether they look at all shares or only large cap shares, low risk portfolios consistently outperform high risk portfolios in the long-term. Their results, similar to other studies, suggest that the low beta and volatility quintiles outperformed the high beta / volatility quintiles. The authors' initial results indicate that a dollar invested in the lowest beta portfolio grew to $60.4. Once inflation was accounted for, the real return value was $10.28. A dollar invested in the highest beta portfolio grew to $3.77, with the inflation adjusted value of 64 cents. Therefore underperforming the low beta portfolio by 964%. Baker *et al.* (2011) uses behavioural finance and institutional benchmarking limitation as the main explanation for the anomaly. Thus attributing the superior returns of the low risk to investors' preference for positive skewness or lottery payoffs with high volatility shares and the institutional limitations on using leverage (similar to Black, 1972).

Frazzini and Pederson (2014) in their paper find empirical evidence that portfolios with high beta assets have lower alphas and smaller Sharpe ratios than those of low-beta share portfolios; both for shares traded in the US market and in international markets. The authors find that the security market line is flatter than predicted by the CAPM model in the U.S. market and in eighteen of the nineteen international markets tested. The authors argue that this is due to funding constraints and margin requirements faced by investors, who are then unable to invest in the portfolio with the highest expected excess return per unit of risk and then leverage their portfolio to match their risk preferences. The authors believe that this deviation from the CAPM model can be captured by investors using portfolios with Betting Against Beta Factors – BAB. These portfolios can be constructed through selling high-beta assets and using leverage in order to invest in low-beta assets (Frazzini & Pedersen, 2014).

Baker and Haugen (2012) analyse 33 different markets over the period 1990 – 2011. They find that low risk shares had better performance than high risk shares in all the markets. They

attribute the persistence of the low volatility effect in global markets to the fund manager's preference for high volatility shares as they have a better and more attractive compensation structure.

Goldberg and Mohmoud (2013) observe three risk-only investment strategies including minimum variance, risk parity and low beta, over four asset classes (Equity, Treasury Bonds, US Investment Grade Corporate Bonds and Commodities). They find that all three risk-only strategies outperformed an equally weighted strategy over the period of 1988-2010.

Among others: Haugen and Baker (1991, 1996, 2010); Pettengill, Sundaram, and Mathur (1995) Clarke, de Silva and Thorley (2010); Poullaouec (2010) found further evidence supporting the persistence of the low risk anomaly in the US market. Blitz, Pang and Van Vliet (2012) studied the Low Beta Anomaly within developing markets. Baker, Bradley and Taliaferro (2013) studied the outperformance of low beta shares through a decompositions using micro and macro effect.

2.2.2 Presence of the Low Beta Anomaly – South African Context

Regarding the specific analysis of the South African market, Van Rensburg and Robertson (2003a) find numerous effects similar to international literature such as the inverse relationship between size and return as well as between the PE ratio and return. The authors interestingly also discover an inverse relationship between beta and return. They attribute this anomaly to the fact that the shares are thinly traded on the JSE. Over the 10 year period, the low beta quintile outperforms the highest beta quintile by 0.9% using one month holding periods.

Strugnel, Gilbert and Kruger (2011) confirm the inverse beta-return findings of Van Rensburg and Robertson (2003a), amongst other findings including a valid size and value effect. To check for the thin trading explanation of the Low Beta Anomaly, Strugnel *et al.* (2011) test various measures of beta including traditional OLS beta, Scholes and Williams's beta and the Dimson Aggregate coefficients. The statistical significance of the better performing low beta quintile remains when using the Dimson model as well as the Scholes and Williams beta. The authors conclude that beta is irrelevant with regard to return generation on the JSE and their results provided no support for the positive relationship between risk and return suggested by finance theory.

Ward and Muller (2012) study the relationship between beta and returns on the JSE over the period 1985 to 2011. The authors estimate betas for each company listed on the All Share Index (ALSI) from which five separate portfolios are formed. The cumulative returns of these portfolios are compared over the time period and a price-relative is constructed. The authors notice that the lowest-ranked beta portfolio exhibited the highest per annum return for the period, whilst the graphing of the price-relative shows a negative relation between beta and returns over 1986-2004, and no relationship from 2005-2011. The authors conclude overall that an inverse relationship between beta and returns exists on the JSE.

2.2.3 Explanations of the Low Beta Anomaly

Recent papers have focused on explanations of the low-beta anomaly. These explanations can be broadly grouped into those based on behavioural demand and those based on limits to arbitrage. Jay Ritter, a forefather of behavioural finance, suggests that market inefficiency depends on two conditions being met at the same time:

1) A degree of investor irrationality (which speaks to behavioural demand theories)

2) Arbitrage being limited

Analysing the first condition, Baker *et al.* (2011) believe that in the context of the low risk anomaly, the preference for lotteries, biases of representativeness and overconfidence leads to an increased demand for higher volatility shares relative to the lower volatility shares. The second condition is 'limits to arbitrage' which is thought to explain why "smart money" does not off set the price impact of irrational demand (Baker *et al.* 2011).

a) Behavioural Demand Theories

i) Preference for lotteries

The following example illustrates the theory behind the "preference for lotteries". There are two gambling options. Where it costs R100 to play; Option 1, 50% chance of losing R100 versus 50% chance of winning R110. Option 2, there is a 98.8% chance of losing R1 and a small (0.12%) chance of winning R5000. Both options have an expected payoff of R5. However, the majority of people would take the second option. The reason why most people would take Option 2 is due to positive skewness and not volatility. Barberis and Huang (2008) use Tversky and Kahneman (1992) prospect theory to illustrate that a share's skewness can be seen as an additional factor. In the behavioural framework of Tversky and Kahneman (1992), they

suggest that a positively skewed share may appear to be overpriced and earn a negative excess return. This is thought to explain the preference of lotteries, as a small chance of a large win combined with a large change of a small loss is a typical example of a payoff with positive skewness. Mitton and Vorkink (2007) pointed out that volatile individual shares with limited liability are positively skewed. Therefore, buying low priced volatile shares is similar to buying a lottery ticket. There is a small chance of doubling or tripling your value in a short period of time, but a larger chance of the value declining, but the loss value is limited. Blitz and Van Vliet (2007) refer to Shefrin and Statman (2000) behavioural theory and argue that an investor will overpay for shares they perceive as lottery tickets as they want the opportunity to make higher returns. Thus explaining why investors deviate from risk averse behaviour that may lead to high risk shares being overpriced and low risk shares being under-priced.

Numerous studies provide evidence to support these theories; Falkenstein (2009), Kumar (2009), Boyer, Mitton and Vorkink (2010) and Baker *et al.* (2011) linked skewness preference or preference of lotteries to the risk effect. These preferences contribute to the demand for high volatile shares and thus explain their low returns.

ii) Representativeness

Representativeness is one of the heuristics proposed by Kahneman and Tversky (1974). A heuristic for judging frequency and probability using representitiveness is used when making decisions under uncertainty. Representativeness is when people tend to judge the probability of an event by finding a 'comparable known' event and assuming that the probabilities will be similar.

Within finance theory, investors use representativeness to make decisions under uncertainty. They believe that the history of a firm's performance is representative of general performance that is expected to continue in the future. Therefore leading investors to bid up prices and reduce the expected return (Boussaidi, 2011). For example: A small number of high beta shares exhibit abnormally high return like Internet shares Amazon and Google. However, the chances of finding the few high performers among all the high beta shares are very low. The average investor ignores the low probability of success and buys high beta shares with the belief that they will act "like" Amazon and Google, rather than like the common, low performing shares (Boussaidi, 2011).

iii) Overconfidence

Overconfidence is expected to be another bias underlying the preference for high volatility shares (Fischoff, Slovic & Lichtensten, 1977). Overconfidence explains that investors are overly optimistic about their ability to forecast future share returns. This optimism seems to increase the more uncertain the outlook for a given share. The net result is higher demand, higher prices and lower expected return for volatile shares with the opposite implication for low volatility shares. Overconfidence is seen as the difference in opinion between various investors whereby the extent of disagreement is likely higher for more uncertain shares.

Cornell (2009) viewed overconfidence as an important part of demand for volatile shares. He argues that investors who believe they possess superior abilities will want to invest in high volatile shares because this is where they will receive the highest return for their selection. However, Cornell (2009) noted that another assumption needs to be present in order to connect overconfidence to the demand of volatile shares. The other assumption is that there are pessimistic investors, who act less aggressively than the optimist investors, whereby the pessimistic investors need to be more reluctant to short shares than to buying them, leading to prices being set by optimists as suggested by Miller (1977).

b) Limits to Arbitrage

Finance theory states that in an efficient market, if an arbitrage opportunity exists (where investors can earn a riskless profit). The arbitrage will disappear due to investors taking advantage of the opportunity. However, the low volatility anomaly has persisted for decades despite the possibility of being arbitraged away. The market therefore seems to be inefficient, violating the no arbitrage condition. This has bought about a large amount of "limits to arbitrage" literature as an explanation to the Low Beta Anomaly. The limits to arbitrage arguments include benchmarking, leverage constraints, and investor compensation schemes.

i) Benchmarking

Benchmarking can be seen as an agency problem. If the average individual investor has the tendency to demand highly volatile shares due to psychological demand, a common question asked by academics is why the "institutional / sophisticated investor" does not exploit such behavioural bias (Baker *et al.* (2011).

Baker *et al.* (2011) believe that sophisticated investors (institutional investors) are prevented from taking advantage of individual investor biases due to benchmarking. Institutional investors have a mandate to manage a portfolio against a benchmark. The indirect mandate for the vast majority of institutional managers is to maximise the information ratio relative to a specific benchmark. This benchmark is generally an index which is taken to represent the broad market or specific segment of the market, without leverage. Using the framework set out by Brennan (1993), Baker *et al.* (2011) derive the implication of fixed benchmark strategies for low risk shares. The institutional investor's performance is their realised return versus the benchmark (i.e. active return), their realised tracking error (i.e. active risk) and information ratio. The information ratio is the average difference between the return earned by the manger and the return of the benchmark scaled by the volatility of the tracking error, whereby the tracking error is the standard deviation of the return differences. Ultimately an investor should be more concerned regarding the total risk rather than the tracking error. However, it is easier to measure and understand the abilities of an investment manager and the risk taken by comparing return with a well-known benchmark. This prevents institutional investors from taking advantage of the Low Beta Anomaly.

Baker and Haugen (2012) note that the low volatility shares provide fewer opportunities for managers to earn performance based bonuses, therefore persuading managers not to buy them (I.e. option like compensation causes active managers to award low volatility shares).

Institutional investors therefore tend to buy higher beta shares in order to limit the divergence between the tracking errors. However, if institutional investors were allowed leverage, they could achieve similar results if they invested in low beta shares. Restrictions on borrowing including long only mandates lead to the elimination of the possibility of exploiting arbitrage opportunities between low beta - high alpha shares and high beta - low alpha shares.

ii) Leverage Constraints

Brennan (1971) and Black (1972) highlight that due to borrowing constraints, the security market line is flatter than predicted by CAPM. This leads low beta shares to have higher returns than predicted by the CAPM model. The CAPM model assumes that the market is efficient and that there is only one efficient portfolio whereby investors lever or de-lever their position in the portfolio based on risk aversion. However, when there is leverage restrictions,

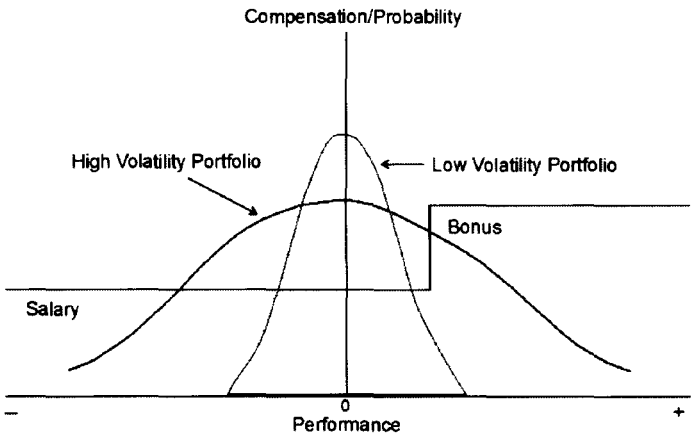
investors wanting to increase their return have no choice but to increase the proportion of high beta shares in their portfolio in order to increase their exposure to gather more equity risk premium. This results in a greater demand for high beta shares.

Frazzini and Pedersen (2010) agree with Black (1972) and attribute the risk effect to leverage constraints. By examining the cross sectional risk return relation, Frazzini and Pedersen (2010) ascertain that when funding constraints tighten, betas tend to be compressed to one and the risk return relationship becomes flatter. The authors predict that less leverage constrained investors, such as private equity, will prefer to hold low beta shares while the opposite holds true for leverage constrained investors such as mutual funds. The authors concluded that investors with restrictions on leverage seek excess return by investing more heavily in risker assets. This eventually reduces the expected return of the share.

iii) Institutional investor/manger compensation scheme

Investing according to a benchmark, as discussed in the previous section, helps explain the possible flat or even negative return between risk and return. However, Baker and Haugen (2012) identify another agency issue which concerns the institutional investor's incentive scheme, which can be compared to a call option. Generally, portfolio managers are paid a base salary and on top of that, they receive a bonus based on their performance. The authors believe that the compensation resembles a call option as shown in Figure 1 below (as shown in Baker and Haugen 2012). The figure shows two probability distributions; one is for a volatile portfolio and the other for a less volatile portfolio. It indicates that the expected value of compensation increases as the institutional investor sends their client towards a more volatile portfolio. This incentive leads to a conflict of interest between the professional risk seeking investor and their clients who are typically risk averse as assumed by CAPM.

Figure 1: Option like Manager Compensation



Source: Baker and Haugen (2012) pg. 11

2.3 International Equity Flows

Due to globalisation and technological advancements, the ability of investing in foreign markets has become common practice. Brennan and Cao (1997) document positive correlations between international equity flows and share returns in the US market. A more recent study by French and Ahmad (2011) confirms the strong dynamic relationship between equity flows and returns in the US market.

Based on a model of international investment flows, Brennan and Cao (1997) observe that US investors tend to purchase foreign equities if the foreign market return is high. Brennan *et al.* (2005) extend the 1997 paper to analyse investors' responses to information signals from foreign markets. They show that global financial institutions are more optimistic if the foreign market return increases, and vice versa. These findings, according to the authors, are consistent with the assumption that foreign investors are less informed, since they react on lagged information. This is a direct result of the asymmetrical information theory, whereby foreign investors are less well-informed about the returns on foreign investment; therefore they tend to be more sensitive to new information than domestic investors (French, 2011).

International investors can therefore be said to be more bullish about a market that has high returns, investing in high beta shares in search of greater returns, but withdraw when returns decrease (termed 'return chasing' by Bohn and Tesar, 1996). It is believed that international equity investment leads to price overreaction and contagion when withdrawn. This relates to Baker *et al.* (2011) theory whereby behavioural biases lead to higher demand, higher prices

and lower expected returns for high volatility shares, with the opposite implication for low volatility shares.

2.4 Idiosyncratic Risk

The relationship between idiosyncratic risk and share returns has been widely studied in international markets with mixed results. According to Modern Portfolio Theory idiosyncratic risk should have no effect on expected returns if investors have fully-diversified portfolios. Therefore classic asset pricing models like the CAPM only price systematic risk. However, it has been acknowledged that in reality investors may not be able to hold perfectly diversified portfolios. As Campbell, Lettau, Malkiel, and Xu (2001) find after examining the standard deviation of portfolio returns, in order to achieve relatively complete portfolio diversification an investor needs to have at least 50 randomly selected shares. Given the above, the theory behind an idiosyncratic risk premium is theoretically straightforward. However, empirical evidence of such a risk premium seems to be mixed.

2.4.1 Studies Finding a Negative Relation between Idiosyncratic Risk and Expected Returns

The finding that high idiosyncratic volatility shares have low risk adjusted returns is perceived as another anomaly. Ang *et al.* (2006) is seen as a pioneer paper with regards to the recent literature that identified the negative relationship between idiosyncratic risk and expected return. Ang *et al.* (2006) measure idiosyncratic volatility as defined relative to the Fama and French (1993) three Factor Model. Examining the cross sectional relationship between idiosyncratic volatility and returns of US shares, the authors find that shares with high idiosyncratic risk have abnormally low average returns during the period 1964-2000. The authors control for a number of factors such as size, BTM, liquidity, volume, turnover and bid-ask spread. Their results indicated that the negative relation could not be explained to any of the aforementioned exposures. Ang *et al.* (2009) the authors extended their original study to investigate 23 other countries as well as examining the relationship between lagged idiosyncratic volatility and future average returns. They found the same negative relationship existed and that the low return for shares with high idiosyncratic risk could be found in global markets and thus was not a country specific phenomenon. However, this study has been

criticised by academics like Fu (2009) who believed that Ang *et al.* (2006) results were driven by a short term reversal effect.

2.4.2 Studies Finding a Positive Relation between Idiosyncratic Risk and Expected Returns

Early studies such as Levy (1978) and Merton (1897) believe that based on under-diversification of a portfolio, idiosyncratic risk should be positively related to expected returns. The authors suggested that an investor unable to fully diversify their position would demand a return compensation for holding idiosyncratic risk. This was supported by Tinic and West (1986) as documented by Malkiel and Xu (2002). Lehmann (1990) finds that the idiosyncratic risk measured as residual variance has a positive significant coefficient in cross sectional regression: however he does mention that this result is sensitive to different economic specifications.

Later studies such as Malkiel and Xu (2002) find that high idiosyncratic risk portfolios generate higher returns than low idiosyncratic risk portfolios in the US market. This result is supported by Fu (2009), who estimated idiosyncratic risk using an EGARCH Model. Fu (2009) found a positive relationship between the estimated conditional idiosyncratic volatility and expected return. Barberis and Huang (2001) support the positive relationship between idiosyncratic risk and expected returns using behavioural models.

2.4.3 Studies Finding No Relation between Idiosyncratic Risk and Expected Returns

After addressing the issues raised by Miller and Scholes (1972), Fama and Macbeth (1973) finds no relation between idiosyncratic risk and expected return. Similarly Guo, Kassa and Ferguson (2010) and Fink, Fink and Hui (2010) further investigate Fu's (2009) results and suggest that his results were driven by a look ahead bias. The authors suggest that the look ahead bias was incorporated into the recursive volatility forecasts by including the month t return in the estimation of the month t EGARCH idiosyncratic volatility measure. Once they correct the volatility forecasts for this bias, they find no relation between the EGARCH idiosyncratic volatility and returns.

Bali and Cakici (2008) believe the conflicting empirical evidence surrounding the relation between idiosyncratic risk and return is due to the methodological difference in previous studies. They highlight four areas where methodologies differ when calculating idiosyncratic

risk 1) data frequency mainly referring to the daily versus monthly data used to estimate idiosyncratic risk 2) the weighting schemes used to compute average portfolio returns, 3) breakpoints in sorting shares in quintiles portfolios and 4) different filter rules. The authors believe that using monthly data for the idiosyncratic volatility measure produces a more accurate proxy for the future expected volatility than the daily version. They find the relationship between idiosyncratic risk and return to be flat or very weak. Furthermore, the significance of the negative relationship found when using daily data decreases when equally weighted portfolios are used. Therefore the authors conclude that there is no negative trade-off between idiosyncratic risk and return.

The existence of a positive relationship between idiosyncratic risk and return could be a contributing factor of the Low Beta Anomaly. As the superior performance of low beta portfolio could be explained by an accompanied high idiosyncratic risk factor. Therefore further supporting the inability of the current asset pricing models in accurately explaining expected share returns.

2.5 Market Concentration

The concentrated nature of the South African equity market is a topic that has been examined by several academics; Bradfield and Kgomari (2004), Kruger (2004), Kruger and Van Rensburg (2008) and Raubenheimer (2010) to name a few. The JSE's high levels of concentration both in terms of market capitalisation and liquidity are further complicated by a large and volatile resources sector which poses a problem with regard to what constitutes the appropriate benchmark to use when evaluating securities (Kruger & Van Rensburg, 2008).

Strongin, Petsch and Sharenow (2000) suggest that their finding that the market capitalisation weighted benchmarks are not adequately diversified is attributed to the primary reason for most of the tracking error incurred by active fund managers rather than their share selection. By analysing the share selection skills of portfolio managers and their influence on portfolio construction, one can determine the underlying cause for the persistent underperformance of US large-cap portfolio managers. Strongin *et al.* (2000) find that the underperformance is a direct result of concentration of share specific risk in a small number of large-cap shares that depicts the market capitalisation weighted benchmark (Stronin et al., 2000). This characteristic is likely to be inflated in more concentrated markets such as the JSE.

Bradfield and Kgomari (2004) as documented by Kruger and Van Rensburg (2008) undertake a study of concentration on the JSE over a three-year period. They determine that the ALSI demonstrates a degree of concentration almost one and a half times greater than the average concentration of general equity funds in the market. In order to relate the effect of concentration to overall benchmark risk, they calculate the variance and covariance elements of risk for the ALSI. The remaining portion of risk, which is almost one third of total ALSI risk, is attributed to the effects of concentration. Their analysis also indicates that the benefits of diversification on the JSE are limited due to the high correlations between shares in the market. As a result, while traditional literature indicates that as few as 10 shares are required in order to effectively diversify a portfolio, Bradfield and Kgomari (2004) find that at least 30 and as many as 45 shares are required for effective diversification on the ALSI. They therefore conclude that it is both these high inter-correlations as well as the extensive concentration on the exchange that is responsible for limiting the effectiveness of diversification on the JSE.

Kruger (2004) explains the effect of concentration on portfolio risk and diversification using the risk of an equally weighted portfolio and compares it to that of a concentrated portfolio. Kruger (2004) illustrates, that when evaluating the variance of an equally weighted portfolio, the weight attributed to each share is 1/N where N represents the number of shares in the portfolio. Gruber (2003) describes the equation as follows:

$$\sigma_p^2 = \sum_{i=1}^{N} \left(\frac{1}{N}\right)^2 \sigma_i^2 + \sum_{i-1}^{N} \sum_{j=1, j\neq 1}^{N} \left(\frac{1}{N}\right)^2 \sigma_{ij}\,, \tag{3}$$

$$= \frac{\overline{\sigma_i^2}}{N} + \frac{(N-1)\bar{\sigma}_{ij}}{N}\,, \tag{4}$$

Where:

$\bar{\sigma}_i^2$ is the average variance of the shares in the portfolio,

$\bar{\sigma}_{ij}^2$ is the average covariance of the shares in the portfolio, and

N is the number of shares in the portfolio.

Equation 4 is the simple version reported by Gruber (2003), and it indicates that the risk of the portfolio is dependent on the average variance and average covariance of the shares in the portfolio. Financial theory suggests that as the number of shares increase (i.e. N), firm specific risk is eventually eliminated, thus reducing the risk held to the average covariance of

the shares in the portfolio. If shares are independent as CAPM assumes, so the covariance will be zero and thus all risk would be eliminated through diversification. However in the case of a concentrated portfolio, shares with higher weights and higher variances increase the overall portfolio risk (Bradfield and Kgomari, 2004). This reinforces the findings of Strongin *et al.* (2000) who illustrated the effective number of shares ($\tilde{n}$) as

$$\tilde{n} = \frac{1}{\sum_{i=1}^{N} w_i^2}, \tag{5}$$

Where $\tilde{n}$ - the effective number of shares is the number of equally-weighted shares required to achieve the same share-specific risk as the original portfolio. The smaller the number of effective shares, the more concentrated the benchmark.

Bradfield and Kgomari (2004) went further than Gruber (2000) and indicated that it is assumed that all shares in the portfolio are uncorrelated therefore eliminating the covariance portion of equation 4, leaving the average variance of all the shares in the portfolio:

$$\sigma_p^2 = \sum_{i=1}^{N} w_i^2 \sigma_i^2, \tag{6}$$

If it is assumed that all shares have the same average variance, denoted by $\bar{\sigma}^2$, then the portfolio risk is:

$$\sigma_p^2 = \bar{\sigma}^2 \sum_{i=1}^{N} w_i^2, \tag{7}$$

By substituting in equation 5 (concentration formula) into equation 7, the variance of a portfolio can be illustrated as:

$$\sigma_p^2 = \bar{\sigma}^2 \frac{1}{\tilde{n}}, \tag{8}$$

The above equation indicates that a portfolio's risk is the inverse of concentration (using the simple assumptions mentioned above).

The concentration of portfolio weights directly impacts the specific risk of a portfolio. Therefore full diversification is unable to occur which leads to a risk factor that is not accounted for in the CAPM model. This research seeks to determine if the market benchmark is more in line with equally weighted shares like the actual individual's portfolio. Perhaps the CAPM measures the return series more accurately and therefore the Low Beta Anomaly does not exist. Three different equity benchmarks are used in this study: they include the

commonly used All Share Index (ALSI), the Shareholder Weighted Index (SWIX), the Capped Index (CAPI) and an equally weighted market portfolio (EWMP).

Rousseau and Zwonnikoff (2002) and Maritz (2003) conducted extensive comparisons on the above mentioned benchmark alternatives. Rousseau and Zwonnikoff (2002) find that the SWIX is generally the benchmark choice made by most fund managers; they argued that it still does not make provision for concentration of non dual-listed shares. Similarly, Maritz (2003) in comparing these benchmarks, concluded that the CAPI is still similar to the ALSI and found that the SWIX compares more constructively with the composition of most equity funds' holdings.

Kruger and Van Rensburg (2008) recognized that the concentration risk is further escalated by the volatile nature of the resources sector, which is the main source of concentration. They analysed the ALSI, SWIX, CAPI as well as two down-weighted resource indices (50% and 80% RESI). They find that the SWIX offers a higher effective number of shares and therefore the greatest diversification. The 10% CAPI was found to be the less efficient compared to SWIX. This was due to the fact that it only affected one shares weighting. By reweighting all the other shares, it drove up the weights that were previously below the 10% level. Therefore, the impact of reweighting the shares ends up reduced due to the up-weighting of other large-cap shares. However, the least efficient alternative was the 80% Resources benchmark, which was only marginally less concentrated than the ALSI. They concluded that market concentration in the JSE is largely responsible for the inefficiencies of the available benchmarks that are used for performance measurement.

3. Methodology

The focus of the research is twofold: determining the existence of the Low Beta Anomaly on the Johannesburg Stock Market (JSE) and investigating potential explanations to the existence of the Low Beta Anomaly. This study primarily draws from methodology used in Baker and Haugen (2012), Ward and Muller (2012) and Blitz *et al.* (2013).

3.1 Introduction

The Low Beta Anomaly will be studied on the JSE over the period January 1992 to November 2014. This will be done by examining whether the risk return relationship is positive, as theory suggests, or similar to findings both international and domestic, where the relationship is flat or even negative. The second part of the methodology will focus on ascertaining whether the three variables identified, namely; net international equity flow, idiosyncratic risk and market concentrations, can explain the anomaly, diminish its persistency in the context of the CAPM a FF3F asset pricing models.

3.2 Data

Population and Sample

The population of this study is the total number of companies that are listed on the JSE. The sample will be adjusted to ensure that there are no missing variables in any of the sample company's information. The data will also be adjusted for thin trading issues, using the thin trading filter as suggested by McClelland, Auret and Wright (2013). Companies for which data for the past 36 months is not available are excluded from the study. This filtering process allows shares that have stopped trading during the study to be removed. This is beneficial as these shares may skew the results as they tend to exhibit high volatility and poor returns. This filtering is suggested by Merton (1987) and Banz (1981). The number of individual shares listed in a given year varies between 294 and 450 with an average of 348 shares listed per year in the overall period. The shares that fall under investigation may vary over the testing period. Therefore, the shares included in the sample will be re-evaluated at the beginning of each year to coincide with the rebalancing of portfolios that occurs at the end of each year (December in this study).

The data sample also consists of monthly net international equity flows (in R'000s) for the same period. It is important to note that these equity flows are different to Foreign Direct Investment (FDI) in the sense that FDI represents an ownership stake in the company, whereas equity flows represent portfolio-related flows from international investors into the JSE that account for a less than 10% ownership stake. The net international equity flows are obtained from the I-Net Bridge Database.

Sources of Data

22 years of JSE monthly share price data from January 1992 to November 2014, in combination with company financial statements reflect the data used in this study. Share price data and company financial data is sourced from findata@wits.

Delistings and New Listings

Where shares delist within a particular year, a zero return is used thereafter. These shares are excluded from the sample for the entire year in which delisting is achieved on the basis of the last price when the company ceased trading on the JSE. This is in line with Ward and Muller (2012). Newly listed shares are included in the analysis when the minimum pre-ranking information is available. In this minimum required data needed for pre-ranking in this study is 36 months.

Actual Returns

Total return data for each share was adjusted for dividends which were obtained from the Findata@wits. Share consolidations and sub-divisions are adjusted for by multiplying the price at the execution date by the factor that would leave the shareholder's ownership stake prior to execution unchanged. Similarly, the shareholders of companies that go through an unbundling are assumed to sell their stake in the newly unbundled company immediately at the going market price, this amount is then treated as a dividend.

Market Returns and Risk Free Rate

The JSE Total Returns All Share Index (J203T) is used as a proxy for the market portfolio. The risk free rate is taken as the South African three month domestic Treasury bill rate, and is adjusted each year to ensure that the most up to date rate is applied.

Thin Trading Issues

Basiewicz and Auret (2009) provide some indication that the JSE is an illiquid market, therefore thin trading is an issue that requires some attention in this study. The method applied in this study is similar to that suggested by McClelland, Auret and Wright (2014). Whereby shares that have an adjustment factor greater than two are excluded from the sample where as in the McClelland *et al.* (2014) study the authors excluded shares that had more than 150 zero daily trades. The reason for the difference is that using the adjustment factor instead allows for the consideration of the actual trading year in question. The adjustment factor is:

$$\frac{Potential\ trading\ days}{(Potential\ trading\ days - Zero\ Daily\ trades)}, \tag{9}$$

The adjustment factor is the trading days divided by days traded. Where trading days is the total number of trading days in the estimation period, and days traded is the total number of days that the dependant variable actually traded (i.e. potential trading days in a year minus the number of zero daily trades of the share).

3.3 Model Construction

3.3.1 The Capital Asset Pricing Model (CAPM)

The CAPM expected return, which has formed the basis for capital asset pricing theory is defined below:

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f], \tag{10}$$

Where:

$E(r_i)$ is the expected return of the share,

r_f is the risk free rate of interest identified above as the 3month treasury bill,

r_m is the return on the market portfolio, and

β_i is the covariance of the share with the market, divided by the variance of the market.

3.3.2 The Fama and French Three Factor Model (FF3)

In order to calculate the expected return on equity by applying the FF3, it is necessary to construct each of three factors; the market risk premium ($E(r_m)$ - r_f), the size premium

(designated as Small minus Big or SMB) and the book-to-market (BTM) premium (designated as High minus Low or HML).

$$E(r_i) - r_f = \beta_i * (E(r_m) - r_f) - \beta_{SMB} * (SMB) - \beta_{HML} * (HML), \quad (11)$$

Where:

$E(r_i)$ is the expected return of the share,

r_f is the risk free rate of interest identified above as the 3month treasury bill,

r_m is the return on the market portfolio,

β_i is the covariance of the share with the market, divided by the variance of the market,

β_{SMB} is the beta equivalent that relates to the covariance of the share with the SMB portfolio, divided by the variance of the SMB portfolio,

SMB is the size premium,

β_{HML} is the beta equivalent that relates to the covariance of the share with the HML portfolio, divided by the variance of the HML portfolio, and

HML is the book to market premium.

3.4 Variables

3.4.1 Excess Return

The excess return of the market is calculated as the total return of the ALSI (J203T) in each period, less the identified risk free rate in each period. Similarly the total excess return for each share is calculated as the total return of each share in question minus the identified risk free rate over the same time period.

3.4.2 Pre-Ranking Market Beta (β_m)

Beta reflects the covariance of a return of a share with the market portfolio divided by the variance of the market portfolio. It describes the relationship between a shares excess return and the market premium. The equation for beta is represented as:

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}, \quad (12)$$

The most common beta estimator used in empirical analysis is the Ordinary Least Squared (OLS) regression model. A linear regression that is applied to calculate the coefficient of the monthly growth in a shares value over a period of 60 months against the returns of the market portfolio (over the same time period). OLS beta (β_{OLS}) estimate is obtained using the following regression:

$$Total\ Excess\ Returns = \beta_i\ Total\ Excess\ Market\ Returns + \varepsilon_{it}\ , \qquad (13)$$

Where $Total\ Excess\ Returns$ equals the total share returns minus the risk-free rate in the same month, α_i is not included as we force the returns through the origin, β_i denotes the coefficient term, $Total\ Excess\ Market\ Returns$ equals the total market return (J203T) minus the risk-free rate in the same month and ε_{it} represents the stochastic error or residual term.

Numerous studies have found the β_{OLS} to be downward bias when shares are traded infrequently; Scholes and Williams, (1973); Dimson (1974) and Fowler and Rorke (1983). Various alternative beta estimates have been suggested throughout the literature. McClelland, Auret and Wright (2014) analysed four possible beta estimation models and found the trade-to-trade model to perform the best followed by the adjusted OLS model. The trade-to-trade model although superior, is data intensive needing daily data and volumes. Therefore as suggested by McClelland *et al.* (2014) the adjusted OLS beta estimation model is used in this study. According to Fowler and Rorke (1983), the adjusted OLS is calculated as follows:

$$\beta_{Adj\ OLS} = \beta_{OLS} \frac{Trading\ days}{Days\ traded}\ , \qquad (14)$$

Where $\beta_{Adj\ OLS}$ is the adjusted Beta, β_{OLS} is the ordinary least squares beta estimate, $Trading\ days$ is the total number of potential trading days and $Days\ traded$ is the actual number of days in which the shares traded (total number of potential trading days minus number of zero daily trades over the beta estimation period).

The β_{OLS} is calculated using an OLS regression that forces the intercept through the orgin. As the slope is calculated assuming the Jensen Alpha is equal to zero. Trailing betas are calculated using the previous 60 months, and in the case where the share has not been trading for this period of time, a minimum of 36 month window is analysed. If a share has less than 36 months of available data the share is excluded from the sample. The 60 month period is in line with

most South African research and is identified by Bartholdy and Peare (2005) as the best frequency of data when calculating beta. As mentioned in Section 3.4.7 the sample is limited to shares that have an adjustment factor less than two.

3.4.3 SMB, HML, β_{SMB} and β_{HML}

The SMB and HML variables are calculated indirectly using the mimicking portfolio method as described in Fama and French (1993). SMB is the total returns of the small portfolio minus the total returns of the big portfolio. HML is the total returns of the high BTM portfolio minus the total returns of the low B/M portfolio.

The β_{SMB} and β_{HML} represent the covariance of the particular share with each of the portfolios that have been identified for SMB and HML. These factors are calculated in the same way as the traditional β_m, by performing a regression of the returns of a share with the returns of the above factors.

3.4.4 Net International Equity Flows (NIEF)

The Net International Equity Flow represents monthly data of net purchases of shares by non-residents. The study looks at the data in two forms namely:

1) The net monthly purchase of shares by non-residents (R'000)
2) The residuals of the net purchases of shares by non-residents

The NIEF data is only available from 1996, and thus the analysis regarding the NIEF and the Low Beta Anomaly is limited to the time period (1996-2014).

Secondly this research tests whether there is a positive correlation between foreign investors' aggregate flow of money into the JSE and the performance of high beta shares relative to low beta shares. This tests involves examining monthly data for foreign investors net purchases of JSE shares and compare them with the difference in monthly excess returns between the highest and lowest pre ranking beta quintiles. This is done to determine whether foreign investors overweigh high beta shares relative to low beta shares as suggested by Baker *et al.* (2011).

Lastly, to ensure robustness of the results from the OLS regression aforementioned, the direct impact of net international equity flows will be measured and will be removed from the

market portfolio. In doing so, we examine whether the Low Beta Anomaly still exists when calculated using equity flow adjusted market residuals.

The impact of net international equity flows on the market portfolio is obtained by the following regression model:

$$Total\ Excess\ Market\ Returns = \alpha_i + \beta_i NIEF_{Residuals} + \varepsilon_{it}\ ,$$

Where $Total\ Excess\ Market\ Returns$ equals total market returns minus the risk-free rate in the same month, α_i denotes the intercept term, β_i denotes the coefficient term, $NIEF_{Residuals}$ is the net international equity flow residuals as generated by the ARMA model and ε_{it} represents the stochastic error or residual term, which are known as innovations. To arrive at the ARMA specifications, the information criteria AIC was used in order to optimise the time series. An ARMA (3, 4) was used to determine the residuals, where AIC was minimised.

In order to remove the effect of international equity flows from the market portfolio the equity flow adjusted market residuals (ε_{it}) need to be calculated according to the following formula:

$$\varepsilon_{it} = Actual\ Excess\ Market\ Returns - Expected\ Excess\ Market\ Returns \quad (15)$$

Once obtained, the beta estimation procedure as specified previously will be repeated. However, the OLS beta estimation (β_{OLS}) calculation will be modified to include the equity flow adjusted market residuals (ε_{it}) in place of the total excess market returns which were previously used. In doing so, the impact of the net international equity flows is removed from the beta estimation procedure. This is done in order to determine whether NIEF has any effect on the persistence of the Low Beta Anomaly.

3.4.5 Idiosyncratic Risk

Two measures of idiosyncratic risk will be used.

1) CAPM Idiosyncratic Risk

Risk of share i consists of market risk (MR_i) and firm specific/ idiosyncratic risk of share i (IdR). The standard deviation of share i (σ_i) is equal to the total risk of share i (TR_i)

$$\sigma_i = TR_i\ , \quad (16)$$

$$TR_i = MR_i + IdR_i\ , \quad (17)$$

The relative market risk of share i is equal to the percentage of market risk relative to the market;

$$\beta = \%\, MR_i\ relative\ to\ market\ , \tag{18}$$

However, total market risk is equal to the market risk of the market. As finance theory suggests that, under these assumptions of a market free from high levels of concentrations, the number of shares in a portfolio increases ($n \rightarrow \infty$) so the idiosyncratic risk tends towards zero.

$$\sigma_m = TR_m = MR_m\ , \tag{19}$$

Therefore;

$$\beta\ x\ MR_m = MR_i\ , \tag{20}$$

Where β is adjusted for liquidity (thin trading) and is calculated without an intercept as mentioned above.

If investors do not completely diversify their share holdings and thus may require additional compensation. Therefore it is expected that idiosyncratic risk is the difference between total risk and market risk of share i.

$$IdR = TR - MR_i, \tag{21}$$

Therefore: $IdR = \sigma_i - \beta\sigma_m$. (22)

2) Fama and French Three Factor Model

Ang *et al.* (2006) defines idiosyncratic risk as the variance of the error term in the Fama and French three Factor Model

$$r_{it} - r_{ft} = \alpha_{it} + \beta_{it}(r_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + \varepsilon_{it}\ , \tag{23}$$

Where idiosyncratic risk is defined as var (ε_{it}). The other factors are standard as defined in Fama and French (1993);

$r_{it} - r_{ft}$ = is the excess return of share I at time t,

$r_{mt} - r_{ft}$= is the excess return of the market,

SMB_t= reflects the return of a portfolio of small shares in excess of large shares,

HML_t= reflects the return of portfolio shares of high B/M ratio in excess of shares with low BTM ratio,

Where $IdR = Var(\varepsilon_i)$.

3.4.6 Alternative Equity Market Benchmarks

The four alternative equity benchmarks used in this study are the ALSI, SWIX, CAPI Indices as well as an equally weighted market portfolio. The Shareholder Weighted Index (SWIX) is similar to the ALSI but excludes the foreign shareholding of listed companies, whilst the Capped Index (CAPI) represents all the companies in the ALSI but the weighting of each company within the portfolio is capped at a maximum of 10% exposure. The equally weighted market portfolio is calculated by taking the average return across all shares on the JSE in that particular month. Both the SWIX and CAPI indices were introduced to the FTSE / JSE Africa Index Series in July 2003. Therefore, the analysis regarding the market concentration is performed over a shorter time period compared to the rest of the study (i.e. 2004-2014).

3.5 Constructing Portfolios

3.5.1 Portfolio Formation

Portfolios are formed using the mimicking portfolio methodology employed by Fama and French (1993). Fama and French (1993) used a mimicking portfolio methodology to explain the abnormal returns attributed to small market capitalisation and high book-to-market firms. This is done by sorting portfolios at the beginning of each re-weighting period into deciles according to the risk characteristic in question. In the case of Fama and French (1993) market capitalisation and BTM ratios. The returns for each period are then calculated for the two extreme portfolios. From this the less risky portfolio's returns are subtracted from the risky portfolio's returns to create a risk-premium time series. This is then used as an explanatory variable to estimate the risk loading of a share. This is used along with any other risk-factors such as the market.

Therefore similarly to Fama and French (1993) equally weighted portfolios are sorted into quintiles from smallest to largest. Portfolio 1 is the quintile exhibiting the smallest measure of any of the four variables being analysed: pre ranking beta, size, BTM and idiosyncratic risk. Whilst portfolio 5 represents the largest and remaining shares are labelled 2, 3 and 4 and the represent the mid-range.

Quintiles are used as opposed to deciles as it maximises the cross sectional power of analysis without comprising stability and reliability of the portfolio. The sorting procedure is consistent and maintains relatively large portfolio sizes (all greater than 30) reducing the probability of idiosyncratic factors affecting the results. The sorting of portfolios are reweighted annually, at the beginning of January each year. This was chosen over the suggested by Van Rensburg and Robertson (2003a) who reweighted monthly as a mechanisms to avoid intensifying the problem of trading costs. Any share that has traded less than 36 months are excluded from the portfolio formation.

Equally weighted portfolios are used instead of the value weighted portfolios, due to the effects of size and value. These effects have been shown to be patent in smaller shares. If portfolios are value weighted, there is a good chance the effects of these risks will be drowned out by the overwhelming effects of larger shares: specifically because the cross-sectional difference in market capitalisation of shares listed on the JSE is so large. In addition Kurger and Van Rensburg (2008) found that when using value weighted portfolios the level of concentration in the resource sector on the JSE is intensified. It also conforms to most international and South African studies of risk factors and therefore allows the easier comparability (Suh, 2009; Basiewicz & Auret, 2010).

The equally weighted portfolios will be calculated in a different manner compared to equally weighted indices. This is due to the difference in frequency of returns (monthly) and the period between reweighting (annually). Generally equally weighted portfolio indices are calculated as the arithmetic average of returns, holding the weighting of shares equal at each point in time. However, due to the fact that the frequency of share return is different to the holding period, a change in weights for every period other January of each annual period needs to be accounted for. This is done by first creating a weighting variable for each share. In January each year the weighting takes a value of one, and then grows according to the equation below

$$W_{i+1} = 1 \times (1 + R_i)\,,$$

(24)

Where R_i is the total return month i.

Each total return is then multiplied by its respective weight to create a weight-adjusted return (A_i):

$$A_i = W_i \times R_i\,, \tag{25}$$

The total portfolio return, sorted according to a particular characteristic x, P_x is then simply the sum of all relevant weight-adjusted returns A_i that have characteristic x, divided by the sum of the shares weights (W_i) that have characteristic x:

$$P_x = \frac{\sum_{i=x} A_i}{\sum_{i=x} W_i}\,, \tag{26}$$

Where A_x and W_x represent the weight-adjusted return and share weight, respectively, for shares that exhibit characteristic x.

The above methodology leads to adjustment of share weighting in the portfolio according to the shares relative performance in comparison to the overall portfolio. Therefore, shares with above average performance will have a greater weighting in subsequent periods, whilst those with below average performance will have a smaller weighting but still have equal weights at each portfolio formation period.

3.5.2 Transaction Costs:

Transaction costs have been ignored relating to the rebalancing of each portfolio on the grounds that these will be approximately the same between portfolios, and therefore immaterial to the methodology and results. The use of annual reweighting will also make the trading costs immaterial.

3.6 Model Analysis

3.6.1 Low Beta Anomaly Analysis

The beta estimate is calculated as stipulated in Section 3.6.2 and the five portfolios are sorted according to the methodology outlined in Section 3.7.1. To assess the excess return of the five portfolio's, the mean monthly return, ex-post monthly standard deviation and Sharpe ratios are calculated and evaluated. The Sharpe ratio is used to measure perfromance as it uses standard deviation as the risk variable, unlike the Treynor ratio which uses beta. For reasons mentioned above, beta tends to be downward biased and thus not used to measure risk adjusted performance. For the monthly return, the geometric average is reported in order

to account for compounding effects as suggested by Vliet, Blitz and van der Grient (2011). Each of the 5 portfolios under each model were visually compared to assess whether the portfolios that have the lower beta actually generated the highest return over the 1997 to 2014 period. The use of cumulative returns as a visual comparison measure is in line with Ward and Muller (2012), who describe that this methodology is preferable to traditional statistical regression techniques.

This will be done in order to test whether the low beta quintile (LB) earns significantly higher return than the higher beta quintile (HB)

H_0: $E(r_{LB}) = E(r_{HB})$

H_1: $E(r_{LB}) > E(r_{HB})$

For robustness, the potential effects of size and value are taken into account. Shares are sorted into four portfolios according to market capitalisation, and then each portfolio is resorted into four more portfolios according to their book-to-market ratio. This will result in 16 portfolios where each share will be in a particular size-value portfolio. To adjust for the effects of size and value, each share will have the average return of its own size or value portfolio (excluding the returns of the share in question) subtracted from its released return each done separately. After the adjustments are made, all shares are again sorted into their beta quintiles to test whether the difference in returns between the high and low beta quintiles persist.

3.6.2 Net International Equity Flow Analysis

To test the ability of net international equity flows to explain the Low Beta Anomaly, a two variable OLS regression will be used. The OLS regressions will test the relation between NIEF and beta sorted portfolio returns during the sample period of 1997 to June 2014. The explanatory variable is the monthly NIEF. The response variable is the differential between the returns from the low beta portfolio and the highest beta portfolio denoted as LMH. The equation below represents the OLS regression.

$$LMH = \alpha + \beta_{NIEF}(NIEF) + \varepsilon_{it}\,, \qquad (27)$$

Where LMH is the differential between the high beta and low beta portfolios. LMH is used in order to investigate only the relationship between NIEF and the returns of the LMH, α_i

denotes the intercept term, β_i denotes the coefficient term and ε_{it} represents the stochastic error or residual term.

This will be done to test whether β_{NIEF} is statistically significant, therefore suggesting that NIEF may contribute to the explanation of the Low Beta Anomaly.

H_0: $\beta_{NIEF} = 0$

H_1: $\beta_{NIEF} \neq 0$

3.6.3 Idiosyncratic Risk Analysis

This study will investigate whether the presence of idiosyncratic risk (IdR) is a possible explanation for the Low Beta Anomaly. Once IdR has been calculated, shares will be sorted in quintiles based on the IdR to examine the effect of IdR. As mentioned above in 3.6.6 the idiosyncratic risk variable will be calculated using both the CAPM and FF3 Factor Model.

The first step is to ascertain whether low idiosyncratic shares do in fact outperform high idiosyncratic shares. Therefore testing whether:

H_0: $E(r_{L(IdR)}) = E(r_{H(IdR)})$

H_1: $E(r_{L(IdR)}) > E(r_{H(IdR)})$

Then similar to testing for the size and value effect, we will determine through the mimicking portfolio method to ascertain whether low beta is robust after IdR has been taken into account. To adjust for the effects of idiosyncratic risk, each share will have the average return of its own IdR portfolio (excluding the returns of the share in question) subtracted from its realised return. After the adjustments are made, all shares are again sorted into their beta quintiles to test whether the difference in returns between the high and low beta quintiles persist.

3.6.4 Benchmark Analysis (Market Concentration)

A key requirement of any benchmark is the ability of an investor to replicate the benchmark by being able to invest in all the shares listed in the index. There is some contention in the literature regarding the composition of the proxy for the market portfolio, as the (Markowitz, 1952) concept of the market portfolio requires that the global portfolio of risky assets should be included.

This section of this study analyses the impact of using different equity benchmarks on the persistence of the Low Beta Anomaly. I.e. is the Low Beta Anomaly an equity benchmark anomaly due to concentration and liquidity issues arising from using market capitalisation weighted equity benchmarks? The indices are compared based on their current constituents as at the December 2014 Index, as well as on their performance over the last 10 years.

When examining the effect of alternative equity benchmarks on the Low Beta Anomaly, the procedure is the same as when testing for the Low Beta Anomaly in Section 3.8.1 except the market proxy will be varied.

Four separate tests are run, where the ALSI, SWIX, CAPI indices and the equally weighted market portfolio are tested as the market portfolio. All four equity benchmarks are used for the period 2007-2014. The reason for the shorter time period is due to the fact the SWIX and CAPI indices were only introduced onto the JSE in 2004. Therefore to allow for at least a three year trailing beta, the period of examination begins in 2007.

This study analyses the following South African Equity Market benchmarks namely the

- FTSE/JSE All Share Index (ALSI),

- FTSE/JSE Shareholder Weighted Index (SWIX),

- FTSE/JSE Capped Index (CAPI),

The SWIX is similar to the ALSI but excludes the foreign shareholding of listed companies. The SWIX index was developed primarily for the institutional investment market where the available (investable) pool of securities in the local market is better reflected. The CAPI represents all the companies in the ALSI but capped at a maximum of 10% exposure to any one company. This index serves as a better and more appropriate benchmark to evaluate fund management performance than the conventional ALSI index because similar share exposure rules apply in the investment management industry.

The fourth alternative benchmark is the equally weighted market portfolio (EWMP). Whereby the returns are calculated by estimating the average return across all shares on the JSE. This is done monthly for the same time period. The EWMP as the name suggests, allows for all the shares on the market to contribute equally to the return of the market portfolio, in order reduce the effect of market concentration.

3.7 Limitations

This research is limited to shares that were traded on the JSE during the time period under study 1997-2014. The sample was further limited to shares that met the trading frequency required in order to have non biased results. This meant shares that had traded less than 150 days were excluded from the sample.

Another limitation of this study is using the JSE All Share Total Returns Index (J204T) as the market portfolio benchmark. Therefore not all risky shares are incorporated into the market portfolio. With regards to the market concentration analysis, a relatively short time horizon is evaluated as the CAPI and SWIX indices were only introduced on the JSE in 2004. Therefore the reader needs to take into consideration when viewing the results of the market concentration section, that only eight years were evaluated. Especially as the low beta outperformance was less persistent in the latter years of the study.

4. Results

The results are split into 4 sections. The first Section (5.1) examines the beta anomaly within the South African equity market. This is to determine the existence of the Low Beta Anomaly on the JSE and justifies the tests that subsequently flow in Sections 5.3 to 5.4. The next 3 sections test the three identified possible explanations of the Low Beta Anomaly within this study.

4.1 Low Beta Anomaly Analysis

Panel A of Table 1 reports the average annualised excess returns, the standard deviation and the Sharpe ratio of each beta quintile portfolio. The portfolios of low beta shares tend to produce high average returns with lower standard deviations than the high beta portfolios. As a result the low beta portfolio has a higher Sharpe ratio as shown graphically in Figure 2. The Sharpe ratio is the total excess return divided by volatility. When portrayed as Sharpe ratios, returns are monotonic decreasing as risk increases except for portfolio 4 and 5. These results are the inverse to the theory that financial markets should reward investors for taking risk.

Panel B of Table 1 above reports the annualised return of each portfolio in excess of the market portfolio return. Like before, it is clear that the high beta portfolio underperforms compared to the low beta portfolio with a difference of 3.09% in average annual returns. The tracking error which measures the difference between the benchmark and the actual return of the portfolio is higher for the low beta portfolios. However this is consistent with Baker *et al.* (2011) who suggested that investment managers tend to avoid low beta shares due to them increasing the tracking error and, therefore, affect the manager's relative performance to the benchmark. This may be unhelpful to the portfolio manager to underperform the benchmark during bull markets only to be compensated with outperformance during bear markets. The information ratio measure the portfolios manager's ability to generate excess return relative the benchmark, but is also a good measure to identify the consistency of an investor.

The results in Table 1 indicate the high beta shares tend to yield low information ratios due to low average returns. However, when comparing performance of portfolios against the market, it should be noted that the market is value-weighted whereas the beta portfolios in

this study are equally weighted. Therefore, the market does not always fit as an aggregate of the five portfolios because the market is over-weighted in the large market capitalisations shares.

Table 1: Annualised Returns by beta-sorted quintile equal weighted portfolios (January 1997 – November 2014)

	Low	2	3	4	High
Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	3.8%	1.4%	1.3%	-1.7%	0.7%
Standard Deviation (%)	14.7%	15.3%	17.6%	18.8%	23.3%
Sharpe Ratio	0.2556	0.0934	0.0727	-0.0887	0.0292
Panel B: r_p-r_m					
Average r_p-r_m (%)	4.28%	1.94%	1.79%	-1.15%	1.19%
Tracking Error (%)	18.2%	13.8%	12.1%	12.6%	15.4%
Information Ratio (%)	0.235	0.141	0.148	-0.091	0.078

Note: ** and * denote significance at 5% and 10% levels respectively

Figure 2: Sharpe Ratio (Annualised) by Quintiles of Beta, 1997-2014

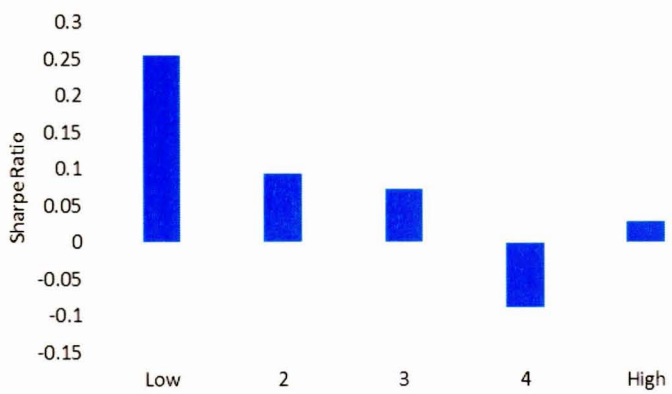


Table 2 below reports the CAPM's / Jensen alpha. The alpha is the intercept term in a time series regression of a portfolios excess return on the market portfolios excess return for each of the five portfolios. Figure 2 displays the annualised CAPM alpha where returns are adjusted for each shares beta or market risk for each quintile. Both

Table 2 and **Figure 3** indicate that the Jensen alpha is positive only for the first portfolio (lowest beta portfolio) and negative for the other 4 portfolios. The difference in alphas of the low beta portfolio and the high beta portfolio is large indicating that the relation between the

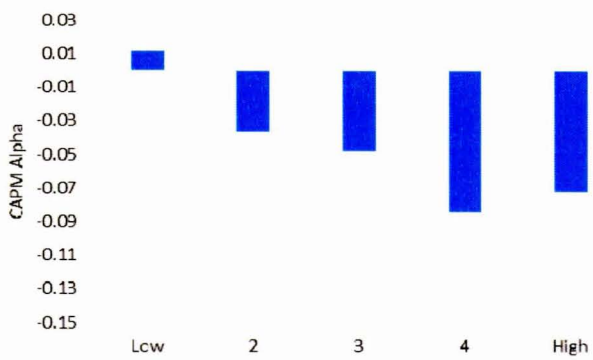
beta and average excess return for the 5 portfolios is not merely flat (as found by many academics i.e. Black *et al,* 1972) but actually is negative which is opposite to what is predicted by CAPM. All the beta coefficients for each quintile are significantly different from zero at the 95% level. Whilst all the alpha's except for the low beta portfolio are statistically significant at the 10% significance level. Therefore highlighting the negative relation between excess return and beta.

Table 2: Annualised Returns by beta-sorted quintile equal weighted portfolios – CAPM Analysis (January 1997 – November 2014)

CAPM Regression					
	Low	2	3	4	High
Beta	0.356	0.555	0.706	0.746	0.891
(t stat)	(7.195)**	(14.961)**	(19.004)**	(18.409)**	(16.806)**
Alpha	0.001	-0.003	-0.004	-0.007	-0.006
(t stat)	(0.270)	(-1.233)*	(-1.778)*	(-2.805)**	(-1.828)*

Note: ** and * denote significance at 5% and 10% levels respectively

Figure 3: CAPM Alphas of Beta Quintiles, (1997-2014)



Literature has shown that return series need to be adjusted for both the size and value effects as suggested by Fama and French (1993). As the underperformance of the high beta portfolio may be due to the fact that low beta shares have higher BTM ratios and or small market capitalisations. Table 3 below shows the results of the three factor regression. The three Factor Model suggested by Fama and French (1993) includes the market portfolio's excess return, the small minus big (SMB) factor and the high minus low (HML) factor.

Although the intercept for the first 2 low beta portfolios are not statistically significant, the intercepts for the other three portfolios including the high beta portfolio are negative at the 95% significance level. Therefore, even after taking size and value effects into account, the

high beta portfolio underperforms the low beta portfolio. The Beta significance is incomparable to the other factors with respect to significance because it only illustrates a relationship to market wide factors but does not show the cross-sectional relationship between this sensitivity and returns. Across all five portfolios the SMB and HML factors are not statistically significant which seems to suggest that there is no relation between pre ranking beta portfolios and HML (value) risk and SMB (size) risk.

Table 3: Annualised Returns by beta-sorted quintile equal weighted portfolios – Fama and French 3 Factor Model Analysis (January 1997 – November 2014)

Fama and French 3 Factor Model					
	Low	2	3	4	High
Beta	0.356	0.553	0.704	0.745	0.888
(t stat)	(7.881)**	(14.818)**	(18.786)**	(18.240)**	(16.632)**
HML	0.011	0.011	0.009	-0.001	0.017
(t stat)	(0.600)	(0.722)	(0.550)	(-0.072)	(0.755)
SMB	0.036	0.012	0.009	0.017	-0.010
(t stat)	(0.194)	(0.486)	(0.348)	(0.621)	(-0.274)
Alpha	-0.001	-0.003	-0.004	-0.006	-0.007
(t stat)	(-0.296)	(-1.501)	(-1.690)*	(-2.387)**	(-1.995)**

Note: ** and * denote significance at 5% and 10% levels respectively

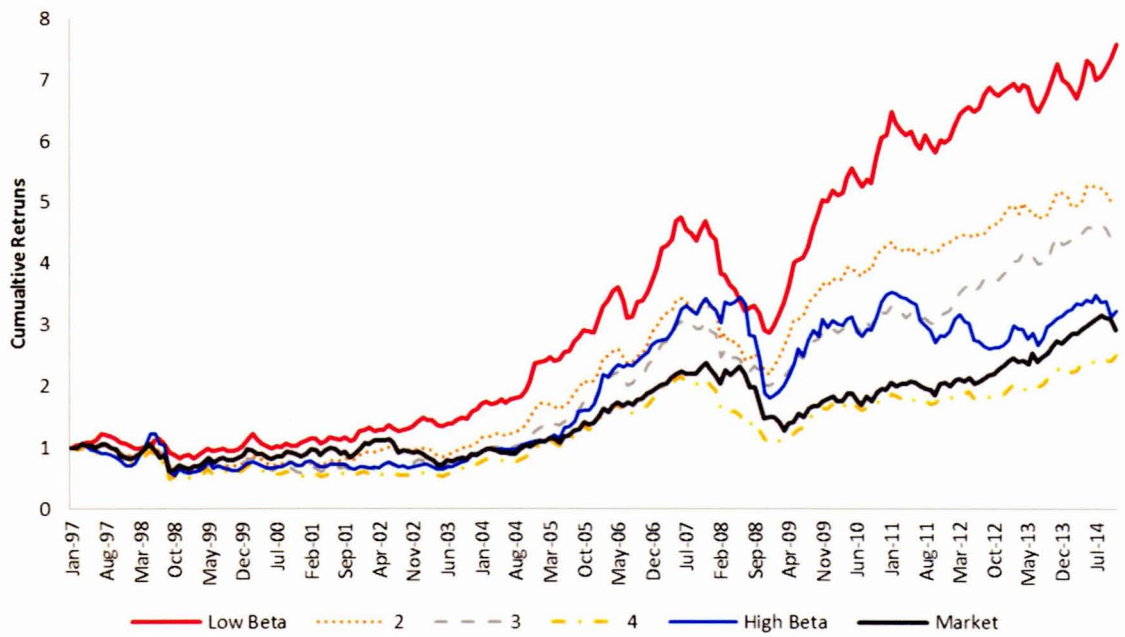
Figure 4 shows the cumulative monthly excess returns of the five beta portfolios and the market portfolio. By examining the cumulative return series, one is able to view the performance if an investor invested R1 into each of the respective portfolio in January 1997. Based on the cumulative values the low beta portfolio outperforms the high beta portfolio by a factor of 2.39. This is in line with Ward and Muller (2012). It is evident that the low beta portfolio consistently outperforms relative to both the market and the highest beta portfolio. Based on these results its can be said a monotonic inverse relationship exists between betas and the betas and excess return for the period 1997 – 2014. Therefore, the Low Beta Anomaly exists on the JSE and is robust to both CAPM as well as FF3 risk models. These results support the finding of existing South African studies including Ward and Muller (2012), Van Rensburg and Robertson (2003) and McClelland (Masters Report 2014).

If an investor invested R1 in 1997 in each respective portfolio, they would have achieved an end value of R7.11 for the low beta portfolio and R3.22 for the high beta portfolio and R3.04

for the market portfolio. Hence the low beta achieved more than double the compound growth compared to both the market and high beta portfolio.

An interesting result is that the high beta portfolio outperformed the market portfolio from September 2005 to the end of the sample 2014 as shown in Figure 4 below. However the two portfolios return converged in the later part of the sample with high beta portfolio only marginally outperforming the market.

Figure 4: Pre-Ranking Beta Sorted Quintiles and Market Portfolio - Cumulative Returns



When comparing the low beta portfolio cumulative returns against the high beta cumulative returns as shown in Figure 5 below, it is clear that the high beta portfolio underperforms. However, when analysing the period of the global financial crisis i.e. 2008 -2012, the difference in performance between the two portfolios narrows substantially with what appears for the period January 2008 to October 2008 (as seen in Figure 5 and Figure 7) the high beta portfolio outperforms the low beta portfolio.

Figure 5: Low and High Pre-Ranking Beta Sorted Portfolios - Cumulative Returns during the Period, 1997 - 2014

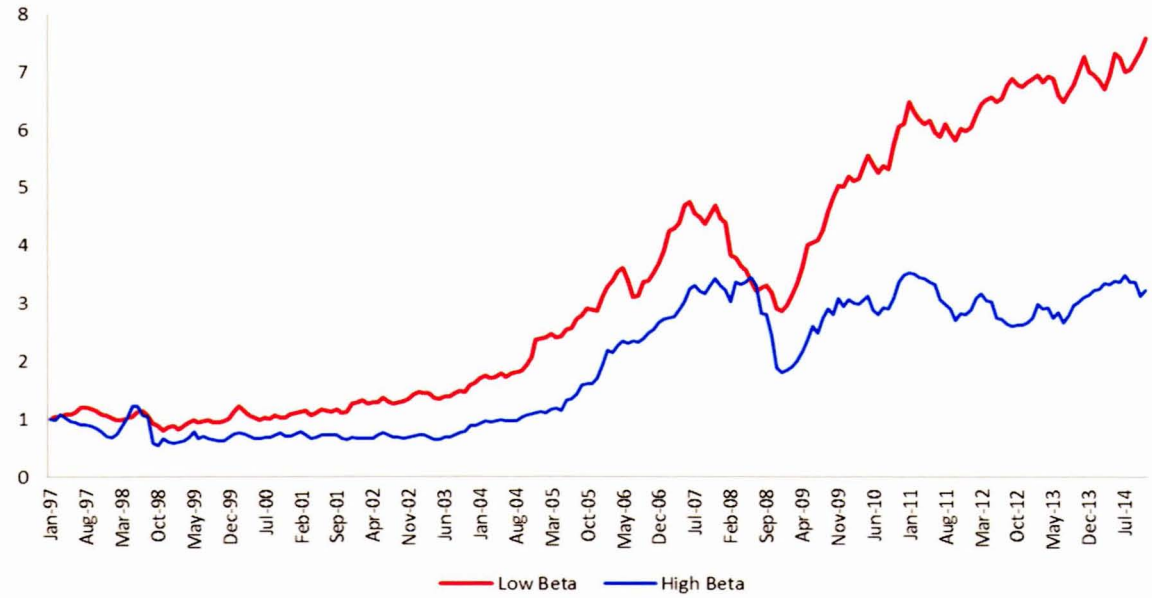


Figure 6, 7 and 8 display the cumulative returns of the high and low beta portfolio, for three different time periods. This was done in order to determine, whether high beta portfolios do outperform the low beta at any point during the sample period. It appears during 1997 and 1998, high beta outperformed low beta portfolio, and this coincides with the timing of the burst of the internet bubble (Figure 6). Similarly during the early days of the Global Financial Crisis (January 2008 till October 2008) the high beta portfolio outperformed the low beta portfolio as shown in Figure 7. This indicates that conditions in the market have a major effect on the performance of high beta shares relative to low beta shares. Figure 8 shows that in the latter 2 years of the sample period (2012-2014), the low beta outperformance has been marginal. In the beginning of 2014 both beta portfolios were achieving similar cumulative returns.

Figure 6: Cumulative Returns of the Pre-Ranking Beta Portfolios during the Period, 1997 – 2007

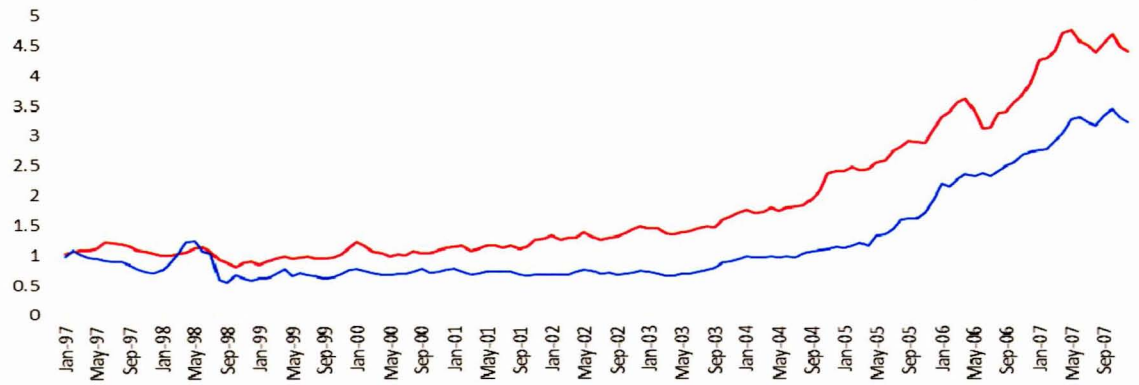


Figure 7: Cumulative Returns of the Pre-Ranking Beta Portfolios during the Period, 2008 - 2011

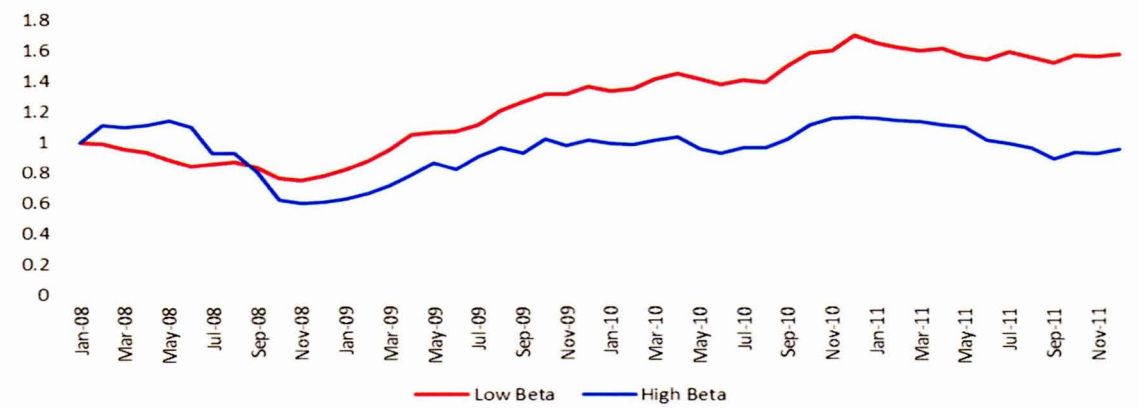
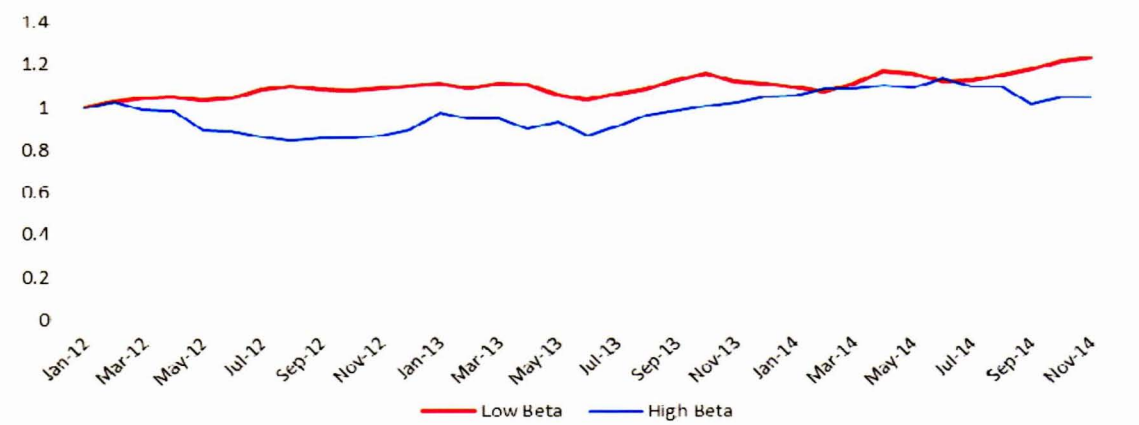


Figure 8: Cumulative Returns of the Pre Ranking Beta Portfolios during the Period, 2012 - 2014



Figures 9 and 10 below show that the Low Beta Anomaly is pervasive even after adjusting total excess return for the value or size quintile to which each share belongs. However, the outperformance of the low beta portfolio is slightly decreased once adjusted for size and

value. Looking at the ratio of cumulative returns for the low beta portfolio compared to the high beta portfolio, the low beta portfolio outperforms the high beta portfolio by a factor of 2.03 and 2.3 when adjusted for size and value respectively versus 2.4 before the adjustment. Therefore removing the size effect reduces the magnitude of the outperformance of low beta shares more than removing the value effect.

Figure 9: Cumulative Returns of Pre Ranking Beta Quintiles Adjusted for Size, 1997-2014

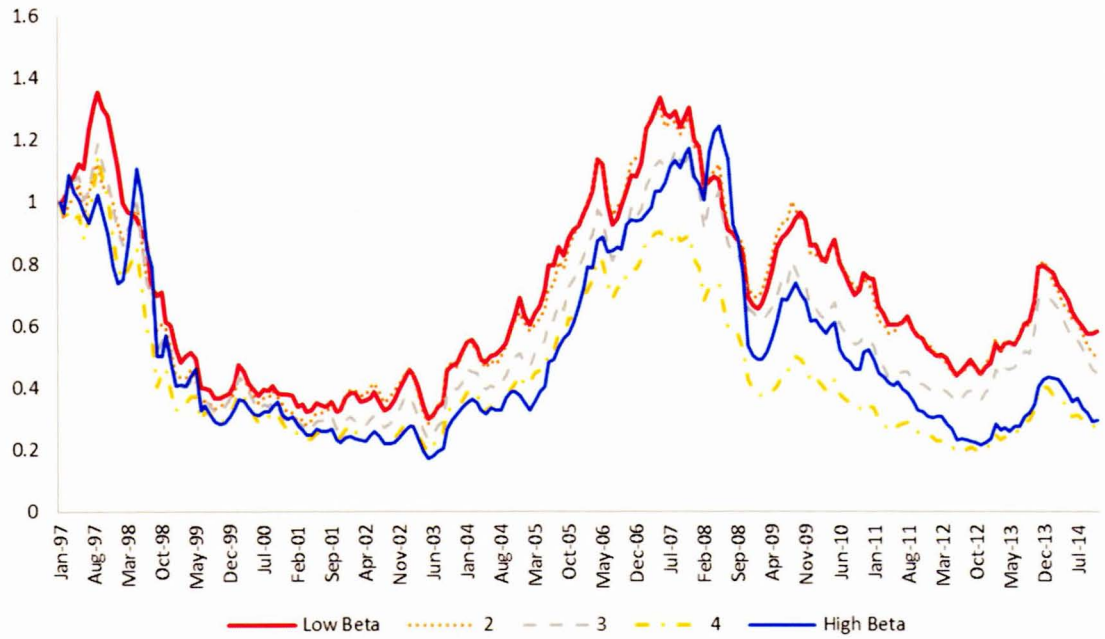
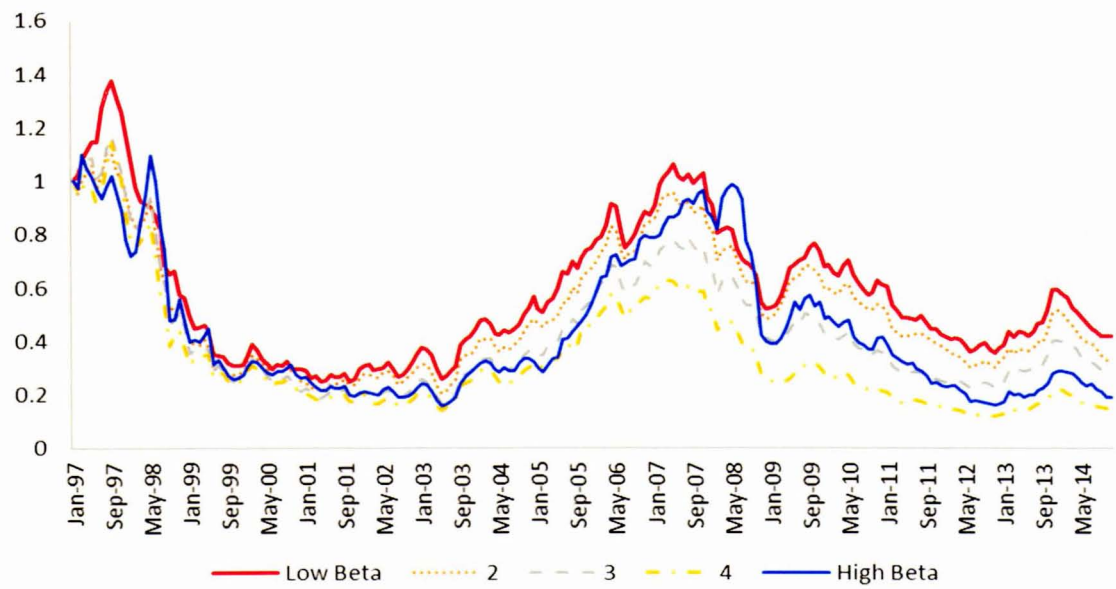


Figure 10: Cumulative Returns Value Adjusted, 1997-2014



The above results indicate that the Low beta Anomaly is pervasive on the JSE, similar to the findings of Van Rensburg and Robertson (2003a).

4.2 Net International Equity Flows

The Net International Equity Flows is tested using a simple OLS regression. Where the explanatory variable is the monthly net international equity flows denoted by 'NIEF'; whilst the response variable is the differential between the returns on the portfolios exhibiting the lowest-betas (Portfolio 1) and the highest-betas (Portfolio 5). Figure 11 below displays the differential between the low beta portfolio and the high beta portfolio. The net international equity flow account for the net purchases of shares by non-residents in South Africa. The explanatory variable will be tested in two forms. The first form is the actual net international equity flows and the other form is the residuals of the net international equity flows. The NIEF residuals are tested as the NIEF actual time series does not follow a random walk there long term trends (i.e. cyclical trends) are present in the series. Therefore it is found to follow an auto-regressive process. Through the ARMA process only changes that are unanticipated (i.e. innovations) need to be measured and thus the residuals of the NIEF are used.

Figure 11: Low minus High Beta Return Series (Differential), 1997 – 2014

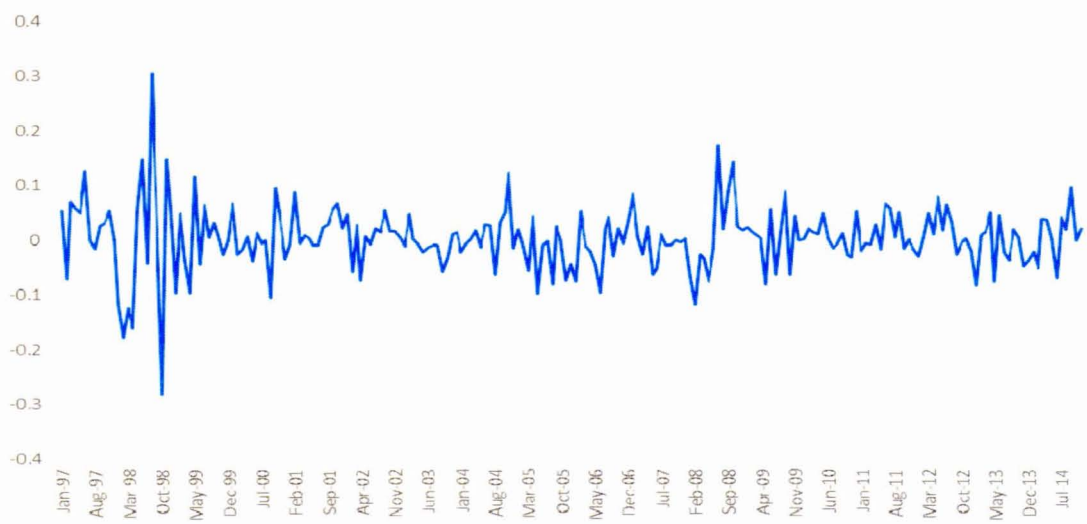


Table 4 below reports the results from the OLS regression described as

$$LMH = \alpha_i + \beta_i NIEF + \varepsilon_{it} \quad (28)$$

Where NIEF measured as

a) The net purchases of shares by non-residents (R'000) and
b) The NIEF residuals

Analysis of the regression results between the differential between the lowest and the highest beta portfolios indicates when NIEF (actuals) are used indicate negative relationship between the LMH differential and NIEF. The beta coefficients are small but significant, the reason for the small size of the coefficient may be due to the scale of flows vs the returns. This occurs for both forms of NIEF, however the NIEF residual variable is significant at the 10% level. Therefore when net purchase of shares from international investors increases so this has a negative or decreasing effect on the low and high beta portfolio differential. However, the R^2 of both regressions illustrates that NIEF does explain at least 1% of the differential series.

Table 4: Regression Results – LMH against NIEF (Actual) and NIEF residuals

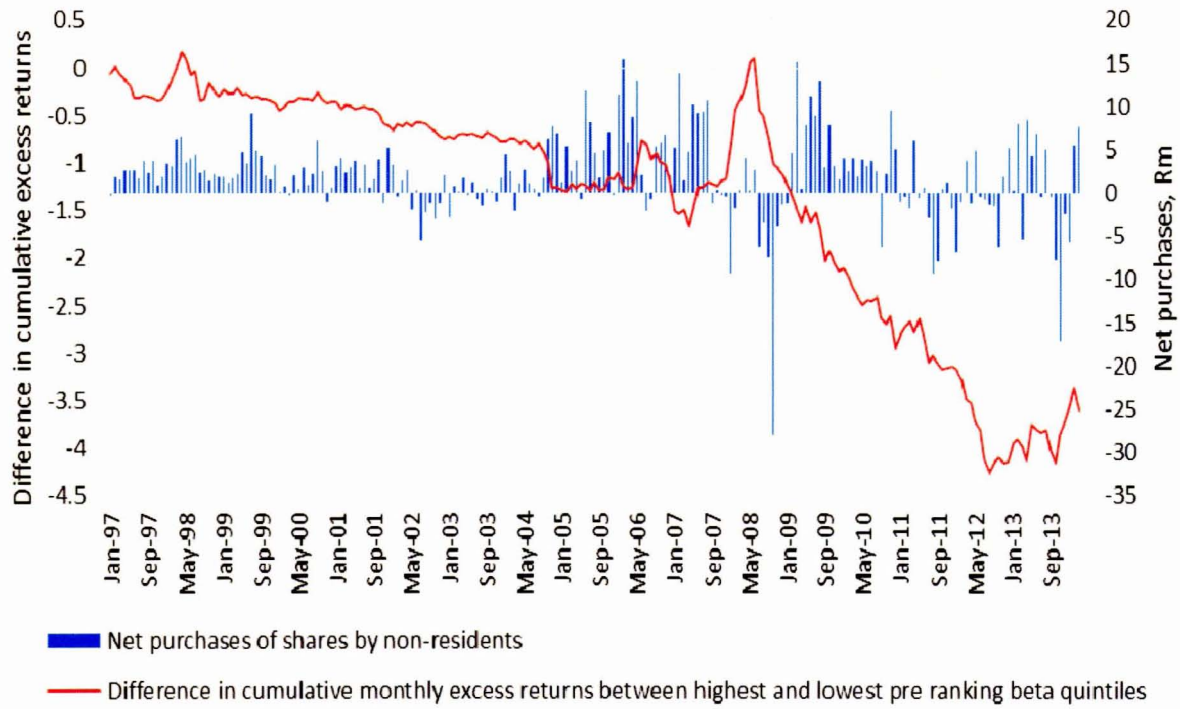
	Net International Equity Flows (R'000)	Net International Equity Flow Residuals
Alpha	0.005 (1.004)	0.003 (0.742)
B_{NIEF}	-0.0001 (-1.500)	-0.000 (-1.844)*
R^2	0.012	0.019
F Stat	0.135	0.162

*Note: ** and * denote significance at 5% and 10% levels respectively*

A second test was conducted to determine whether foreign investors do in fact overweigh high beta shares relative to low beta shares, the correlation between the net purchases of shares of foreign investors/ non-residents and the difference between the cumulative excess returns of the high and low pre ranking beta portfolios was calculated. The results in Figure 12, where the bar chart shows the foreign investors net purchases of JSE shares and the line graph shows the cumulative difference between the highest and lowest pre raking beta quintiles. While the performance of the high beta portfolio relative to the low beta portfolio tends downwards, when foreign investor's net purchases of JSE shares are positive, the trend weakens or reverses. The correlation coefficient between the monthly foreign investor's net purchase and the difference in monthly excess returns between highest and lowest pre

ranking beta quintiles is 0.11. Therefore, these results support Baker *et al.* (2011) as the underperformance of high beta shares weakens or reverses when investments by foreign investor's increases while it strengthens when their investment decreases indicating some relationship between the Low Beta Anomaly and net purchases of foreign investors.

Figure 12: Foreign investors net purchases of JSE shares and the cumulative difference in average return between the high and low beta portfolios, 1997-2014



To test the robustness of the Low Beta Anomaly, market returns are adjusted for NIEF. Analysis of the regression results (as shown in Table 5) between the market and monthly net international equity flows indicates that a positive relationship between the equity flows and the market exists however the coefficient is not significantly different from zero. Therefore no inference regarding the relationship can be concluded. When the net equity flow residuals were included in the regression rather than the net equity flows, a positive relationship is still documented. However, this relationship is only statistically significant at the 10% confidence levels.

Table 5 below reports the results originating from the regression between the market portfolio excess returns and the net international equity flow, both in actual terms and residuals. The regressions is defined as

$$Total\ Excess\ Market\ Returns = \alpha_i + \beta_i NIEF + \varepsilon_{it} \qquad (29)$$

Analysis of the regression results (as shown in Table 5) between the market and monthly net international equity flows indicates that a positive relationship between the equity flows and the market exists however the coefficient is not significantly different from zero. Therefore no inference regarding the relationship can be concluded. When the net equity flow residuals were included in the regression rather than the net equity flows, a positive relationship is still documented. However, this relationship is only statistically significant at the 10% confidence levels.

Table 5: Regression Results: Market Portfolio excess Returns against NIEF (actual) and NIEF Residuals

	Net International Equity Flows (R'000)	Net International Equity Flow Residuals
Alpha	0.003 (0.688)	0.005 (1.330)
NIEF	0.001 (0.0008)	0.000 (1.786)*
R^2	0.024	0.015
F Stat	0.015	0.076

*Note: ** and * denote significance at 5% and 10% levels respectively*

Subsequent to the removal of the effects of the monthly net international equity flows from the market, it is evident that the low-beta anomaly persists. The average annualised return series, in Table 6, indicates that low beta portfolio still outperforms all other portfolios by a factor of 1.52, which is lower than the factor before the NIEF residual adjustement. However, the Low Beta Anomaly still exists. With regard to the individual portfolio characteristics, the low beta portfolio experiences an increase in risk, the standard deviation increases subsequent to the removal of the effects of the equity flows. However the Sharpe ratio of the low beta portfolio increases due to the increased overall portfolio performance, whilst the high beta portfolio has the greatest risk as well as the second lowest Sharpe ratio. The low-beta portfolio therefore still outperforms the high-beta portfolio on a total return as well as on a risk-adjusted basis.

Table 6: Annualised Returns of Beta Quintiles (adjusted for NIEF residuals), 1997 - 2014

	Low	2	3	4	High

r_p-r_f (%)					
Average r_p-r_f (%)	4.1%	1.5%	1.7%	-3.6%	0.6%
Standard Deviation (%)	16.3%	16.4%	17.0%	18.4%	21.6%
Sharpe Ratio	0.3104	0.0909	0.0989	-0.1900	0.0271

4.3 Idiosyncratic Risk

4.3.1 Idiosyncratic Risk Portfolio Performance

Figure 12 and 13 below illustrate the cumulative returns of idiosyncratic risk quintiles, where the idiosyncratic risk is calculated using the traditional CAPM and the Fama and French (1993) three Factor Model respectively. Analysing idiosyncratic risk measured using CAPM, a similar anomaly to the Low Beta Anomaly can be seen. Whereby low idiosyncratic portfolio outperforms high idiosyncratic portfolios in the long run. However, the outperformance is sensitive to market conditions. As high idiosyncratic risk portfolios outperform the market in turbulent times i.e. the internet bubble during the late 90s, and the global financial crisis during 2007-2012 this is evident in Figure 13. Therefore suggesting that low idiosyncratic risk performs better in bull markets and inversely for bear markets.

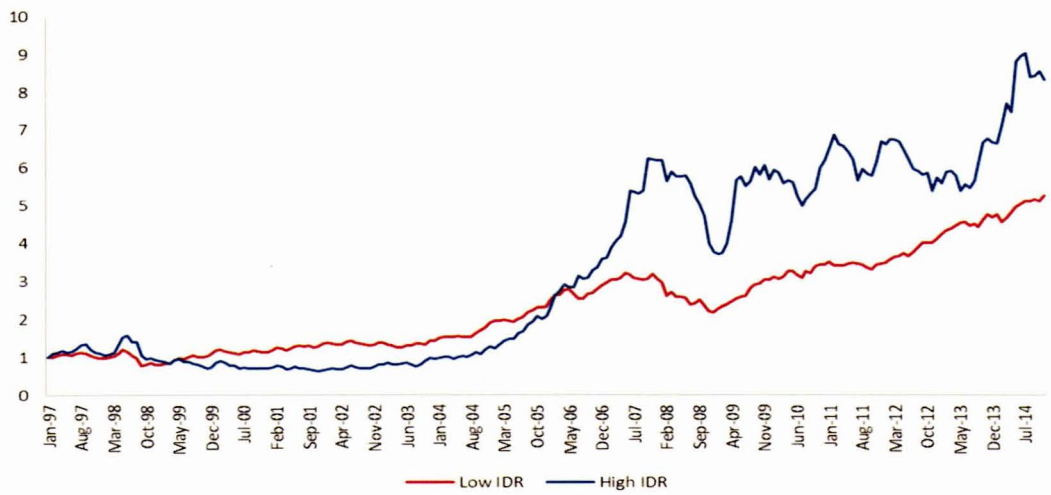
Figure 13: Cumulative Returns of Idiosyncratic Risk Quintiles Calculated Using CAPM, 1997-2014



Idiosyncratic risk calculated using the three Factor Model, high IdR outperforms low IdR more persistently compared to the IdR calculated using CAPM. As seen in

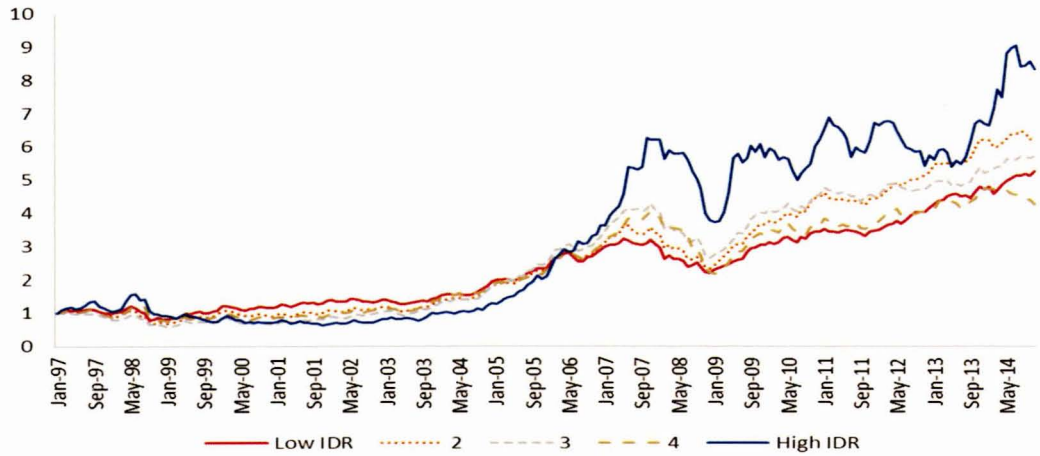
Figure 14, the cumulative returns of the high idiosyncratic risk portfolios outperforms that of the low idiosyncratic risk portfolios. This is in line with the findings of Malkiel and Xu (2002).

Figure 14: Cumulative Returns for Idiosyncratic Risk Quintiles calculated using the FF3 Factor Model, 1997-2014



Interestingly the Fama and French three Factor Model seems to describe the returns for all 5 portfolios accurately as very little deviation from one another occurs as shown in Figure 15, however high idiosyncratic risk underperforms all portfolios during the period 1999-2006, after mid 2006 the high idiosyncratic portfolio begins to outperform all the portfolios and the difference in cumulative returns grows larger during the end of the period. This indicates perhaps the existence of another risk factor that the Fama and French 3 Factor Model cannot explain.

Figure 15: Cumulative Returns for Idiosyncratic Risk Quintiles calculated using the 3FF (All 5 portfolios), 1997-2014



4.3.2 Low Beta Anomaly Analysis

To determine the whether the Low Beta Anomaly still exists after adjusting for idiosyncratic risk each Individual shares is adjusted for the return attributed to idiosyncratic risk. Then portfolio are resorted into beta portfolios. Figure 15 below illustrates the cumulative return of each beta quintile after adjusted for CAPM idiosyncratic risk. If you compare Figure 4 shows the cumulative monthly excess returns of the five beta portfolios and the market portfolio. By examining the cumulative return series, one is able to view the performance if an investor invested R1 into each of the respective portfolio in January 1997. Based on the cumulative values the low beta portfolio outperforms the high beta portfolio by a factor of 2.39. This is in line with Ward and Muller (2012). It is evident that the low beta portfolio consistently outperforms relative to both the market and the highest beta portfolio. Based on these results its can be said a monotonic inverse relationship exists between betas and the betas and excess return for the period 1997 – 2014. Therefore, the Low Beta Anomaly exists on the JSE and is robust to both CAPM as well as FF3 risk models. These results support the finding of existing South African studies including Ward and Muller (2012), Van Rensburg and Robertson (2003) and McClelland (Masters Report 2014).

If an investor invested R1 in 1997 in each respective portfolio, they would have achieved an end value of R7.11 for the low beta portfolio and R3.22 for the high beta portfolio and R3.04 for the market portfolio. Hence the low beta achieved more than double the compound growth compared to both the market and high beta portfolio.

An interesting result is that the high beta portfolio outperformed the market portfolio from September 2005 to the end of the sample 2014 as shown in Figure 4 below. However the two portfolios return converged in the later part of the sample with high beta portfolio only marginally outperforming the market.

Figure 4 and Figure 16 below, after adjusting for idiosyncratic risk, the differential between the cumulative return of the lowest and highest beta portfolio decreases insignificantly as the low beta portfolio outperforms the high beta portfolio by factor of 2.2 compared to a factor of 2.39 before the adjustment.

Figure 16: Cumulative Returns of Beta Quintiles Adjusted for CAPM Idiosyncratic Risk Returns, 1997-2014

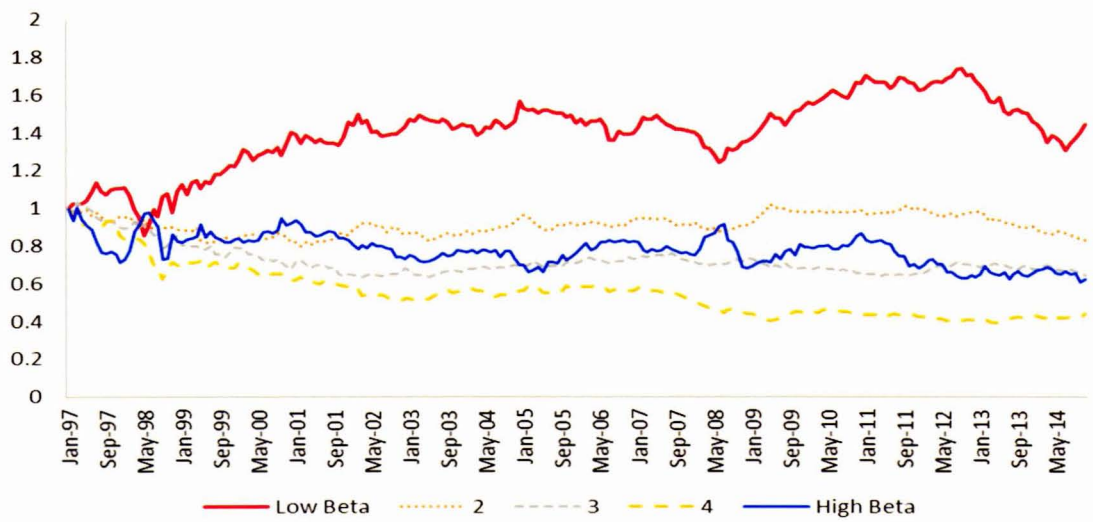


Table 7: Summary of Results for Beta Quintiles Adjusted for CAPM Idiosyncratic Risk Returns, 1997-2014

	Low	2	3	4	High
Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	-6.32%	-9.74%	-10.95%	-13.03%	-10.64%
Standard Deviation (%)	9.50%	5.58%	6.70%	8.27%	13.41%
Sharpe Ratio	-0.665	-1.744	-1.635	-1.577	-0.793
Panel B: r_p-r_m					
Average r_p-r_m (%)	-5.80%	-9.23%	-10.44%	-12.52%	-10.12%
Tracking Error (%)	24.74%	20.13%	17.42%	17.53%	17.45%
Information Ratio (%)	-4.264	-2.182	-1.669	-1.400	-1.724

Panel A in

Table 7 below similar to Table 1 presents the average annualised excess returns of the pre-ranking beta quintiles, however

Table 7 represents the excess returns adjusted for IdR. Once the beta portfolios are adjusted for idiosyncratic risk, the average returns form all 5 portfolios is negative. However the high beta portfolio still underperforms the low beta portfolio in average and risk adjusted terms.

Panel B of

Table 7 reports the beta portfolio returns in excess of the market return. Similar to earlier results the tracking error is largest for the low beta portfolio whilst the information ratio is highest for the high beta portfolio due the low average returns.

Table 8 reports the results of the traditional CAPM regression and the Fama and French 3 Factor Model respectively. The results indicate that the Jensen alpha is negative and statistically significant across all 5 portfolios as the effects of the market have been removed from all the portfolios. It must be noted for both models, the lowest beta portfolio has a negative beta coefficient which is significant at the 5% significance level. The size of the beta coefficient for each portfolio is significantly smaller once the returns have been adjusted for idiosyncratic risk due to the removal of the market effect.

Similar to the results in Literature has shown that return series need to be adjusted for both the size and value effects as suggested by Fama and French (1993). As the underperformance of the high beta portfolio may be due to the fact that low beta shares have higher BTM ratios and or small market capitalisations. Table 3 below shows the results of the three factor regression. The three Factor Model suggested by Fama and French (1993) includes the market portfolio's excess return, the small minus big (SMB) factor and the high minus low (HML) factor.

Although the intercept for the first 2 low beta portfolios are not statistically significant, the intercepts for the other three portfolios including the high beta portfolio are negative at the 95% significance level. Therefore, even after taking size and value effects into account, the high beta portfolio underperforms the low beta portfolio. The Beta significance is incomparable to the other factors with respect to significance because it only illustrates a relationship to market wide factors but does not show the cross-sectional relationship between this sensitivity and returns. Across all five portfolios the SMB and HML factors are not statistically significant which seems to suggest that there is no relation between pre ranking beta portfolios and HML (value) risk and SMB (size) risk.

Table 3, the size and value factors are not statistically significant, except for the two high beta portfolios, where the size factor is statistically significant at the 5% level.

Table 8: Summary of Results for Beta Quintiles Adjusted for CAPM Idiosyncratic Risk Returns - Risk Model Analysis, 1997-2014

CAPM					
	Low	**2**	**3**	**4**	**High**
Beta	-0.161	0.025	0.173	0.197	0.345
(t stat)	(-5.186)**	(1.311)	(8.624)**	(7.799)**	(8.602)**
Alpha	-0.004	-0.008	-0.01	-0.012	-0.011
(t stat)	(-2.337)**	(-7.500)**	(-8.994)**	(-8.429)**	(-4.890)**
Fama and French 3 Factor Model					
	Low	**2**	**3**	**4**	**High**
Beta	-0.161	0.024	0.17	0.196	0.34
(t stat)	(-5.140)**	(1.244)	(8.540)**	(7.862)**	(8.489)**
HML	-0.001	0.005	0.004	-0.007	0.01
(t stat)	(-0.091)	(0.646)	(0.475)	(-0.637)	(0.577)
SMB	0.004	0.002	0.033	0.048	0.568
(t stat)	(0.021)	(0.131)	(2.480)**	(2.887)**	(2.128)**
Alpha	-0.004	-0.008	-0.009	-0.011	-0.01
(t stat)	(-2.072)**	(-7.103)**	(-7.802)**	(-6.914)**	(-4.060)**

*Note: ** and * denote significance at 5% and 10% levels respectively*

The performance of the beta quintiles after adjusting for the FF3 Factor Model idiosyncratic risk measure are in line with the performance of CAPM idiosyncratic risk adjusted returns.

Although high idiosyncratic outperforms low idiosyncratic risk when using the Fama and French 3 Factor Model and the opposite is true for CAPM idiosyncratic risk. The adjustment does not impact the superior performance of the low beta portfolio. Figure 17 below, indicates the persistent outperformance. However, there is a slight decrease in the differential between low and high beta portfolios, where the low beta portfolio outperforms the high beta portfolio by a factor of 2. Compared to the differential between the low and high beta portfolios for the unadjusted portfolios of 2.4.

Figure 17: Cumulative Returns of Beta Quintiles Adjusted for FF3 Factor Model Idiosyncratic Risk, 1997-2014

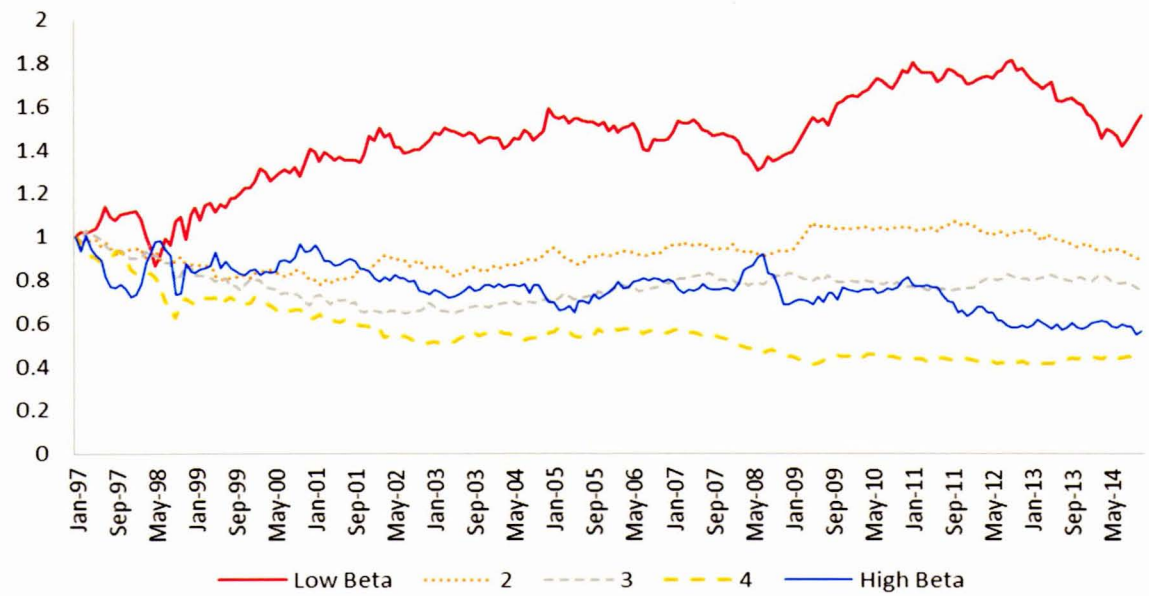


Table 9 reports similar results to those of the CAPM idiosyncratic risk adjusted return. The second highest beta portfolio has the worst average excess return, whilst the highest beta portfolio has the highest standard deviation.

Table 9: Summary of Results for Beta Quintiles Adjusted for FF3 Factor Model Idiosyncratic Risk Returns, 1997-2014

	Low	2	3	4	High
Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	-5.87%	-9.31%	-10.12%	-12.81%	-10.19%
Standard Deviation (%)	9.41%	5.87%	6.64%	8.03%	13.49%
Sharpe Ratio	-0.624	-1.584	-1.524	-1.594	-0.830

Panel B: r_p-r_m					
Average r_p-r_m (%)	-5.36%	-8.79%	-9.61%	-12.29%	-10.68%
Tracking Error (%)	24.64%	20.16%	17.40%	17.42%	17.45%
Information Ratio (%)	-0.218	-0.436	-0.552	-0.706	-0.612

The CAPM and FF3 Factor Model regressions shown in Table 10 below, produce similar beta coefficients and intercept values. Once again the value factor is insignificant, however the size factor is statically significant for portfolio 3, 4 and 5.

Table 10: Summary of Results for Beta Quintiles Adjusted for FF3 Factor Model Idiosyncratic Risk Returns- Risk Model Analysis, 1997-2014

CAPM Regression					
	Low	**2**	**3**	**4**	**High**
Beta	-0.157	0.028	0.173	0.197	0.348
(t stat)	(-5.087)**	(1.365)	(8.708)**	(8.073)**	(8.639)**
Alpha	-0.004	-0.008	-0.01	-0.012	-0.011
(t stat)	(-2.162)**	(-6.834)**	(-8.482)**	(-8.607)**	(-5.079)**
Panel D : Fama and French 3 Factor Model					
	Low	**2**	**3**	**4**	**High**
Beta	-0.157	0.027	0.171	0.196	0.344
(t stat)	(-5.041)**	(1.314)	(8.623)**	(8.089)**	(8.541)**
HML	-0.001	0.005	0.002	-0.006	0.007
(t stat)	(-0.075)	(0.577)	(0.278)	(-0.621)	(0.392)
SMB	0.004	0.002	0.033	0.048	0.568
(t stat)	(0.185)	(0.165)	(2.149)**	(2.217)**	(2.107)**
Alpha	-0.004	-0.008	-0.009	-0.011	-0.01
(t stat)	(-1.927)*	(-6.561)**	(-7.346)**	(-7.229)**	(-4.193)**

*Note: ** and * denote significance at 5% and 10% levels respectively*

The contrasting results regarding idiosyncratic risk are in line with the mixed views found in the literature. Although they decrease the average returns achieved by the low beta portfolio, idiosyncratic risk does not explain the Low Beta Anomaly.

4.4 Market Concentration / Alternative Benchmarks

The ALSI is the most popular used market index in South Africa. However, many academics and practitioners have identified issues regarding using the ALSI as the market portfolio proxy. The main issue of the ALSI is the market concentration mainly in resources, whereby Raubenheimer (2010) in a study on long-only equity funds recorded that at times, two resources companies can make up over 20% of ALSI when measured by market capitalisation. The second issue surrounding the ALSI is that it is not completely investable as it included foreign shareholding of listed companies. These shares are not available to South African investors, therefore making it a constrained comparison.

This section compares the four alternative equity benchmarks and determines whether utilising a different equity benchmark as the market portfolio has any effect on the persistence of the Low Beta Anomaly.

4.4.1 Top 5 Constituents

The section below evaluates the composition of each Index and the amount of market concentration that exists within each index. However, as the EWMP equally weights all the shares on the JSE at the specific time, it will not have top 5 constituents. Therefore EWMP is not included in this specific analysis.

Table 11: Top 5 Constituents of the ALSI (J203), December 2014

Share	ALSI
SABMiller	9.1%
BHP Billiton	8.8%
Naspers	8.7%
Richemont	7.3%
Anglo American	5.9%
Total	39.9%

Source: FTSE Fact Sheet- ALSI February 2015

The ALSI has the highest concentration risk of the three indices with the top 5 constituents making up approximately 40% of the total index.

Table 12: Top 10 Constituents SWIX, December 2014

Shares	SWIX
Naspers	11.6%
MTN Group Limited	6.8%
Sasol Limited	4.4%
British American Tobacco PLC	3.9%
SABMiller	3.5%
Totals	30.2%

Source: FTSE Fact Sheet SWIX February 2015

The SWIX reduces the concentration risk as the top 5 constituents only make up 30% of the total index. The constituents are different from the ALSI with Naspers taking the top position and Steinhoff, FirstRand and Remgro being included and Richemont, Old Mutual, Anglo American and BHP Billiton being excluded. Therefore the concentration in resource shares is decreased in the SWIX index.

Table 13: Top 10 Constituents CAPI (All share), November 2014

Share	CAPI
BHP Billiton	9.9%
SABMiller	8.7%
Anglo American	6.5%
Richemont	6.2%
MTN Group	6.0%
Total	37.4%

Source: JSE data, November 2014

The CAPI constituents are similar to that of the ALSI. The CAPI only slightly reduces the concentration risk as the top 5 constituents make up 37% of the index.

Overall the SWIX down-weighted dual listed shares which resulted in a reduction in weights of SAB Miller, Anglo American and total exclusion of Richemont and BHP Billiton. The weightings of Naspers, MTN, Sasol, Standard Bank increased by 2.9%, 1.7%, 1.1% and 0.9% respectively. The weightings of the CAPI are similar to that the ALSI with the greatest difference being the cap of 10% which none of the shares in the ALSI exceeded.

4.4.2 Performance of the Indices

Figure 18 below show the performance of the four equity benchmarks over the last 10 years (2004-2014). The ALSI has marginally outperformed both the SWIX and the CAPI over the last 10 years. Before 2007, the EWMP outperformed the other three indices. However, after 2007 until the end of the period the EWMP significantly underperforms the other three benchmarks. Figure 18 illustrates that the SWIX and EWMP outperformed both the ALSI and CAPI during the first few years of the test period from 2004-2008, however all four equity benchmarks fall significantly during the global financial crisis. With regards to downturns, the ALSI seems to be more volatile experiencing higher highs and lower lows compared to the CAPI and SWIX. The ALSI, SWIX and CAPI returns seem to follow the same pattern with no great deviations from one another. Conversely, EWMP seems to deviate significantly from the group after 2009.

Figure 18: Cumulative Excess Returns ALSI, SWIX and CAPI Indices and the EWMP, 2004-2014

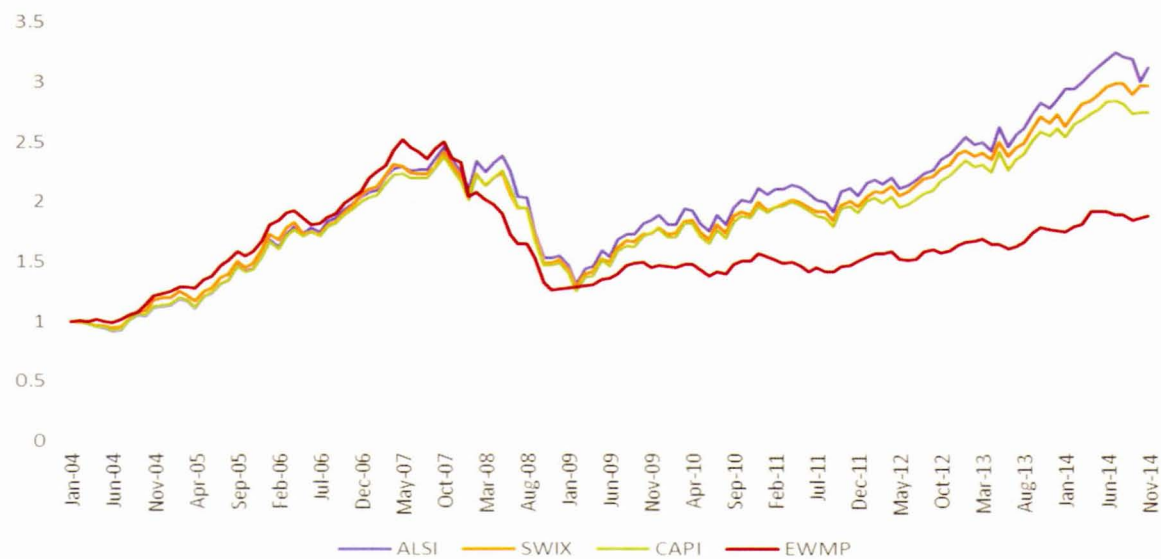
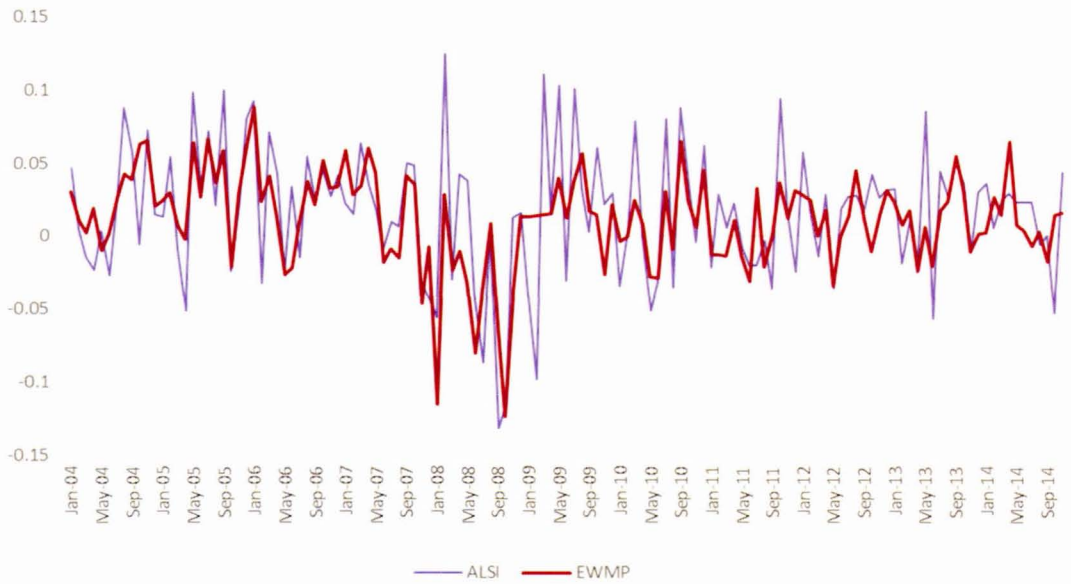


Figure 18 provides a comparison between the ALSI and the EWMP returns. EWMP seems to experience similar movements as the ALSI, however there seems to be a lag with the EWMP

returns, whereby its experience upward/ downward movements later than the ALSI. EWMP seems sensitive to downward pressure, as it has greater downturns than the other three equity benchmarks. The next section will evaluate whether the Low Beta Anomaly exists when using the four alternative benchmarks as the market portfolio.

Figure 19: Return Series of the ALSI and EWMP for the period 2004-2014



4.4.3 Low Beta Anomaly Analysis

As mentioned beforehand, the test period for this section is significantly shorter than the rest of the study due to the CAPI and SWIX only being introduced onto the JSE in 2003. Therefore, the results from this section should be analysed with this in mind.

Table 14 to

Table 17 report the excess returns of each beta quintile for the respective equity benchmarks.

Firstly it is interesting to note, during the specific time frame, the Low Beta Anomaly does not seem strong compared to earlier in the period i.e. 1994 to 2008. Similar to the results in Section 5.1, Panel A of

Table 14 reports that the lowest beta portfolio has the highest average excess return, the lowest standard deviation resulting in the best Sharpe ratios among the beta quintiles. Panel B of

Table 14, similarly shows the tracking error is the lowest for the second highest beta portfolio. Indicating the outperformance of the low beta portfolio over the high beta portfolio.

Table 14: Annualised Returns by Beta-Sorted Quintile, ALSI 2007-2014

	Low	2	3	4	High
Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	1.24%	1.19%	2.90%	-0.36%	-4.04%
Standard Deviation (%)	12.38%	12.23%	13.39%	14.22%	18.54%
Sharpe Ratio	0.100	0.097	0.217	-0.025	-0.218
Panel B: r_p-r_m					
Average r_p-r_m (%)	1.30%	1.25%	2.97%	-0.30%	-3.98%
Tracking Error (%)	14.69%	14.86%	13.76%	11.53%	13.41%

Information Ratio (%)	0.089	0.084	0.216	-0.026	-0.297

Panel A in Table 15 and 16 report the excess returns of each beta quintile, compared to the results in

Table 14 panel A (i.e. ALSI), the difference between the lowest beta portfolio average return is 0.94% and 0.12% for the SWIX and CAPI respectively. An Interesting result is that the low beta portfolio is not the best performer, portfolio 3 seems to be the best performer with regards to raw and risk adjusted returns across all three equity portfolios.

With regards to the SWIX, portfolio beta 4 and 2 both have superior average returns than the lowest beta portfolio for both risk free adjusted and when taking into consideration the market return.

Table 15: Annualised Returns by Beta – Sorted Quintiles, SWIX Index, 2007-2014

	Low	2	3	4	High
Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	0.30%	1.35%	2.34%	0.50%	-3.61%
Standard Deviation (%)	12.31%	14.19%	12.92%	13.79%	16.48%
Sharpe Ratio	0.024	0.095	0.181	0.036	-0.219
Panel B: r_p-r_m					
Average r_p-r_m (%)	1.27%	2.32%	3.31%	1.47%	-2.63%
Tracking Error (%)	12.97%	12.81%	11.81%	9.08%	11.84%
Information Ratio (%)	0.098	0.181	0.280	0.162	-0.222

Panel A in Table 16 reports the excess returns of the beta quintiles when CAPI used at the market portfolio. The high beta portfolio is the worst performing portfolio, similar to the findings of the other two equity benchmarks. Across all three equity benchmark analysis, portfolio 4 has the highest standard deviation and the lowest tracking error compared to the other portfolios.

Table 16: Annualised Returns by Beta-Sorted Quintile, CAPI Index 2007-2014

	Low	2	3	4	High
Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	1.12%	1.18%	2.45%	-1.26%	-2.64%
Standard Deviation (%)	12.27%	12.42%	12.89%	13.85%	18.77%
Sharpe Ratio	0.091	0.095	0.190	-0.091	-0.141
Panel B: r_p-r_m					
Average r_p-r_m (%)	2.62%	2.68%	3.95%	0.24%	-1.14%
Tracking Error (%)	13.90%	13.81%	12.35%	10.55%	12.91%
Information Ratio (%)	0.189	0.194	0.320	0.023	-0.088

Table 17 below reports the results of the annualised returns when using EWMP as the market proxy. The high beta portfolio underperforms the low beta portfolio but only by a factor of 1.2 when analysing cumulative returns. This is almost half the differential factor experience when ALSI is the equity benchmark. Illustrating a slight reduction in the magnitude of the Low Beta Anomaly. Similar to the other equity benchmarks, portfolio 3 has the high annualised excess return. An interesting result with regards to the EWMP is the tracking error, all results up to this point have resulted in the low beta portfolio having the highest tracking error. However, when using the EWMP the opposite occurs, whereby high beta has the highest tracking error.

Table 17: Annualised Returns by Pre Ranking Beta-Sorted Quintile for EWMP, 2007-2014

	Low	2	3	4	High

Panel A: r_p-r_f (%)					
Average r_p-r_f (%)	1.05%	1.16%	2.10%	-2.81%	-1.27%
Standard Deviation (%)	13.97%	11.87%	12.99%	13.30%	13.66%
Sharpe Ratio	0.075	0.098	0.162	-0.211	-0.093
Panel B: r_p-r_m					
Average r_p-r_m (%)	0.99%	1.10%	2.04%	-2.87%	-1.33%
Tracking Error (%)	11.85%	12.29%	12.99%	14.73%	17.10%
Information Ratio (%)	0.083	0.089	0.157	-0.195	-0.078

Figure 19, 20, 21 and 22 illustrate the cumulative returns of the five beta portfolios for the four different equity benchmarks. The average excess return differential between the lowest beta portfolio and the highest beta portfolio for ALSI, SWIX, CAPI and EWMP indices were 0.44%, 0.33%, 0.31% and 0.22% respectively.

Figure 20: Cumulative Returns for All Share Index, 2007-2014

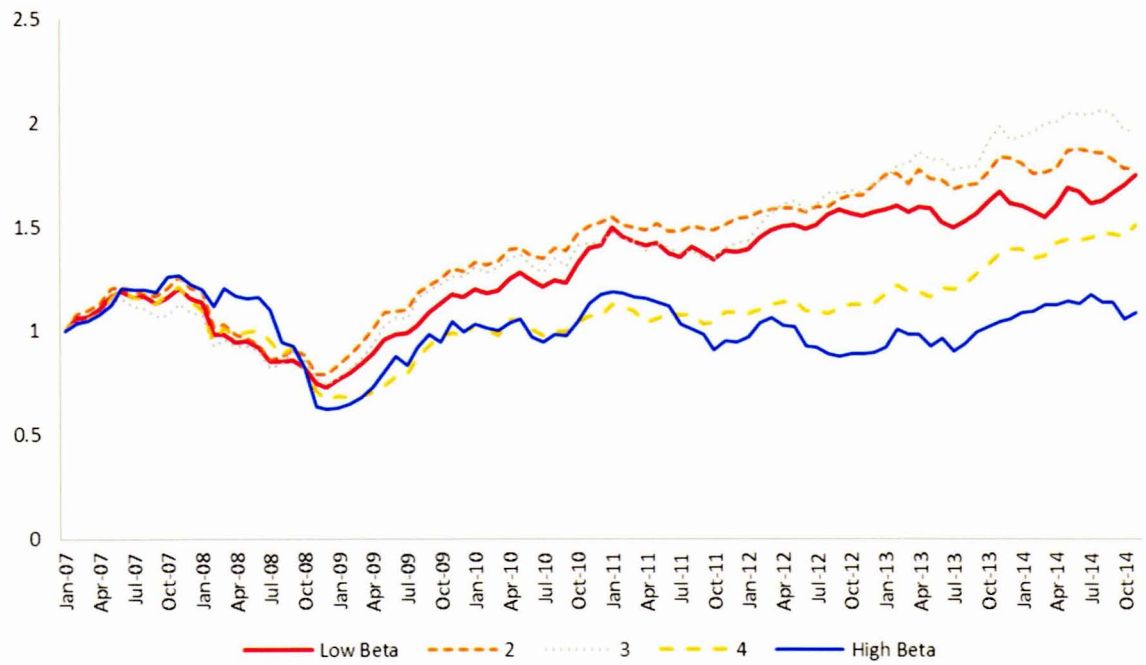


Figure 21: Cumulative Returns for SWIX Index, 2007 – 2014

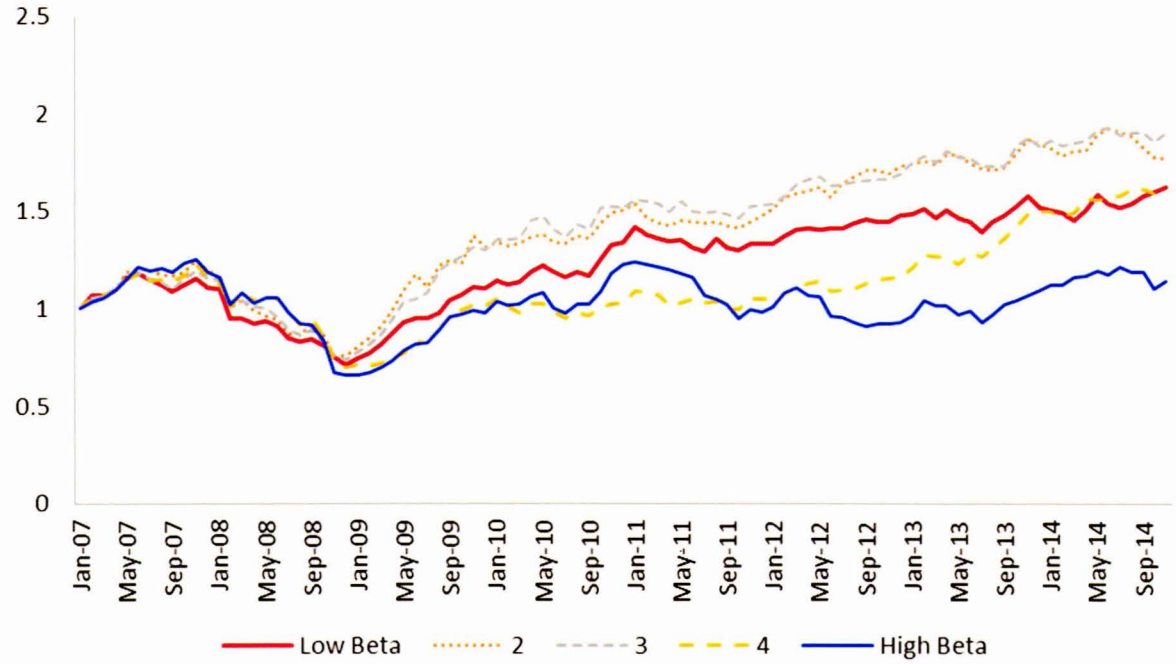


Figure 22: Cumulative Return for CAPI Index, 2007 - 2014

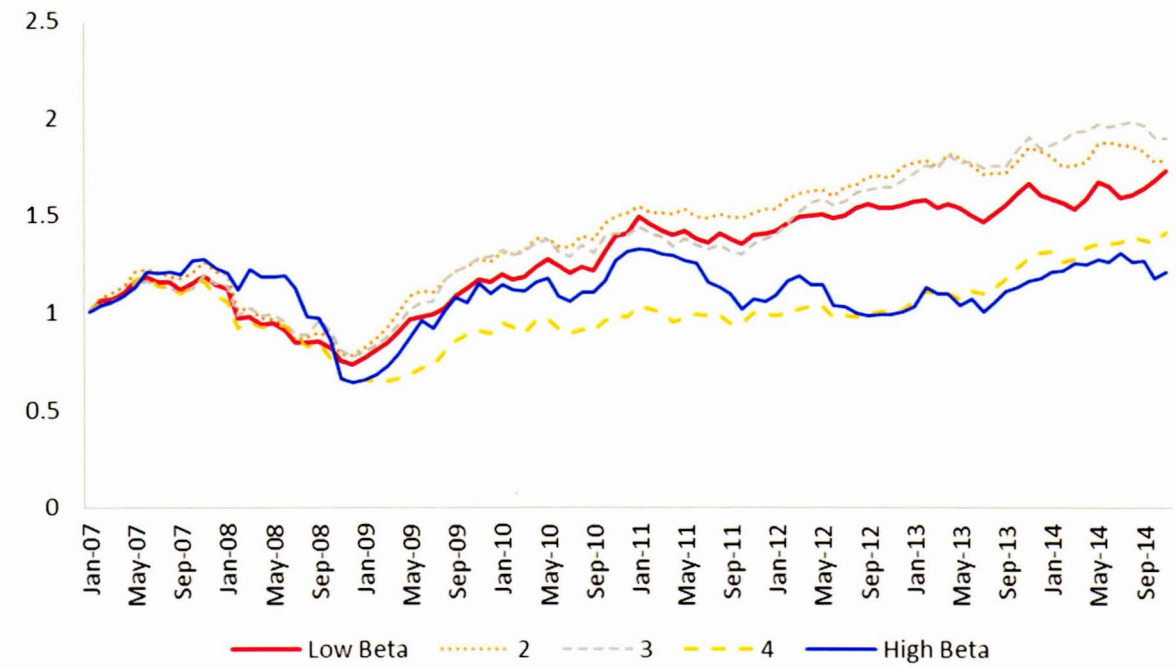
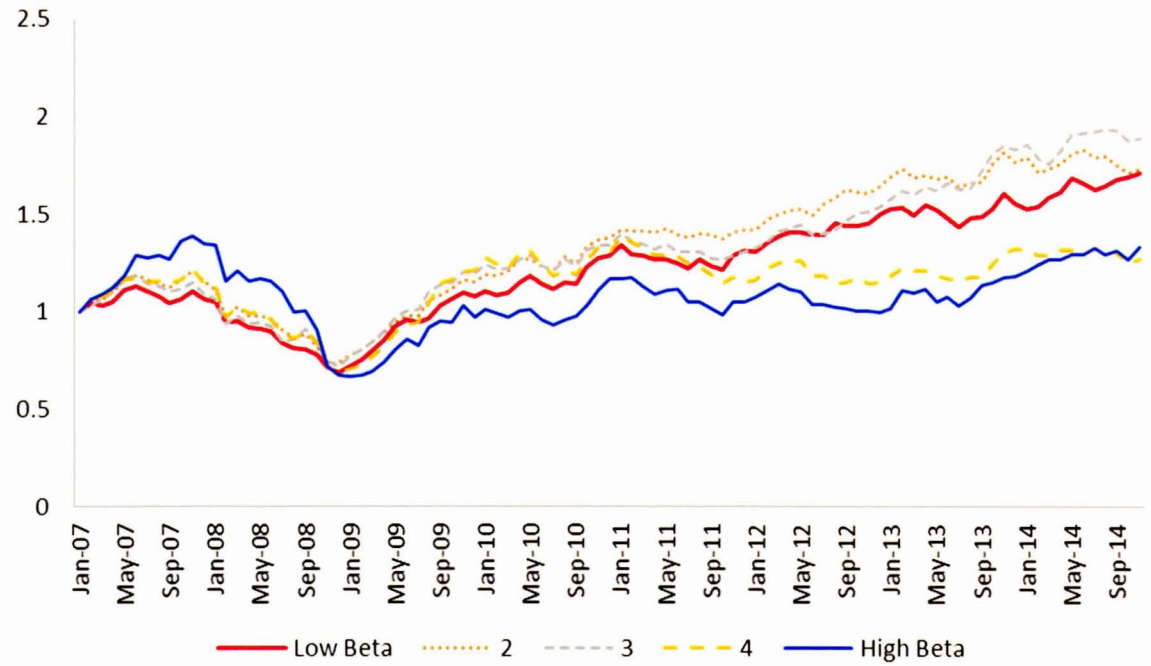


Figure 23: Cumulative Return for EWMP, 2007 - 2014



Studying the cumulative returns of the beta portfolios for the various equity benchmarks, the ratio of the low beta portfolio to high beta portfolio decreases however the reduction is greater for EWMP. The low beta portfolio outperforms the high beta portfolio by a factor of 1.6, 1.5, 1.4 and 1.3 for the ALSI, CAPI, SWIX and EWMP respectively. The use of different equity benchmarks (other than the ALSI) does lead to a reduction in the magnitude of the superior performance of the low beta portfolio. However when studying these results one needs to remember that the outperformance of the low beta portfolio is significantly smaller during the short period of this test (2007-2014). The results of the alternative benchmarks suggest that market concentration risk does not explain the Low Beta Anomaly.

The next section summaries the findings of this study as well as highlights the studies limitations and provides recommendations for future research.

5. Conclusion

The basic risk-return relationship has received an overwhelming amount of attention in the past few decades. Evidence is mixed regarding the relationship that forms one of the basic principles of the finance theory. Whereby investors expect higher return for taking on additional risk. This research focuses on the relationship between market risk and return.

The phenomenon that low beta shares outperform high beta shares has become known as the Low Beta Anomaly. There is a vast amount of studies suggesting that this anomaly exists across international markets including Baker *et al.* (2011), Baker and Haugen (2012), Blitz *et al.* (2012) and Franzzini and Perdersen (2011). The existence of the Low Beta Anomaly has not been extensively researched within the South African context. However, a few papers do exist highlighting this phenomenon including Van Rensburg and Robertson (2003a), Strugnel *et al.* (2011) and McClelland (2013).

In this research the Low Beta Anomaly using South African data is analysed. The relation between market risk and excess returns on the JSE for the period 1992-2014 is investigated. By utilising the mimicking portfolio methodology employed by Fama and French (1993), it is evident that in accordance to the internationally documented outperformance of low beta shares relative to high beta shares is present on the JSE. An interesting finding of this research is that high beta shares tend to outperform low beta shares in during turbulent market conditions such as the internet bubble during the 1999 and the Global Financial Crisis starting in 2008, this in line with many papers suggesting behavioural biases as a explanation for the Low Beta Anomaly.

Three potential explanations with regards to the Low Beta Anomaly were examined within this research. The first explanation was that of Net International Equity Flows. Whereby foreign investors overweight high beta shares relative to low beta shares due what has been termed "return chasing" behaviour (Bohn & Tesar, 1996). This is when foreign investors are bullish about a market that has high returns, they then invest in high beta shares in search of greater returns, but withdraw when returns decrease. This results in price overreaction. A positive relationship was found between NIEF and the LMH beta differential indicating that when foreign investors increase their investment in the JSE, it exacerbates the superior performance of the low beta shares. However, the ability of NIEF to explain the LMH beta

differential is limited therefore indicating the existence of other risk factors that lie behind the Low Beta Anomaly.

The second explanation explored, was the existence of an idiosyncratic risk factor. According to finance theory behind CAPM, the only risk priced is systematic risk as idiosyncratic risk can be diversified away. However, in reality it has been found that it is difficult for an investor to fully diversify their portfolio. The empirical evidence surrounding the idiosyncratic volatility puzzle is mixed, with academics finding a positive, negative and even a flat relationship between IdR and return. This research analysed two measures of IdR, one measure is IdR calculated using the CAPM model and the other measure is IdR calculated using the FF3 Factor Model. The results were mixed depending on the measure of IdR, as the IdR calculated using CAPM resulted in low IdR shares outperforming high IdR shares. This is in line with papers such as Ang *et al.* (2009). However, when using IdR calculated using the FF3 Factor Model, the high IdR shares outperformed the low IdR shares, and this result is in line with Malkiel and Xu (2002). After adjusting the shares returns for IdR and reforming the pre-ranking beta portfolios. The low beta portfolio outperformed the high beta portfolio by a factor of 2.2 and 2 for the IdR CAPM measure and IdR FF3 measure respectively. An interesting result regarding the IdR adjustments, is that the high beta portfolio outperformed the low beta portfolio during the bear market condition of the Internet bubble, however this outperformance of the high beta portfolio relative to the low beta portfolio no longer existed during the Global Financial Crisis.

The last explanation that was tested was the effect of market concentration. The JSE has been characterised as being highly concentrated in terms of resource shares. This is evident as out of the top 5 constituents of the ALSI, three of the shares are resource based, and make close to 40% of the total Index. Three other equity benchmarks were used as market proxies to determine the effect of market concentration on the existence of the Low Beta Anomaly. The SWIX, CAPI and an equally weighted market portfolio were used as they alternative equity benchmarks. Although the CAPI adjusts the weightings of shares to below 10%, the results were very similar to that of the ALSI. The SWIX experienced similar market movements as the ALSI, however, resulted in the low beta portfolio outperforming the high beta portfolio by a factor of 1.4 which is less than both the ALSI and CAPI of 1.6 and 1.5 respectively. The EWMP outperformed the other three equity benchmarks up until 2007, after which it significantly

underperformed. The use of EWMP resulted in the low beta portfolio outperforming the high beta portfolio by a factor of 1.3. Which is the lowest throughout the entire research. However, an important limitation regarding the market concentration analysis is that it is only over a 10 year period due to the SWIX and CAPI being introduced onto the JSE at the end of 2003.

It is evident that the Low Beta Anomaly exists on the JSE. However, future studies are required to investigate the true source of economic risk or any other risk factor that lies behind the phenomenon causing low beta shares to have higher expected returns relative to high beta shares.

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